Taxes and the Global Spillovers of AI Investments*

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Abstract: Artificial Intelligence (AI) is transforming businesses and the technological frontier, yet cross-border spillovers remain understudied. Using a novel panel dataset, we find that AI investment strongly propagates internationally in the form of growth in foreign subsidiaries' assets, employment, and revenues. We construct a measure of European country-industry exposure to U.S. firms' AI investments and document significant spillovers of U.S.-originating AI investment into European industries. However, these effects vary with local tax policies: European countries with attractive R&D tax incentives experience faster, larger AI-driven growth, while low corporate tax rates further amplify revenue spillovers. To test the mechanisms behind these results, we exploit variation within U.S. firms across their foreign subsidiaries. Spillovers occur because U.S. firms not only expand capital inputs and output, but also increase their labor productivity, R&D activities, and market presence, particularly in foreign markets with attractive corporate tax regimes, following AI adoption. Our findings highlight the role of fiscal policy in shaping AI diffusion and offer new insights into how digital-era investments influence global economic growth.

Keywords: AI investment; intangible assets; growth; tax policy; tax competition; real effects of taxation

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1 Introduction

Since 2012, Artificial Intelligence (AI) has rapidly emerged as a new general purpose technology, reshaping business models, industries, and both domestic and global markets (Agrawal et al., 2019). Anecdotal and empirical evidence suggests that U.S. firms are making substantial investments in AI technologies, which have immediate and significant effects on firm growth in the U.S. (Furman and Seamans, 2019; Babina et al., 2024*a*; Rattner and Dean, 2025). However, less is known about how these AI-driven investments spill over into foreign markets. Recent policy events, such as the AI Action Summit in February 2025 held in Paris, demonstrate that the potential of U.S.-originating AI investments to influence foreign markets is a critical question given AI's potential to influence global competition, economic growth, and inequality (Agrawal et al., 2019; Reuters, 2025).[1]

In this paper, we investigate how U.S. firms' AI investments affect foreign markets and explore whether a country's tax environment—a key determinant of foreign investment—shapes how the U.S. firm's AI investments affect corporate investment, employment, and output abroad. We focus on geographic spillovers[2] of AI investments: what happens abroad when U.S. industrial firms across various sectors invest in AI capabilities to enhance their existing business models? This is a potentially potent transmission channel of AI-related economic effects because multinational firms are key drivers of global trade, with a significant portion of trade occurring within firm boundaries (Antràs and Yeaple, 2014; Cravino and Levchenko, 2017). Beyond the eco-

[1] For instance, at the AI Action Summit in Paris, U.S. Vice President JD Vance noted in his speech: "*The United States of America is the leader in AI and our administration plans to keep it that way.*". Furthermore, AI-related investments by U.S. firms are seen a key driver of economic growth in Europe, and policymakers hope for effects on *local* economic growth associated with these investments. For instance, see Microsoft's announcement to invest in Germany (Reuters, 2024).

[2] For the purpose of our study, we define a *geographic spillover* as a measurable effect on economic outcomes in foreign markets resulting from an AI investment made by a firm within the U.S.. In our data, such an investment by U.S. firms is proxied by the hiring of AI-skilled workers, following Babina et al. (2024*a*). We measure geographic spillovers by examining the relationship between economic outcomes in foreign markets and U.S.-originating AI investment in prior years. We acknowledge that some spillovers occur within firm boundaries, which may not necessarily be classified as pure spillovers (i.e., a U.S. firm's foreign, majority-owned subsidiary increases investment after the U.S. firm invests in AI). Our analysis explicitly distinguishes between within-firm spillovers and spillovers onto peer firms, both of which impact aggregate effects in the broader economy.

nomic significance of AI adoption within corporations, our research questions are motivated by two important but unexplored factors, both stressed in Goldfarb and Trefler (2019). First, while AI is expected to reshape international trade patterns, the extent and nature of these effects remain understudied, leaving first-order economic policy questions unanswered. Second, governments may consider tax incentives to particularly attract AI-related investments, given their potential multiplier effects on growth.

The unique characteristics of AI—including its remote deployability, intangibility, and scalability—may alter firms' responses to tax incentives compared to other technologies or traditional investments like capital expenditures (capex), which depend on physical infrastructure, past fixed capital, and existing supply chains. While non-AI investments can generate international spillovers, AI-related spillovers are distinct as firms adopting AI often undergo fundamental shifts in business models and investment strategies. Consequently, firms' global capital allocation and output decisions following AI investments may be more flexible and rely heavily on intangible value creation, potentially making their tax responsiveness particularly high (e.g., Dischinger and Riedel, 2011; Akcigit and Stantcheva, 2022).

In brief, our study provides the first large-scale empirical evidence that U.S. corporate AI investments generate distinct foreign spillovers on the European economy. Following AI investment at the U.S. parent firm level, foreign subsidiaries increase capital input and output, ultimately contributing to aggregate industry-level growth in European countries. Compared to traditional corporate investments, these spillovers are large and especially pronounced in European countries with favorable corporate income and R&D tax incentives.

For our analyses, we construct a novel panel dataset by combining data on AI investments from nearly 2,000 U.S. firms from Babina et al. (2024*a*) with economic outcomes from these firms' more than 40,000 subsidiaries across multiple European countries and industries. The AI investment data captures the AI-skilled human capital of U.S. industrial firms in both the software sector and many other industries. An example from our sample is the pharmaceutical firm Johnson & Johnson, which increased

its AI-skilled workforce from 24 employees in 2010 to 132 in 2021. At the same time, the company has developed AI tools to enhance customer experiences, retention, and R&D.[3] Annual reports from Johnson & Johnson's German subsidiary further suggest that a significant portion of this R&D occurs in European countries (Johnson & Johnson Medical GmbH, 2019). This example aligns with recent case-specific research (Furman and Seamans, 2019; Brynjolfsson et al., 2025) and the consistent cross-industry results in Babina et al. (2024*a*), both of which indicate that firms can increase productivity and growth by enhancing existing business models through AI adoption. Moreover, this case is representative of our broader sample of industrial firms enhancing their AI capabilities, as 89% of the U.S. firms' subsidiary observations come from industries outside the information and telecommunication sector. Consequently, we expect AI spillovers on foreign economic outcomes to arise primarily from product innovations and efficiency gains driven by AI-related technological advances applied across U.S. industrial firms since 2012, rather than being confined to AI-technology leaders or the large-scale language models that saw mass adoption after 2021.[4]

Our data show that U.S. firms with an operational footprint in Europe have significantly increased their AI investments—measured by the number of newly hired employees in AI-related roles—over the past decade. Specifically, we observe that in 2010, U.S. firms with subsidiaries in Europe employed fewer than 10,000 AI-related workers. By 2018, this number had risen to nearly 60,000– a substantial increase in the exposure of U.S.-owned European subsidiaries to in-house AI investments within their multinational firms. Notably, this growth has outpaced the firms' overall growth, as evidenced by an increasing share of AI employees relative to total employees (Figure 1).

However, how and the extent to which AI-related investments of U.S. firms affect foreign markets is an open empirical question. On one hand, AI investments may gen-

[3]For example, in 2018, the firm had launched a customer service which they framed as *a new, cutting-edge tool and app, you can scan and analyze your skin in just a few minutes to get real-time information about everything from moisture levels to the state of your pores—without having to leave the house.* For details, see the firm's website at https://www.jnj.com/tag/artificial-intelligence.

[4]This mechanism differs from the effects of sudden technological breakthroughs, such as the development and deployment of entirely new AI products like OpenAI's ChatGPT, which, notably, was launched after our sample period in 2022.

erate a scale effect, where firms expanding AI capabilities in the U.S. also experience growth in their foreign subsidiaries. On the other hand, AI-driven innovation could lead to more localized expansion within the U.S. due to a lower cost of production domestically, potentially limiting or even reducing growth at foreign subsidiaries. Even if U.S. AI investments generate positive spillovers abroad, the role of tax policy in shaping these effects remains uncertain. Unlike traditional investments, which are strongly influenced by tax incentives (e.g., De Mooij and Ederveen, 2003), AI technologies can be deployed remotely and are less dependent on a physical presence in foreign markets. As a result, it is unclear whether AI-driven growth necessarily expands the assets and tax bases that make tax incentives effective in foreign markets—unlike scenarios where firms expand their physical infrastructure, such as through new production plants. However, if AI investments drive follow-on R&D and business model expansion as suggested in Babina et al. (2024*a*) and anecdotal examples, these activities can occur globally. As a result, R&D tax incentives and low corporate tax rates can significantly impact the after-tax profitability of U.S. firms' operations following AI investment.

Our analysis proceeds in three steps. First, we examine the correlation between U.S. firms' AI investments and the subsequent growth of their European subsidiaries' total assets, employment, and revenues. Examining these outcomes to capture a broad set of capital inputs and outputs, we find that U.S. firm investment in AI strongly predicts subsidiary growth, with particularly pronounced effects on total assets, which can be considered as a broad proxy for investment.

Our second and main set of tests examine whether this within-U.S. firm foreign expansion generates significant spillovers in foreign markets. To this end, we examine aggregate European country-industry level outcomes and employ a Bartik-style shift-share design leveraging ex-ante variation across European country-industries exposure to U.S. firms that eventually invest in AI. Specifically, our exposure measure captures the relative presence of U.S.-owned subsidiaries in a given European country-industry as of 2010, ensuring that treatment intensity is predetermined and not driven

by contemporaneous shocks.[5] The shift is given by changes in U.S. firms' AI investments, which are arguably influenced by factors such as domestic technological advances and firm-wide strategic considerations rather than local economic conditions in specific European markets. We further interact this instrument with country-level tax policy variation, exploiting differences in R&D tax incentives and corporate tax rates across countries to assess how fiscal environments mediate AI spillovers. By including industry-country and country-year fixed effects, we ensure that identification relies solely on within-industry variation in AI exposure over time, rather than being influenced by persistent industry characteristics or broader country-level policy and macroeconomic trends. To address the remaining empirical challenge—that our exposure measure could be correlated with the same country-industries' exposure to U.S. firms' general growth or investments in other technologies that co-move with AI investments and aggregate economic outcomes—we enhance our specification by including analogous measures of exposure to U.S. firms' total U.S. (non-AI-specific) employment and worldwide capital expenditures (capex), a widely used proxy for traditional corporate investment (e.g., Bakke and Whited, 2010; Becker et al., 2013).

We find that country-industries with greater exposure to U.S. firms' AI investments experience substantial growth in total assets and revenue, but show a weaker, mostly insignificant response in employment. We also show that the tax environment in foreign markets significantly shapes the magnitude of these foreign spillovers of AI investment originating in the U.S., although we do not observe a differential effect for employment. Specifically, countries with lower tax burdens on R&D-related activi-

[5]Our measure captures the exposure of European country-industries to U.S. AI investment. For country c, industry i, and year t, the instrument is constructed as follows: $U.S.\ AI_{c,i,t-1} = \frac{\sum_{f=1}^{F}(U.S.\ Subs_{f,c,i,2010} * AI\ Empl._{f,t-1})}{\sum_{f=1}^{F}(MNE\ Subs_{f,c,i,2010})}$. Consequently, we interact the relative share of U.S. firm-controlled subsidiaries relative to all multinational firm subsidiaries in a given European country-industry with a time-varying variable that captures U.S. firms' investment in AI as measured in Babina et al. (2024*a*). The underlying intuition is that the greater the presence of U.S. firms in a given country-industry, the more likely it is that U.S. AI investments influence aggregate economic outcomes. Similarly, the intensity of AI investment, measured as the number of U.S. parent firm-level AI employees of U.S. subsidiaries, determines the extent of these effects. To ensure that U.S. subsidiary presence in a country-industry, as well as subsidiaries' economic outcomes, are not endogenously influenced by contemporaneous AI investment decisions, we use time-invariant shares of U.S.-owned subsidiaries relative to all foreign-owned subsidiaries as of 2010, the start of our sample period.

ties as well as lower corporate income tax burdens overall attract significantly more AI-driven growth in total assets. These effects are particularly pronounced in countries with generally favorable tax regimes, including low corporate income tax rates and broader incentives for business investment. Notably, while R&D-specific tax incentives primarily attract spillovers on investment, low overall tax rates appear to additionally influence the allocation of taxable income, as reflected in stronger effects on aggregate revenues relative to assets and employment. These results are specific to the spillovers of AI investments, as we find economically and statistically insignificant—or significantly weaker—effects for European country-industries' exposure to U.S. firms' overall U.S. employment or worldwide capex growth.

Third, we explore the mechanisms behind foreign AI investment spillovers by analyzing how AI investments affect European subsidiaries of the same U.S. firm in the same year, conditional on local tax incentives. These within-firm-year tests show that spillovers are driven by U.S. firms expanding assets, employment, and revenue at subsidiaries in European countries with favorable tax environments. Supplemental tests further suggest that increases in foreign R&D activities, labor productivity, and U.S. firms' European market presence—proxied by a larger number of operating entities following AI investments—likely contribute to these spillovers. Taken together with the aggregate-level tests, these findings indicate that firms are particularly responsive to foreign tax incentives when deciding where to expand following AI adoption.

In terms of magnitudes, our results indicate economically meaningful effects. On average, a one-standard deviation increase in the share of U.S. firms' AI-related employees relative to total employees in the U.S. is associated with a 4.5%, 2.1%, and 1.5% increase in the total assets, employment, and revenues of their European subsidiaries, respectively. At the European country-industry level, a one-standard deviation increase in exposure to U.S. AI investment leads to 5.9% growth in aggregate total assets and a 3.7% increase in revenues, respectively, while the average effect on employment is inconclusive. For the average European country-industry, these estimates suggest that aggregate total assets, often considered a proxy for overall corporate in-

vestment, increase by approximately 4 billion USD due to AI investments originating in the U.S.. Importantly, these effects mostly represent spillovers of U.S. AI investment onto foreign markets through the U.S.-controlled subsidiaries, as the aggregate results are smaller and statistically less significant when excluding U.S. AI firm-owned subsidiaries from the aggregated data. Regarding the role of tax incentives in attracting U.S. AI-related investment that generates domestic industry-wide growth, we also document economically very meaningful results. Specifically, in countries with attractive R&D tax regimes, spillover effects on the total assets of firms in the European country-industries are approximately 1.7 times stronger, and they are more than three times stronger in environments with attractive R&D tax regimes and relatively low corporate income tax burdens.

Regarding the mechanisms, our findings support the notion that market expansion, greater efficiency, and innovation within U.S. firm boundaries drive these aggregate spillovers in tax-attractive European countries. Specifically, we document that a one-standard-deviation increase in AI investment within a U.S. firm is associated with 4.4%, 3.1%, and 4.9% greater growth in the total assets, employment, and revenues of its European subsidiaries, respectively, when these subsidiaries are incorporated in countries with attractive R&D tax incentives and low corporate income tax burdens. Moreover, in European countries with such attractive tax environments, U.S. AI firms' subsidiaries experience a 5.8% greater increase in labor productivity compared to those in other European countries, and U.S. firms expand their presence by 1.8% more subsidiaries in tax attractive countries, respectively. For a small subsample with available R&D expenditure data, we find evidence that U.S. firms' subsidiaries significantly expand local R&D activities as their parent firms increase AI capabilities. These effects are particularly responsive to R&D tax incentives in European countries.

In supplemental analyses, we further explore the dynamics underlying our main results by estimating several (long)-differences specifications. Consistent with the finding that the impact of AI investment on firms' overall sales and employment unfolds gradually (Babina et al., 2024*a*), we find robust evidence of international spillovers

emerging with a two-year lag. These effects become stronger as we extend the period over which we measure changes in AI exposure and economic outcomes, but notably, they remain concentrated in countries with favorable tax regimes. Additional tests confirm that our results are not driven by secular industry trends or the influence of individual sample countries. While we acknowledge that the variation in tax policies we exploit may be correlated with other country-level factors influencing industry-wide outcomes, our inclusion of country-year fixed effects ensures that any such factor would need to systematically affect outcomes conditional on a country-industry's specific exposure to U.S. firms' AI investment. Taken together, our comprehensive set of analyses corroborate the inference that U.S. AI investments generate significant economic spillovers into European markets, but primarily in countries where corporate tax regimes support a high after-tax return on follow-on investment and profits.

This paper contributes to the emerging literature on the economic effects of AI by providing new evidence on the propagation and spillover effects of AI investments across borders. Existing research has documented that firm-level investments in AI capabilities via the workforce are followed by increases in firm-wide sales and market valuation (Babina et al., 2024*a*; Eisfeldt et al., 2023; Babina et al., 2024*b*). Another emerging strand of literature examines the effects of AI adoption on within-firm efficiency gains and workforce composition (Brynjolfsson et al., 2025; Babina et al., 2023; Abis and Veldkamp, 2024). However, less is known about how these effects extend beyond the investing firms and their domestic economies. By demonstrating that AI-related firm expansion in the U.S. generates significant growth in foreign subsidiaries and spills over into broader country-industry outcomes in Europe, our findings inform some of the open questions on how AI impacts growth (Aghion et al., 2019). Our results complement recent work on the diffusion of new technologies (Kalyani et al., 2024), highlighting that AI investments do not remain confined to the firms making them but instead contribute to wider economic growth—though the extent of this diffusion varies with local institutional factors.

By showing how fiscal incentives shape the spillovers from AI investment, our study

also advances the literature on the effects of tax policy on foreign investment and economic growth. Prior research has established that tax incentives play a crucial role in attracting capital investment and fostering innovation (e.g., Lester and Olbert, 2024; Djankov et al., 2010; De Mooij and Ederveen, 2003; Chen et al., 2023; Akcigit and Stantcheva, 2022; Akcigit et al., 2021). However, given AI's distinct characteristics—particularly its scalability, reliance on intangible assets, and remote deployability—it remains unclear whether existing tax policies that target tangible local investment meaningfully influence AI-driven spillovers. Our findings provide new evidence that R&D tax incentives and low corporate income tax rates enhance the diffusion of AI-driven investment abroad. The effects are particularly strong for revenue expansion, which is likely contributing to tax base growth, at least in the longer run.

We also offer a fresh perspective on the emerging literature on local (labor) market effects of tax policy (e.g., Suárez Serrato and Zidar, 2016), particularly how multinational firms act as channels for global resource allocation (Cravino and Levchenko, 2017; Hoopes et al., 2023). By showing that U.S. AI investments not only impact foreign subsidiaries but also spill over into broader industry-level growth, we provide new evidence on the role of tax incentives in shaping these dynamics. Moreover, our findings connect to the broader literature on spillover effects from within-firm productivity gains, demonstrating how AI adoption by U.S. firms propagates beyond the investing firms themselves, influencing firms within the same industry and across borders (Giroud et al., 2024). These insights contribute to the debate on how tax policy can facilitate technology-driven economic development in an increasingly digital and globalized economy.

2 Data

2.1 AI Investment Measure

Our analysis relies on the firm-level AI investment dataset compiled by Babina et al. (2024*a*) for U.S. public firms. Recognizing that AI adoption is primarily driven by human capital, Babina et al. (2024*a*) proxy for AI investment by measuring the prevalence

of AI workers in each firm and year based on a novel data-driven approach. First, they analyze 180 million job postings provided by Burning Glass to determine the AI-relatedness of specific job skills, based on how frequently these skills co-occur with a set of unambiguous core AI skills. Next, the authors use employee resume data from Cognism, comprising over 535 million individual profiles, to classify employment records according to these AI-related skills. These individual-level employment records are then linked to firms in Compustat via employer names. Finally, individuals in a given firm are deemed AI employees if their job role or description references any AI-related skills as established in the first step or if they have obtained AI-related patents, publications, or awards. Scaling the number of these AI-skilled employees hired in the U.S. by the total number of U.S. employees, Babina et al. (2024*a*) finally derive their main firm-year measure of AI investment at U.S. public firms.

As discussed in detail in Babina et al. (2024*a*), this measure offers advantages over methods that rely on pre-specified keywords to identify AI-related positions. In addition, the measure avoids overstating AI employment by focusing on actual employment records rather than job postings, and it also accounts for acquired AI investment. Babina et al. (2024*a*) conduct multiple validation tests. First, they confirm that AI workers constitute a small fraction of the workforce, consistent with their status as highly skilled and well-compensated specialists. They also document a plausible distribution of AI workers across industries and find that AI investment correlates positively with R&D expenditures. Second, they demonstrate that AI-related skills are correctly identified while excluding broader data-analytic skills. This ensures that the measure only captures AI-specific human capital without inflating it with other IT-related employment.

2.2 Sample Construction

We construct two distinct samples to analyze the spillover effects of U.S. AI investment on Europe, both leveraging that U.S. parent firms operate in Europe through their subsidiaries. We retrieve AI investment data for publicly listed U.S. firms from Babina et al. (2024*a*) as detailed above. This sample is based on the universe of publicly listed

U.S. firms from 2010 to 2021. In this period, Babina et al. (2024*a*) successfully measure AI investment at least in one year for 2,397 unique firms.

Key to our analysis is that we identify the majority-owned European subsidiaries of these U.S. AI firms using annual ownership information from Orbis Generics for the period 2010-2021. We first identify the U.S. publicly listed firms as a business group's parent entity using Bureau van Dijk's (BvD) linking table to map BvD firm identifiers to the U.S. firm's ISINs. We then iteratively loop through direct equity shareholding links to construct a group of subsidiaries controlled by the U.S. firms as in Olbert (2023), Hoopes et al. (2023) and Kaenzig et al. (2023). For 1,898 of the U.S. AI firms, we successfully merge at least one European subsidiary.

To examine the within-firm effects of parent-level U.S. AI investment on European subsidiaries, we complement the ownership ties described above with consolidated financial information on U.S. parent firms from Compustat and unconsolidated financial data on European subsidiaries from Orbis. For our study, we focus on subsidiaries located in the 27 member countries of the European Union (EU-27), as well as Iceland, Liechtenstein, Norway, and Switzerland, which are part of the European Economic Area and/or Free Trade Association (EEA/EFTA), and the United Kingdom, a former EU member state with significant economic ties and regulatory overlap with other European countries. This European setting is unique because widely harmonized and enforced financial reporting mandates allow us to observe high-quality and comparable subsidiary financial outcomes across a representative set of countries (Kalemli-Özcan et al., 2024; Breuer, 2021; Breuer et al., 2025). This is central to our analyses, as these countries form an important part of the global market and exhibit significant intra-firm links to the U.S. as our data show. Furthermore, while these countries share similar policy standards and institutional qualities, as well as harmonized trade and industrial regulations under the EU, EEA, and EFTA, they maintain sovereignty over specific tax policies. This creates tax competition and introduces rich variation for our analysis (Glaeser et al., 2023; Chen et al., 2023). In these countries, we observe non-missing unconsolidated financial information for over 325,000 subsidiary-years per-

taining to 43,000 unique European subsidiaries of nearly 2,000 unique U.S. firms with non-missing AI investment data at least once in the sample period (see Table A-1).

When focusing on the aggregate effects and spillovers on European countries, we construct a country-industry-year level sample. Following prior research using aggregate country-industry data and consistent with aggregation levels of certain administrative data (e.g. Eurostat and OECD data) (Breuer, 2021; Breuer and Breuer, 2022), we use industries defined based on two-digit NACE Rev. 2 codes. The variables of interest are aggregate variables based on all firms operating in Europe for which Orbis provides unconsolidated financial and industry information in their Orbis Generics flatfiles as of 2024 for the financial years 2010-2021. This includes firms belonging to groups of foreign multinational firms, domestic groups, and standalone firms. Using Orbis ownership information, we can, however, identify those European firms that are subsidiaries of U.S. AI-investing parents. Thus, to capture true spillover effects on local peer firms, we additionally construct aggregate variables that exclude these subsidiaries owned by U.S. AI-investing parents. Finally, we complement the country-industry sample with the U.S. AI exposure measure, along with our exposure measures for total U.S. employment and consolidated capex. Our final sample includes 87 unique industries across 31 countries in Europe (in total, 18,486 country-industry-years).

To construct our exposure measures further discussed in Section 3.2 , we rely on additional data on the full universe of foreign-owned subsidiaries incorporated in European countries. While the exposure variables are defined at the country-industry-year level, their construction is based on a more granular dataset with MNE-country-industry-years as unit of observation. Using Orbis data, we identify foreign-held European subsidiaries with industry information of all MNEs globally—not just those from the U.S. For each MNE, we count the number of subsidiaries it owned in each European country-industry in 2010. We then complement the time-invariant subsidiary count data with time-variant U.S. AI investment and total U.S. employment data from Babina et al. (2024*a*), along with information on consolidated capex from Compustat. This allows us to determine for each MNE with foreign-held European subsidiaries (i)

the number of subsidiaries it had in each European country-industry in 2010 and (ii) its yearly U.S. AI investment, total U.S. employment and consolidated capex in the case of U.S. multinational firms.

We complement our samples with information on corporate income tax rates from the Tax Foundation and R&D tax subsidy rates as well as GDP data from the OECD.

2.3 Descriptive Statistics

Our final sample covers 1,898 U.S. firms from the sample of U.S. firms with workers' resume and CV data from Cognism and Burning Glass (Babina et al., 2024*a*), which we successfully merge to at least one European subsidiary with available unconsolidated financial information. 1,160 of these firms have at least one AI-skilled worker during the sample period, as identified in Babina et al. (2024*a*). Table A-1 presents the distribution of U.S. firms' subsidiary-year observations across industries and European countries. In total, our sample comprises 43,049 unique subsidiaries majority-owned by the 1,898 U.S. AI firms. As Figure 1 shows, these U.S. firms collectively employed fewer than 10,000 AI-skilled employees at the beginning of the sample period, increasing to nearly 60,000 by the end. Notably, this growth reflects a relative increase in AI-skilled labor compared to total employment, thus AI-related investment growth is distinct from general firm expansion.

The heatmap in Panel A of Figure 2 shows the cross-country distribution of the aggregate number of AI-skilled employees of U.S. firms with at least one subsidiary in a given European country as of 2021. The figure provides suggestive evidence that U.S. AI investment may have significant impacts across many European countries. For example, the aggregate number of AI-skilled employees in 2021 at U.S. firms with at least one subsidiary exceeds 10,000 in smaller countries like Austria, reaches approximately 30,000 in major central European economies such as Spain, France, Italy, and Germany, and surpasses 30,000 in the U.K.

Similar to multinational firm samples in other studies using subsidiary-level data from Orbis, most subsidiaries are located in major European economies such as Germany and France, with a particularly strong subsidiary footprint in the Netherlands

and the U.K. This distribution reflects both historical and cultural proximity as well as potential locational incentives for U.S. foreign direct investment. Just like their U.S. parent firms, these subsidiaries are dispersed across industries. Notably, our observations are not concentrated in the software industry. The Information and Communication sector (NACE Section J), which includes software firms, represents 10.9% of observations. Instead, our sample reflects an industry mix which is broadly representative of an entire economy. This shows that our sample and setting reflect AI adoption that influences business models across diverse industries, rather than capturing the production of novel AI products within the software sector.

Table 1 presents summary statistics for the samples used in the analysis. Panel A reports subsidiary-year-level statistics on U.S. firms' AI investments and the financial characteristics of their European subsidiaries. The dataset includes 325,713 subsidiary-year observations with non-missing parent-level AI investment data. On average, AI employees constitute 0.13% of the U.S. workforce of parent firms, consistent with the summary statistics in Babina et al. (2024*a*). This suggests that our sample includes the representative set of U.S. AI firms. The subsidiaries in the sample exhibit mean total assets of 181.1 million USD, operating revenue of 70.4 million USD, and an average workforce of 185 employees, with labor productivity averaging at 940,000 USD per employee. To mitigate the influence of outliers, all subsidiary-level financial variables are winsorized at the 1st and 99th percentiles.

Panel B presents statistics at the aggregated European country-industry level. Our key independent variable of interest, $U.S.\ AI$, has a mean of 6.48 and a standard deviation of 21.83, indicating substantial heterogeneity in country-industries' exposure to U.S. firm AI investment via subsidiary shares. The alternative exposure measures $U.S.\ Empl.$ and $U.S.\ Capex$ have mean values of 3.38 and 168.24, respectively. To aid readability, the employment instrument is presented in thousands and capex in millions. For the average country-industry, our sample includes firms that, in total, report 66.2 billion USD in total assets, employ more than 52.5 thousand workers, and generate 17.6 billion USD in revenue. When excluding subsidiaries owned by U.S. AI firms

from the aggregation, total assets are 8.2% lower, employment is 3.3% lower, and total revenues decline by 7.0%. These statistics highlight the significant footprint of U.S. AI firms in Europe relative to overall economic activity and suggest that U.S. AI firms employ fewer workers relative to their total assets and revenues when benchmarked to the average firm in these country-industries. The average R&D subsidy rate in the sample period is 0.14, and the average corporate income tax rate is 23.08%. As shown in Figure A-1 and Tables A-2 and A-3, there is substantial variation in these policy parameters over time and across countries.

3 Effects of U.S. Firms' AI Investments and Taxes in Europe

3.1 The Propagation of U.S. Firms' AI Investments at European Subsidiaries

As a baseline analysis to examine whether U.S. firm AI investment is correlated with the same U.S. firms' foreign subsidiary outcomes, we illustrate the bivariate relationship between U.S. firms' AI investments and the growth of their European subsidiaries. Specifically, we employ binscatter methods following Cattaneo et al. (2024) as they offer a structured way to explore bivariate relationships in the data by partitioning the independent variable into discrete bins and plotting the average outcome per bin. Unlike classical scatter plots, binscatters allow for interpretable visualization and a controlled assessment of functional form while accounting for additional covariates. This is helpful in our setting as we want to hold constant country characteristics and general time trends.

Panel A of Figure 3 examines the correlation between the growth in total assets of U.S. firms' European subsidiaries and the share of AI-skilled employees in the parent U.S. firms from the previous year. Following the recommendations in Cattaneo et al. (2024), we provide a nonparametric visualization of the relationship between the change in a subsidiary's total assets (scaled by lagged total assets) and its parent firm's lagged AI employment share. This approach allows us to flexibly estimate conditional means while controlling for subsidiary country and year fixed effects. For comparison, the figure also includes the results of a standard OLS regression, providing an alterna-

tive parametric estimate of the same relationship. Panels B and C extend this analysis to additional subsidiary-level outcomes: subsidiary-level employment (Panel B) and revenue (Panel C).

We find intuitive evidence of a link between AI adoption at the parent-firm level and economic expansion in foreign subsidiaries. For example, Panel A suggests that total asset growth increases from approximately 20% to 25% as a firm's AI employee share rises from 0.2% to 0.4%. While the absolute and relative relationships are weaker for employment and revenue outcomes (Panels B and C), they remain substantial. Additionally, the figures indicate that the positive association weakens as the AI employee share approaches 1%. Using linear OLS regressions, we corroborate these patterns. A 1% increase in AI-skilled workers (relative to all employees in the U.S. firm) is associated with a 13.95% increase in total assets, a 6.58% increase in employment, and a 4.8% increase in revenue for foreign subsidiaries.

For comparison, Babina et al. (2024*a*) finds that a one-standard-deviation increase in U.S. firms' annual AI investments is associated with 1.5%–2% total sales growth after two years, with similar effects on U.S. firm-level employment and equity market value. In our sample, the standard deviation of the firm-level AI employee share is 0.31 percentage points. Thus, our subsidiary-level findings align quantitatively with the positive relationship estimated at the U.S. firm level in Babina et al. (2024*a*).[6]

Our analysis cannot fully rule out that the documented positive relationship between U.S. firm AI investment and subsidiary-level growth in subsequent years is also driven by unmodelled endogenous factors. However, Babina et al. (2024*a*) conduct an array of tests to support a causal interpretation of the positive relationship between AI investment and sales growth and market capitalization at the consolidated firm level. Thus, we interpret our evidence as a strong baseline that motivates our main analyses in the following section, which rest on the assumption that AI investment presents a significant shock that likely affects the boundaries and operational outcomes of the

[6]For example, considering the OLS point estimate of 4.80 for revenues in Panel B, a 0.31 percentage-point increase in the AI employee share corresponds to a 1.5 percentage point greater growth rate in subsidiary-level revenues.

firms.

3.2 Empirical Design - Exposure to U.S. AI Investment and Local Tax Policies

3.2.1 European Country-Industries' Exposure to U.S. AI Investment

Having established that U.S. firm-level AI investment is strongly correlated with the growth of their European subsidiaries in terms of inputs and output, we now turn to our central research question: Do U.S. AI investments generate spillovers onto foreign markets, and if so, to what extent does the tax environment mediate these effects?

However, relating aggregate economic outcomes in foreign markets to the growth of U.S. AI firms' subsidiaries would likely suffer from endogeneity issues. A natural concern is that U.S. firms may increase AI investments precisely because they foresee growth potential in specific European industries. In particular, potentially unobserved confounding factors—such as country- and industry-specific developments, policy changes, competitive forces, and macroeconomic shocks—may simultaneously influence both the performance of U.S. AI firms' foreign subsidiaries and the broader economic outcomes we study. Moreover, the subsidiaries of U.S. AI firms might adjust their investment and operational decisions in response to anticipated or actual changes in aggregate economic conditions, further complicating causal inference due to reverse causality.

Aiming to isolate the causal impact of U.S. firms' AI investments on economic outcomes in European markets, we employ a Bartik-style shift-share strategy as our primary empirical approach. This method leverages plausibly exogenous variation in U.S. AI investment to construct an instrument for AI-induced investment at the local industry level. Our identification strategy builds on the finding that U.S. firms' AI investments significantly predict subsidiary-level investment, employment, and revenue (Figure 3). Thus, the *shift* in our design is captured by changes in U.S. firms' AI investments over time. Additionally, as further discussed below, we incorporate European countries' tax policies as a second time-series shift, reflecting changes in the after-tax profitability of U.S. AI firms' foreign operations.

To construct the exposure *share* for a given European market, we define a contin-

uous treatment measure that captures the ex-ante exposure to U.S. AI investment at the country-industry level. Specifically, we measure this exposure as the relative presence of U.S.-owned subsidiaries compared to all foreign-owned subsidiaries in a given country-industry at the beginning of our sample period. Using an ex-ante measure mitigates endogeneity concerns that would arise from a contemporaneous relationship between U.S.-owned European subsidiaries' investment levels and local economic outcomes, as discussed in prior work on shift-share designs (Goldsmith-Pinkham et al., 2020; Breuer, 2022). The exposure share, or treatment weight, is defined as follows:

$$U.S.\ Sub.\ Share_{c,i} = \frac{\sum_{f=1}^{F} U.S.\ Subs_{f,c,i,2010}}{\sum_{f=1}^{F} MNE\ Subs_{f,c,i,2010}} \tag{1}$$

$U.S.\ Sub.\ Share_{c,i}$ is the number of U.S. firm-owned subsidiaries scaled by the number of all foreign-owned subsidiaries within a European country c industry i, classified at the 2-digit NACE Rev. 2 level. We measure ex-ante exposure as of 2010, as this marks the beginning of our observation period for AI investment and aggregate economic outcomes. Additionally, Orbis ownership data coverage is of sufficiently high quality starting in 2010 and allows us to reliably and representatively define the initial exposure shares.

In this definition, $MNE\ Subs_{f,c,i,2010}$ represents the total number of subsidiaries owned by multinational firm enterprises (MNEs) incorporated in country c and operating in industry i, while $U.S.\ Subs_{f,c,i,2010}$ is the subset of these subsidiaries owned by U.S.-based MNEs. This ratio provides a meaningful proxy for the relative importance of U.S. firms in a given European country-industry, allowing us to capture differential exposure to AI-driven investment growth. Figure 2 illustrates the distribution of the raw data used to measure this ratio. Panel B shows that our dataset includes a large number of U.S.-owned subsidiaries, ranging from fewer than 3,000 in smaller economies such as Portugal and Eastern Europe to approximately 8,000 in Germany and France and nearly 12,000 in the U.K. Notably, Panel C reveals that the share of U.S.-owned subsidiaries relative to the overall economy, proxied by the number of all domestic incorporated entities, is more homogeneous across countries. However, with

the ratio ranging from less than 0.01% to 0.025%, with Luxembourg being a notable outlier, there is still considerable variation across countries and industries.

The interaction of the exposure share with the time-series shift in U.S. firms' AI investments—predictably influenced by cross-country variation in tax attractiveness—serves as an instrument for AI-induced investment at the local industry level. Using U.S. firm's AI investment data from Babina et al. (2024*a*), our U.S. AI instrument is then defined as follows:

$$U.S.\ AI_{c,i,t-1} = \frac{\sum_{f=1}^{F}(U.S.\ Subs_{f,c,i,2010} \times AI\ Empl._{f,t-1})}{\sum_{f=1}^{F} MNE\ Subs_{f,c,i,2010}} \tag{2}$$

where $AI\ Empl._{f,t-1}$ is the number of AI-skilled employees at U.S. firm f, as measured in Babina et al. (2024*a*) and discussed in detail in Section 2.1. To illustrate the construction of this instrument, consider a numerical example, which we also visualize in Panel B of Appendix A. Suppose we observe 20 subsidiaries owned by several distinct multinational firms in a given country-industry as of 2010. Two of those firms are based in the U.S., and both firms own one subsidiary each in the country-industry. Further, according to Babina et al. (2024*a*), U.S. firm 1 employs 30 AI-skilled workers, while U.S. firm 2 employs 60 AI-skilled workers in 2011. The instrument in 2012 would then take the value of 4.5.[7]

Using this instrument paired with an extensive set of fixed effects helps eliminate confounding contemporaneous shocks from our empirical design. However, a remaining concern is that our U.S. firm AI exposure measure ($U.S.\ AI_{c,i,t-1}$) may be correlated with European country-industries' exposure to U.S. firms' investments in other technologies or broader growth trajectories that would have occurred even in the absence of AI investments. These factors are also likely to affect economic outcomes at the European country-industry level. To address this concern, we construct two alternative exposure measures that capture country-industries' exposure to U.S. firms' total U.S.-based employment as well as worldwide capex.[8]

[7] $U.S.\ AI_{c,i,t-1} = \frac{1*30+1*60}{20} = \frac{90}{20} = 4.5$.

[8] Technically, we reconstruct the instrument from equation 2 by replacing the *shift* variable $AI\ Empl._{f,t-1}$ with either total U.S. employment from Babina et al. (2024*a*), scaled in thousands, or

As discussed in the results section, including these alternative exposure measures serves two key functions. First, it helps isolate the impact of U.S. firms' AI investment on European economies by distinguishing it from other correlated investments and U.S. firm growth dynamics. Second, it allows us to benchmark international spillover effects, both in general and in response to tax environments for AI investments versus more traditional investments.

3.2.2 Tax Policy Variation and Main Empirical Design

To incorporate the role of domestic tax policy, we interact this instrument with a proxy for a country's tax attractiveness for high-technology-related investment. Specifically, we define $Tax\ Incentive_{c,t}$ using two distinct policy inputs. A key measure is the R&D tax subsidy rate, defined as 1 minus the B-index, which captures the after-tax cost of an expenditure of 1 USD on R&D, normalized by one minus the corporate income tax rate (see also Chen et al., 2023). We focus on R&D related tax attractiveness as investments in the deployment of a new general purpose technology within a firm's business model likely comes with significant R&D spending which benefits from corresponding tax incentives. To assess the broader impact of corporate taxation, we also consider the statutory corporate income tax rate as well as a categorical variable indicating whether a country has preferential corporate tax regimes, following De Simone and Olbert (2022). These alternative specifications allow us to disentangle the effects of targeted R&D incentives from the general corporate tax environment, which applies to all tax bases irrespective of the nature of subsidiary-level activities, in shaping AI-driven spillovers.

Figure A-1 and Tables A-2 and A-3 show substantial variation in tax policies across countries over the years in our sample period, providing us with rich variation to isolate the differential impact of the tax environment on the propagation of AI-driven growth in foreign markets. As noted in prior research and policy discussions, corporate income tax rates have steadily declined over the past decades, while R&D tax incentives have become an increasingly popular policy tool. This trend is reflected

consolidated capex from Compustat, scaled in millions. The resulting variables are labeled *U.S. Empl.* and *U.S. Capex*, respectively.

in a significant increase in the average R&D subsidy rate, which rose from less than 0.11 in 2010 to approximately 0.17 in 2021, representing a 55% average increase across all European sample countries. While some countries have made minimal changes to their policies—either maintaining strong R&D tax incentives (e.g., the Czech Republic and Spain, with rates of 0.20–0.21 and 0.33–0.35, respectively, throughout the sample period) or less attractive regimes (e.g., Switzerland and Luxembourg)—many others have significantly expanded their R&D tax subsidies, often by more than 100% relative to 2010 (e.g., Sweden and Italy). Notably, some countries, such as Germany or Denmark, have only recently introduced substantial changes to enhance R&D tax incentives.

We estimate the following OLS model:

$$\begin{aligned} Y_{c,i,t} = \beta_0 + \beta_1 U.S.\ AI_{c,i,t-1} + \beta_2 (U.S.\ AI_{c,i,t-1} \times Tax\ Incentive_{c,i,t}) \\ + X_{c,i,t-1}\mu + (X_{c,i,t-1} \times Tax\ Incentive_{c,i,t})\nu + \gamma_{i,c} + \delta_{c,t} + \epsilon_{c,i,t} \end{aligned} \tag{3}$$

for the period 2011 through 2021. $Y_{c,i,t}$ represents country-industry-level outcome variables, where industry i is the 2-digit NACE Rev. 2 Industry core activity classification. Throughout our main analyses, we focus on total assets, employment, and revenue, to capture a broad range of capital inputs and firm output.[9] To this end, we aggregate total assets, employment, and revenue at the European country-industry level, considering the sum of all European firms—comprising U.S.-owned subsidiaries, other foreign-owned subsidiaries, and domestic standalone firms. These financial data are derived from the unconsolidated financial statements of all corporate entities operating in Europe, including both foreign-owned subsidiaries and domestically owned subsidiaries and standalone firms, following the approach of other studies examining aggregate market-level outcomes (e.g., Breuer (2021); Breuer and Breuer (2022)).[10]

$U.S.\ AI_{c,i,t-1}$ is our exposure-based instrument for U.S. AI firm investment at the European country-industry level, where U.S. subsidiary shares are measured as of 2010,

[9] Specifically, changes in total assets captures overall firm growth, i.e., including by means of corporate investment in tangible capital or M&A as well as by means of capital raising.

[10] Further details on variable definitions and data sources are provided in Section 2.

and U.S. firm AI investment is measured as of $t-1$. To facilitate an intuitive interpretation of the coefficient β_2 , we interact the U.S. AI exposure measure with dummies for R&D tax incentives and profit tax incentives. The R&D tax incentive dummy equals one for country-years with above-median R&D tax subsidy rates. The profit tax incentive dummy equals one for country-years with either a preferential tax regime (Cyprus, Ireland, Luxembourg, Malta, the Netherlands, Switzerland) or a CIT rate below 21%. The combined dummy equals one when both incentives apply.[11]

In our main specification, we include industry-country fixed effects ($\gamma_{i,c}$), which control for time-invariant factors at the level of the unit of observation, the European country-industry. This allows us to isolate the association between changes in AI exposure and shifts in U.S. AI investment, leveraging the fact that U.S. firms' AI capabilities have generally expanded over time (see Figure 1) and that different country-industries are exposed to all U.S. firms' AI investment to varying degrees based on their subsidiary presence as of the start of our sample period. Additionally, we include European country-year fixed effects ($\delta_{c,t}$), which restrict comparisons to industries within the same country and year while allowing for differential shifts in U.S. firm AI exposure across industries.

$X_{c,i,t-1}$ is a vector capturing alternative European country-industry exposures to U.S. firms' total U.S. employment (i.e., beyond the AI-specific workforce share) and U.S. firms' worldwide capex, which serves as a proxy for their total investment behavior, including in traditional industries. As discussed in Section 3.2.1, including these regressors helps isolate the incremental effect of U.S. firms' AI-specific investments on foreign spillovers in Europe, beyond general U.S. firm growth and investments in traditional technologies, which are typically reflected in capex—a widely used proxy for corporate investment (Bakke and Whited, 2010; Becker et al., 2013; Lester and Olbert, 2024). We also interact these alternative exposure measures with tax policy variables to examine how AI-specific spillovers are moderated by local tax policies, compared to potential spillovers from other types of corporate investment.

[11] In supplemental tests reported in the Online Appendix, we also run the main specifications for each sample country and show the countries' tax policy parameters in Table A-5.

In sum, our design ensures that our identification strategy is not confounded by country-wide policy changes, such as as endogenous (tax policy) responses in anticipation of (foreign) investment, or macroeconomic shocks that might simultaneously affect AI investment and industry-level outcomes. To provide an intuitive example, relating back to our visualization in Appendix A, the baseline coefficient β_1 estimates how an increase in AI investments by U.S. firms, such as Johnson & Johnson, impacts aggregate economic outcomes in European country-industries in subsequent years, holding constant how the U.S. firms' changes in their general U.S. workforce or worldwide capex would affect European country-industries. Specifically, β_1 measures the effect in one industry, such as Manufacture of Chemicals and Chemical Products industry (2-digit NACE code: 20) in Germany, relative to another industry such as Manufacture of Basic Pharmaceutical Products and Pharmaceutical Preparations industry (NACE 21) or the Manufacture of Rubber and Plastic Products industry (NACE 22) in the same year. This comparison leverages the fact that these industries had different ex-ante shares of U.S. AI firm-owned subsidiaries relative to all foreign subsidiaries, allowing us to isolate variation in exposure to U.S. AI investment. β_2 captures how the impact of AI on European country-industry outcomes varies across countries with more or less attractive R&D and corporate income tax regimes in a given year, while holding constant the baseline effect of these policies on economic outcomes within each country and also controlling for who non-AI related U.S. firms' investment spillovers would affect the focal country-industries. [12] Standard errors are clustered at the country-industry c, i level.

3.2.3 Discussion of Identifying Assumptions

For our empirical strategy to be valid, we must assume that the time-series variation in U.S. firms' AI investments which we exploit is exogenous to economic shocks in European markets. The key identifying assumption is that, conditional on the fixed effects and control variables, changes in U.S. AI investment are not systematically influenced by future economic conditions in the specific European markets which are

[12] In supplemental tests, we also include industry section-year fixed effects to control for secular trends that effect broad industry sections like the Manufacturing industry to the same extent.

our unit of analysis. As we aggregate our data at the industry-country level, this endogeneity concern would arise only if it affected all industrial U.S. firms in our sample similarly. However, it is more likely that trends in the U.S. firms' AI investment are primarily driven by factors such as domestic technological advances, regulatory changes, or firm-specific innovation strategies.

By interacting U.S. firm-level time-series variation with a country-industry's predetermined exposure to U.S. firms (measured as of 2010) and including country-industry fixed effects, we ensure that observed differences in AI spillovers reflect ex-ante heterogeneity in market exposure while controlling for all other time-invariant industry characteristics affecting industry-wide outcomes.[13] The causal interpretation of our results rests on the assumption that the share of AI-investing U.S. firms' subsidiaries relative to all foreign-owned subsidiaries in a given market as of 2010 is independent of the firms' total AI investment decisions after 2010 and the relationship between these investments and foreign market developments after 2010. We argue that this assumption is plausible for two reasons. First, multinational firms' location decisions made prior to 2010 are unlikely to have been driven by managers' expectations of AI technology propagation—given that AI was still in its infancy before 2010—or by expectations of how different European country-industries would develop post-2010. Second, for this assumption to be violated, U.S. AI firms' location decisions in Europe before 2010 would have had to systematically differ from those of non-U.S. multinational firms, which contribute to the denominator of our share measure—an unlikely scenario.

Notably, our design also mitigates concerns regarding contemporaneous local policy changes being made in anticipation of AI investment spillovers from the U.S. Specifically, the country-year fixed effects control for country-specific policy changes and other macro-level factors influencing industry outcomes, while also absorbing any global trends in AI investment that could systematically correlate with economic shocks in

[13] In supplemental tests, we include industry-year fixed effects to control for secular trends that could simultaneously influence AI exposure at the aggregate level and aggregate economic outcomes. While these fixed effects absorb a substantial portion of the variation of interest, our findings remain consistent with the main analysis, particularly regarding the differential effects based on countries' tax policies. These results are reported in Table A-4.

specific European countries. Additionally, by interacting U.S. AI investment with cross-country differences in tax incentives, we further sharpen identification, leveraging institutional variation that has been shown to systematically attract foreign investment.

Figure 4 supports our identifying assumptions that the variation in AI exposure is unrelated to country-specific factors that could drive our results. Conditional on a subsidiary's presence in a given European country in 2010, the average growth in AI investment by its U.S. parent at the global level is similar across subsidiaries in different countries which offer different levels of tax attractiveness for corporate investment and tax bases. This suggests that any differential impact of AI investment on subsidiary- or country-industry-level outcomes reflects variation how AI investment spills over onto economic outcomes in foreign markets, rather than how AI investment decisions were made.

While Babina et al. (2024*a*) highlight that AI investment occurs across U.S. firms in various industries and generates similar firm growth effects across sectors, we observe variation in both the level and trends of exposure to U.S. AI investment across industries based on the aggregated European country-industry data. As Figure A-2 in the Appendix intuitively suggests, the information technology, communication, public administration, and defense industries exhibit the highest prevalence of AI workers in the U.S., followed by the services sector. These industries also appear to experience somewhat stronger growth than other sectors. To address the concern that these differential trends may be driven by unobserved confounders that also influence our outcomes of interest, we conduct supplemental tests including industry-sector-by-year fixed effects. However, we do not include these fixed effects in our main analysis, as variation in AI exposure across industries and its associated trends is a key source of our identifying variation.

In sum, our approach ensures that our instrument does not mechanically capture endogenous responses of U.S. firms to anticipated opportunities in European markets but instead identifies spillover effects arising from U.S. AI expansion. Furthermore, by controlling for European country-industry exposures to U.S. firms' total U.S. employ-

ment and worldwide capex, we mitigate concerns that our results could be driven by general trends in specific U.S. firms that might generate foreign spillovers even in the absence of AI-driven technological change.

3.3 Empirical Results - Exposure to U.S. AI Investment and Local Tax Policies

Table 2 presents results from estimating equation 3. We report results for the natural logarithm of aggregated European country-industry-level total assets, number of employees, and operating revenue in Panels A, B, and C, respectively. Column (1) presents results from regressing aggregate economic outcomes on our U.S. AI investment exposure measure, while controlling for exposure to total U.S. employment and consolidated capex.

In Columns (2), (3), and (4) we additionally condition on the European countries' tax environment using the *Tax Incentive* variable, which is defined as follows: Column (2) uses a dummy for R&D tax incentives, equal to one for country-years with above-median R&D tax subsidy rates; Column (3) uses a dummy for profit tax incentives, equal to one for country-years with either a preferential tax regime (Cyprus, Ireland, Luxembourg, Malta, the Netherlands, Switzerland) or a corporate income tax (CIT) rate below 21%; and Column (4) includes the interaction of the two.

Overall, our findings suggest that investments in AI capabilities by U.S. firms have strong effects on foreign economies at the aggregate level. European country-industries with a higher share of U.S. AI firm subsidiaries experience significant increases in aggregate capital stock and total output (measured as the aggregate revenue reported by all firms in the industry), while the employment response remains muted. On average, a one-standard-deviation increase in the exposure measure is associated with a 5.9% increase in total assetsand a 3.7% increase in revenues in European country-industries. Given an unconditional country-industry sample mean in total assets of 66.2 billion USD and revenues of 17.6 billion USD, these magnitudes correspond to an increase of 3.9 billion USD in a country-industry's firms' capital stock and 650.4 million USD in revenues.

Furthermore, we find significantly stronger effects in countries with attractive tax

regimes. In particular, for total assets (Panel A), the effects are almost 180% stronger in countries with above-median R&D tax subsidies, 480% stronger in countries with profitable income tax rates and 360% stronger in countries providing both types of incentives. In terms of absolute economic magnitudes, these results suggest that industry-wide total assets would increase by approximately 2.0 billion USD in countries without favorable tax regimes and by approximately 9.4 billion USD in countries with above-median R&D tax subsidies and low corporate income tax burdens. However, we do not observe similarly strong differential effects when examining total employment (Panel B). For spillovers of U.S. AI investments onto aggregate revenues in European markets (Panel C), our results suggest particularly strong effects in countries with low corporate income tax rates. Notably, we document consistent results when also controlling for secular industry trends (Table A-4).

These findings are consistent with (i) U.S. firms' AI investments generating significant spillovers into foreign economies, influencing aggregate economic outcomes, and (ii) local tax policies playing a dominant role in attracting these spillovers. Importantly, our results highlight the distinct nature of how AI investments respond to tax incentives. While input-based policies designed to subsidize local R&D activities significantly affect total assets, likely reflecting increases in local physical capital required to support local R&D, revenues primarily increase when low corporate income tax rates are present. This suggests that low corporate tax burdens on reported profits enhance the after-tax cash flow of financial returns to AI usage in foreign markets, which incentives firms to increase revenues as the key determinant of tax bases.

Consistent with the idea that profit tax incentives primarily attract tax bases, the estimated coefficient on the interaction term $U.S.\ AI \times Tax\ Incentive$ is zero when considering only R&D tax incentives. This result suggests that U.S. AI firms engage in strategic tax planning behavior at the foreign subsidiary level and that these effects also propagate at the broader market level. Potential mechanisms include peer effects, supply chain relationships, and other market participants benefiting from overall market growth driving primarily by the U.S. firm's subsidiaries' expansions.

In sum, these findings suggest that AI investments made by U.S. firms within the U.S. generate significant spillover effects on the aggregate economy in Europe through the presence and subsequent growth of U.S.-owned subsidiaries. To assess whether these spillovers are attributable solely to within-U.S. multinational firm effects—i.e., spillovers from U.S. firms to their European subsidiaries—or whether they also extend to non-U.S.-owned peer firms in European markets, we re-estimate our analysis using a sample that excludes subsidiaries owned by U.S. AI-investing firms from the aggregated financial data at the European country-industry level.

Table 3 presents the results from regressing aggregate investment and revenue on the U.S. AI investment exposure measure. Columns (1) and (2) display the effects for all firms, while Columns (3) and (4) exclude subsidiaries owned by U.S. AI-investing firms.

We find broadly consistent baseline estimates in Columns (1) and (3), indicating that U.S. AI investments generate broader spillovers, as peer firms in foreign markets also experience growth ex post, which shows up in the aggregate outcomes. While we find no evidence that investment spillovers to non-U.S.-owned peer firms are amplified in countries with more favorable tax policies, the effect on aggregate revenue is significantly larger in countries with a more favorable profit tax environment.

Collectively, these findings at the aggregate level suggest that local tax incentives are a key determinant of within-U.S. firm spillovers of AI investment. When considering spillover effects on peer firms, the impact of tax policies is confined to the revenue response.

3.4 Empirical Results - Dynamics of Aggregate Spillover Effects of AI Investment and Taxes

To account for the gradual diffusion of technology over time (Kalyani et al., 2024) and explore the effect dynamics in our setting, we employ a long-differences estimation as an alternative specification, following the approach of Acemoglu and Restrepo (2020) and Babina et al. (2024*a*). Specifically, we regress within country-industry differences in the aggregate country-industry input and output variables on changes in U.S. AI

exposure, while controlling for country-specific time trends through country-year fixed effects as in our main specifications in Section 3.3.

Figure 5 presents results from estimating long-difference regressions with progressively increasing time horizons, starting at one year and extending to five years, for aggregate investment, employment, and revenues. Panels A, C, and E display results for countries with low tax attractiveness, while Panels B, D, and F show the corresponding coefficients for highly tax-attractive countries, with tax attractiveness based on favorable RD tax subsidy rates and corporate income tax regimes.

The figures indicate that industries in tax-unattractive countries show little to no response to increased exposure to U.S. AI investment, a muted effect observed across all outcome variables. In contrast, industries in tax-attractive countries respond promptly to increases in U.S. AI investment. Our estimates indicate that investment, employment, and revenue effects emerge within one year. The effects on capital stock and revenue grow over time, with coefficients for the five-year horizon being twice as large for total assets and approximately 50% larger for revenue compared to the one-year horizon estimates. The employment response remains relatively small, consistent with our main tests in Section 3.3, and remains relatively stable over time.

In terms of economic magnitudes, the coefficients from these long-difference estimations reconcile with the average effects documented in Section 3.3, where log-level outcome variables are regressed on the exposure measure. Here, the average point estimate on the U.S. AI exposure variable for the full sample is 0.0027 when total assets is the outcome, while the estimates for the interaction term with the R&D and profit tax incentive dummy variables is 0.0051, respectively. The latter estimates align quantitatively with the two-year difference estimations in Panel B of Figure 5, while the estimates from the long-difference tests in this figure increase to approximately 0.009 for the five-year horizon.

As an alternative approach, we also estimate a distributed lead-lag model, which is suitable in settings where treatments occur in multiple periods with varying intensities

(Schmidheiny and Siegloch, 2023). We find broadly consistent results.[14]

3.5 Supplemental Tests by Country and Sensitivity to Sample Choices

While our results show that the positive international spillover effects of U.S. firms' AI investments primarily benefit European countries with favorable tax environments, the specific effects by country may be of interest to our readers and policymakers. Therefore, we rerun our baseline tests based on equation 3 separately for each country sample. Naturally, the interaction terms with the tax incentive variable are excluded for these within-country regressions, and country-year fixed effects reduce to year fixed effects. For parsimony, we also exclude the alternative exposure measures (X in equation 3). We present the beta coefficient estimates for the natural logarithm of total assets and revenues as outcome variables in Table A-5, along with standard errors and the number of observations for industry-years with non-missing data used in each regression. To contextualize these results, we also report key tax policy parameters, including the R&D subsidy rate and corporate income tax rate, over the sample years, as well as their values in the first sample year and in 2021, the final sample year. In this results table, we rank the countries based on the coefficient estimates for U.S. AI when total assets is the outcome variable.

While Table A-5 presents the full range of results by country, a consistent pattern emerges: most countries with positive coefficient estimates—similar to or larger than the main coefficient documented in Table 2—either had a high R&D subsidy rate in place on average over the sample period or at least by 2021, or they offered low corporate income tax rates, or both. Conversely, we document the weakest or even negative estimates for countries with the least attractive tax policy parameters in these dimensions.

[14]Specifically, we regress our logged aggregate outcome variables on multiple leads and lags of U.S. AI exposure. Figure A-3 displays the cumulative impact on investment, employment and revenues, covering the period from two years before to five years after a change in U.S. AI exposure. Panels A (E) and B (F) illustrate the dynamics of aggregate investment (revenues) by comparing the effect on countries with low versus high tax attractiveness. In line with our results from the long-differences estimation and the findings of Babina et al. (2024*a*) on U.S. firm-wide sales, the positive effects accumulate over time, and the effects are significantly positive in countries with high tax attractiveness. Peaking three years after the U.S. AI investment, our results suggest that firms require several years to fully capitalize on the benefits of AI investments.

A natural concern with our international sample is that individual countries might disproportionately drive our main effects, potentially affecting representativeness. This concern is valid because some countries host a significant share of U.S.-owned activity (e.g., Ireland), some offer exceptionally favorable tax regimes (e.g., Ireland, Luxembourg, and the Netherlands), and some are economically much larger than others (e.g., Germany vs. Lithuania). To address this, we conduct a jackknife robustness test, re-estimating the baseline regression from equation 3—again omitting the other exposure variables for parsimony—while systematically excluding one country at a time. Table A-4 visualizes the results, confirming that our findings are not driven by any single country.

4 Mechanisms: U.S. AI Firms' Subsidiary-level Outcomes

4.1 Empirical Design: U.S. AI Firms' Subsidiary-level Outcomes

To conclude our analysis, we examine the effects of U.S. firms' AI investments at the subsidiary level. This analysis is motivated by two questions. First, we seek to further corroborate that the observed spillover effects primarily stem from U.S. firms investing in AI domestically and subsequently expanding the assets, employment, and output of their foreign subsidiaries, with these expansions being responsive to the tax environment. Second, we aim to provide additional insight into the within-U.S. firm subsidiary-level mechanisms that drive the aggregate country-industry growth effects documented earlier.

Identifying causal effects beyond the positive descriptive relationship between U.S. firms' domestic AI investment and foreign subsidiary growth in Figure 3 is challenging due to the endogenous nature of firms' AI investment decisions. A primary concern is that firms may strategically invest in AI-skilled employees precisely because they anticipate growth opportunities in foreign markets, raising concerns of reverse causality. While relating prior-year AI investment to subsidiary-level growth in subsequent years (as in Figure 3) partially mitigates this issue, it does not fully address endogeneity concerns.

To further address endogeneity concerns by simultaneously controlling for a broad set of confounding factors, we design our empirical strategy to exploit within-firm-year variation. Intuitively, we compare how foreign subsidiary outcomes respond to AI investment at the parent-firm level – as a function of the tax environment in the subsidiary's host country. This approach effectively holds constant the firm's overall AI investment decision and other firm-level developments, isolating the differential subsidiary-level responses driven by tax incentives. Consequently, firms' AI investment decisions in anticipation of growth in foreign markets on average cannot bias our estimates unless these selection issues systematically correlate with European countries' tax policy changes.

Specifically, we estimate the following OLS model.

$$\begin{aligned} Y_{s(pci),t} = \beta_1 U.S.\ Firm\ AI\ Share_{p,t-1} \times Tax\ Incentive_{c,t} + \beta_2 Tax\ Incentive_{c,t} \\ + \beta_3 \ln(GDP)_{c,t} + \alpha_{p,t} + \gamma_c + \delta_{i,t} + \epsilon_{s,t} \end{aligned} \tag{4}$$

where Y represents the outcome of interest for subsidiary s in year t, owned by U.S. firm p, incorporated in European country c, and operating in industry i.

We include U.S. firm-by-year fixed effects ($\alpha_{p,t}$), which absorb the baseline effect of firms' AI investment in the prior year ($U.S.\ Firm\ AI\ Share_{p,t-1}$), ensuring that identification comes solely from variation in subsidiary outcomes across European countries with different tax environments within the same parent firm-year. The coefficient of interest, β_1, captures the extent to which a subsidiary's response to its U.S. parent firm's AI investment is amplified in countries with a relatively more attractive tax environment. The country fixed effects γ_c control for time-invariant country characteristics that could motivate U.S. firms' foreign location decisions and local investment. The industry-by-year fixed effects $\delta_{i,t}$ control for secular trends that affect all subsidiaries within the same industry. In addition, we control for European country-level GDP to account for macroeconomic changes that could explain subsidiary-level outcomes that correlate with greater firm-level AI investment. We cluster standard errors at the U.S. firm level.

4.2 Empirical Results: U.S. AI Firms' Subsidiary-level Outcomes

4.2.1 U.S. AI Firms' Subsidiary-level Total Assets, Employment, and Revenues

Table 4 presents results from estimating equation 4. Analogous to our European country-industry-level tests in Section 3.3, we first report results for the natural logarithm of subsidiary-level total assets, number of employees, and operating revenue in Panels A, B, and C, respectively. The *Tax Incentive* variable of interest in Columns (1), (2), and (3) is defined as follows: Column (1) uses a dummy for R&D tax incentives, equal to one for country-years with above-median R&D tax subsidy rates; Column (2) uses a dummy for profit tax incentives, equal to one for country-years with either a preferential tax regime (Cyprus, Ireland, Luxembourg, Malta, the Netherlands, Switzerland) or a corporate income tax (CIT) rate below 21%; and Column (3) includes the interaction of the two.

Overall, our findings suggest that following their U.S. AI investments, U.S. firms increase foreign capital inputs, human capital, and revenue output more significantly at subsidiaries located in European countries with preferential corporate income and R&D tax incentives. While the coefficient estimates for total assets are somewhat inconclusive when considering R&D tax incentives alone, they are economically and statistically strong across all other specifications. Specifically, the coefficient estimates range from 0.21 to 0.41 and are highly statistically significant. Using the within-U.S.-firm standard deviation in AI investment of 0.12 as a benchmark,[15] our results suggest that U.S.-owned foreign subsidiaries' total assets increase by approximately 4.3-4.4% more in countries with either relatively low corporate income tax rates or a combination of low income tax rates and large tax-based R&D subsidies. These estimates are somewhat lower for employment growth and slightly higher for revenues.

[15]We obtain this within-firm standard deviation by regressing our main firm-level AI investment variable—the share of U.S.-based AI-skilled workers relative to all U.S. workers, as in Babina et al. (2024*a*)—on firm fixed effects and computing the standard deviation of the residuals, following the recommendations in Breuer and deHaan (2024).

4.2.2 Additional Mechanisms: Productivity, R&D, and Market Presence

U.S. firms' subsidiaries may contribute to aggregate industry-level growth not only by expanding their scope but also by increasing productivity, which prior research suggests can generate significant spillovers that drive macroeconomic growth. To examine this mechanism, we analyze subsidiary operational efficiency in Panel A of Table 5. The outcome variable, labor productivity, is defined as the natural logarithm of revenues per employee, following prior literature (e.g., Syverson, 2011; Breuer, 2021). The coefficient estimates range from 0.13 to 0.48, indicating that U.S. AI firms' subsidiaries experience significantly higher revenue per employee growth in tax-attractive European countries. These effects are particularly pronounced when R&D tax incentives are combined with a generally favorable corporate tax regime.

Anecdotal examples, such as Johnson & Johnson, along with the findings in Babina et al. (2024*a*), suggest that AI-investing U.S. firms primarily achieve future growth by expanding their product portfolio through additional R&D. For multinational firms with global research staff, this implies that R&D activities may also increase at foreign subsidiaries. At the same time, these foreign R&D activities are often incentivized by foreign governments through specific tax credits and subsidies. Furthermore, subsidiary-level R&D activities of U.S. AI firms may contribute to the positive aggregate outcomes observed post-AI investment, as local R&D is widely regarded as a key driver of economic growth in domestic markets (Jones, 2002; Bayoumi et al., 1999). Additionally, R&D and productivity are typically strongly correlated (Syverson, 2011), suggesting that foreign subsidiary R&D contributes to overall economic spillovers.

Measuring R&D activity is generally challenging, particularly at the subsidiary level. To provide suggestive evidence on this mechanism, we use the available data on R&D expenses of subsidiaries owned by 274 unique U.S. firms. These subsidiaries are incorporated in Denmark, Germany, Luxembourg, Sweden, and the United Kingdom, where financial reporting mandates and corporate transparency are relatively more developed, allowing us to observe these data.[16]

[16]For example, a manual inspection of the 2019 annual report of Johnson & Johnson's German subsidiary, Johnson & Johnson Medical GmbH, reveals that the subsidiary significantly engages in R&D

Using these data, we regress subsidiary-level R&D expenses (scaled by total assets) on our variables of interest, following the approach used in our other subsidiary-level tests. However, given the limited number of countries in this subsample, we modify our empirical design by interacting the *U.S. Firm AI Share* variable with the continuous versions of the R&D subsidy rate and corporate income tax rate, instead of using a tax incentive dummy variable as before. Panel B of Table 5 presents the results. We find strongly significant estimates for the interaction term in Columns (1) and (3). Although suggestive given the small sample, this finding indicates that after investing in AI capabilities, U.S. firms particularly increase R&D activities at subsidiaries in European countries offering a higher after-tax return for R&D-related corporate profits.

Finally, we examine U.S. firms' overall market presence in a given country. This test is motivated by the inconclusive findings when using total assets as the outcome variable in the subsidiary-level tests of Table 4. Even if existing subsidiaries do not experience significant asset growth, U.S. firms may still expand in foreign markets by opening or acquiring new subsidiaries. This growth would not be captured in the results reported in Table 4 but likely contribute to outcomes measured as the aggregate industry level. Table 6 presents results from regressions analyzing the relationship between U.S. firms' European market presence and their AI investment, conditional on European countries' tax attractiveness. For these tests, we aggregate the data at the U.S. firm-European country-year level, measuring the number of majority-owned U.S. subsidiaries in each European country per year for a given U.S. firm.

We employ a Poisson regression framework to analyze the subsidiary count variable, following recommendations in Cohn et al. (2022) and Chen and Roth (2024). We include U.S. firm-by-year fixed effects and further refine the model with firm-country fixed effects, which control for a U.S. firm's average decision to operate in a given country over the sample period. The results support this expansion mechanism, with strongly significant coefficient estimates ranging from 0.06 to 0.14. The findings in Column (3) indicate that U.S. firms increase their market presence by nearly 2% more

activities, with total expenses exceeding EUR 8 million in 2019.

subsidiaries in countries offering attractive tax environments for R&D investments and corporate tax bases, following their U.S.-based AI investments.

Collectively, these U.S. firm subsidiary-level findings support the inference that the differential aggregate effects observed across countries with varying tax environments (as documented in Section 3) are primarily—but not exclusively—driven by the activities of U.S. firm-controlled subsidiaries following the firms' AI expansion. Notably, our findings do not indicate that U.S. firms increase the total asset stock of their existing subsidiaries in response to more favorable R&D tax incentives. However, we do find that R&D incentives significantly affect total assets at the aggregate country-industry level in Section 3.3. This suggests that the aggregate results are driven by additional mechanisms beyond asset expansion within already existing subsidiaries.

One likely mechanism is the market expansion of U.S. firms through acquisitions or the incorporation of new subsidiaries, which contributes to our aggregate estimates but likely not much to the estimates at the subsidiary level. Another possibility is that the documented increases in labor productivity and R&D expenditures at U.S. firms' subsidiaries generate spillovers to the wider economy, as suggested in the literature on productivity-driven spillovers in local markets (Moretti, 2004; Stoyanov and Zubanov, 2012; Breuer, 2021). In terms of employment and revenues, the strong results in Panels B and C of Table 4, combined with the relatively weak aggregate effects when excluding U.S. AI firm-owned subsidiaries (Table 3), suggest that U.S. subsidiaries account for the majority of country-industry-wide spillovers from U.S. AI investment into European countries with favorable tax policies.

Overall, we provide novel evidence that countries' tax policies play a key role in attracting spillovers from foreign investment in new technologies—specifically AI. Given that AI is expected to drive substantial long-term productivity and growth effects in the global economy, our findings are highly relevant for policymakers.

5 Conclusions

This paper examines the international spillover effects of U.S. firms' AI investments that originate in the U.S. and the role of tax policy in shaping these spillovers. While AI

adoption is transforming industries and markets globally, little is known about how AI-driven growth propagates beyond the investing firms and their domestic economies. We construct a novel panel dataset linking AI investment data from more than 1,100 U.S. firms to economic outcomes of their nearly 40,000 European subsidiaries, supplemented with industry-wide data to assess aggregate spillover effects. Our empirical strategy leverages variation in exposure to U.S. AI investment across European country-industries, as well as differences in tax policy environments, to identify the effects of AI investment on capital formation, employment, and output in foreign markets.

We find that AI investment by U.S. firms strongly predicts growth in their foreign subsidiaries, leading to significant increases in total assets, employment, and revenues. These subsidiary-level expansions translate into aggregate spillovers at the European country-industry level, where greater exposure to U.S. AI investment is associated with higher industry-wide growth in capital and output. A key finding is that tax policies significantly influence the magnitude of these spillovers. Countries with more attractive R&D tax incentives and lower corporate income tax rates experience stronger AI-driven growth, particularly in capital investment and revenue expansion. Notably, while R&D-specific tax incentives primarily attract investment spillovers, low corporate tax rates additionally influence the allocation of taxable income, reinforcing their impact on subsidiary revenues. Finally, we provide evidence that these spillovers are driven by U.S. firms expanding their subsidiary-level presence in tax-attractive markets, increasing subsidiary assets, employment, and productivity, and even establishing new entities in these locations.

By demonstrating that AI investment generates cross-border spillovers, we provide new insights into technology diffusion and multinational firm behavior. We also inform the international tax policy debate by showing that fiscal incentives meaningfully shape AI-driven economic spillovers despite AI's remote deployability. More broadly, our findings highlight the role of multinational firms as conduits for AI-driven growth, reinforcing the importance of policy frameworks that balance innovation incentives with equitable global economic development.

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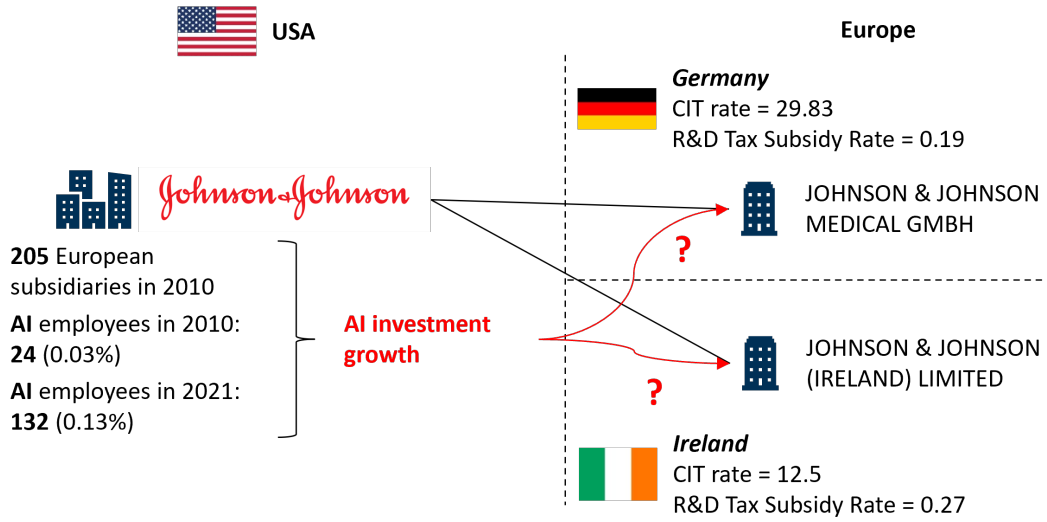
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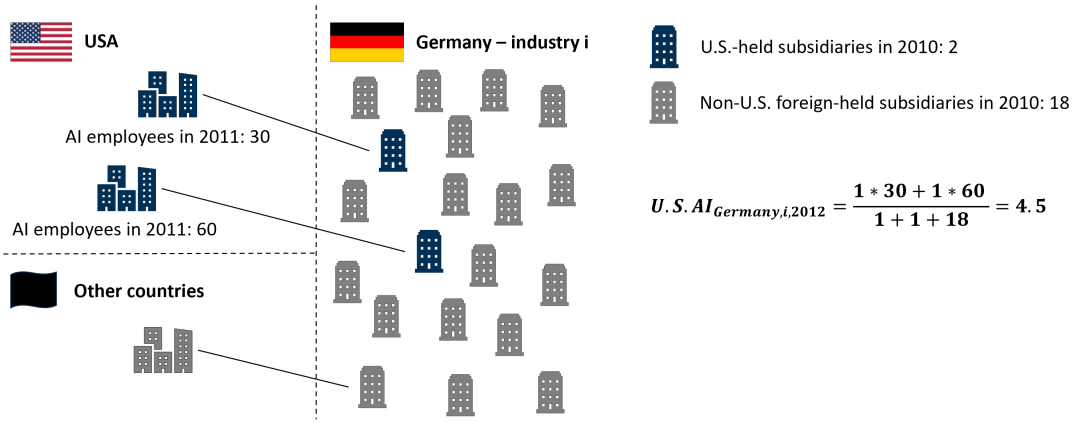
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Appendix A: Data Structure and Identification

Panel A: Example of Firm-Subsidiary Data Structure

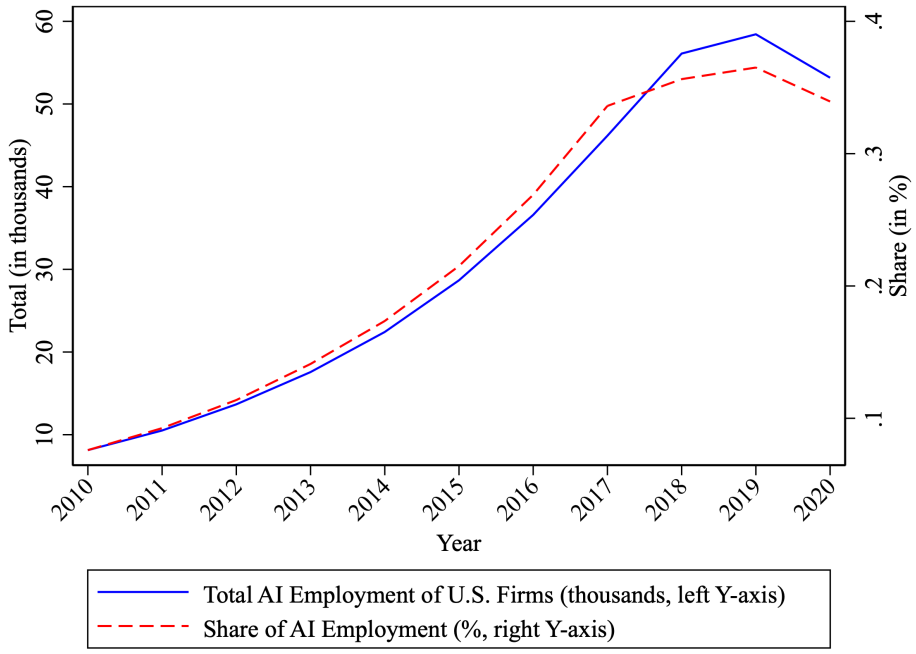


Panel B: Identification via Differential Exposure at the Country-Industry Level



Notes: This figure illustrates the data structure and identification underlying our two approaches to investigate the spillover effects of U.S. AI investment in Europe. In Panel A, we display the U.S. multinational firm Johnson & Johnson as an example from our subsidiary dataset to illustrate the relationship between U.S. AI-investing firms and their European subsidiaries. The multinational firm Johnson & Johnson owns 205 European subsidiaries as of 2010. Among these are a German and an Irish subsidiary, both operating under different national R&D and profit tax incentives. Between 2010 and 2021, Johnson & Johnson increased its U.S. AI investment from 24 to 132 AI workers. Using this setting, we investigate the differential impact of Johnson & Johnson's AI investment growth on its European subsidiaries, which are subject to varying national tax incentives. Panel B details the exposure measure used to quantify the aggregate spillover effects on European country-industries. The illustration reflects a fictious industry within Germany where we observe 20 subsidiaries owned by several distinct multinational firms as of 2010. Two of those multinational firms are based in the U.S., and both firms own one subsidiary each in the German industry. Further, U.S. firm 1 employs 30 AI-skilled workers, while U.S. firm 2 employs 60 AI-skilled workers in 2011. The 2012 exposure measure is then computed using time-invariant ownership data from 2010 and lagged AI investment data from 2011.

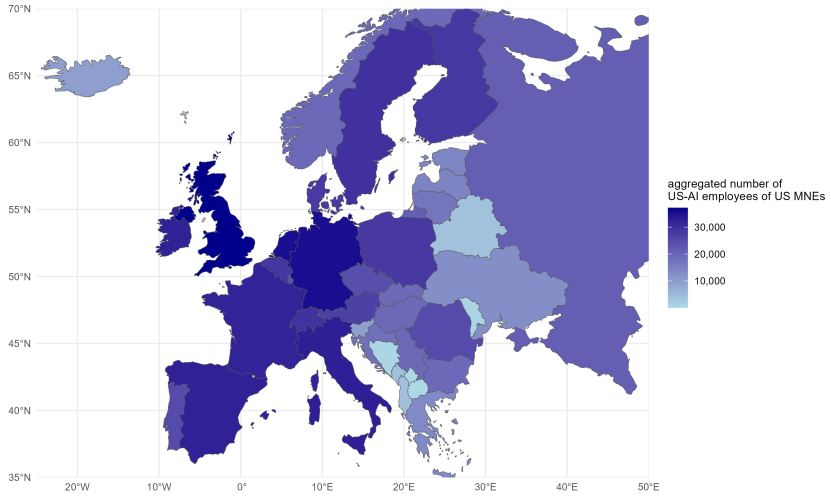
Figure 1: Development of AI Investment of U.S. Firms with European Subsidiaries



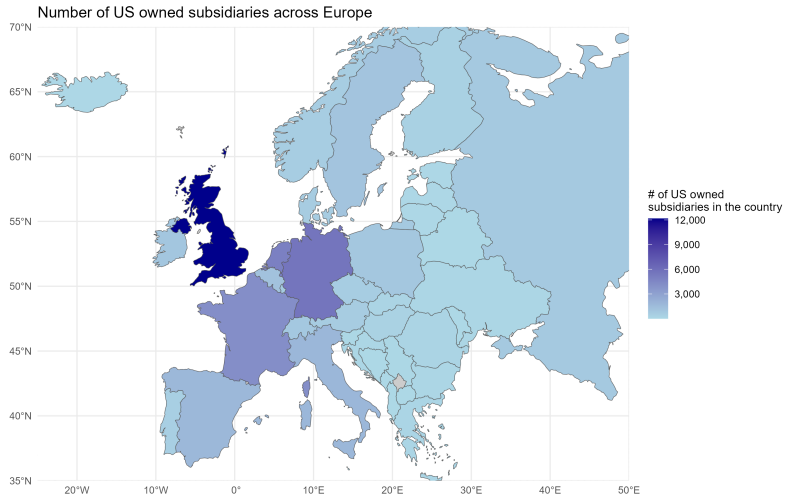
Notes: This figure illustrates the evolution of AI employment in U.S. firms with subsidiaries in Europe over time. The blue solid line represents the total number of AI-related employees in these firms in the U.S. (left y-axis). The red dashed line represents the share of AI-related employment among all U.S. employees in these firms (right y-axis). The share of AI employment measures the proportion of jobs that are classified as AI-related within these firms. The total AI employment metric captures the absolute number of employees working in AI-related roles within the same set of firms. The two metrics are plotted on separate y-axes to account for differences in scale: the total employment figure on the left y-axis is expressed in absolute terms (in thousands), and the share on the right y-axis is a percentage.

Figure 2: U.S.-owned Subsidiaries and U.S. Firm AI Investment in Europe

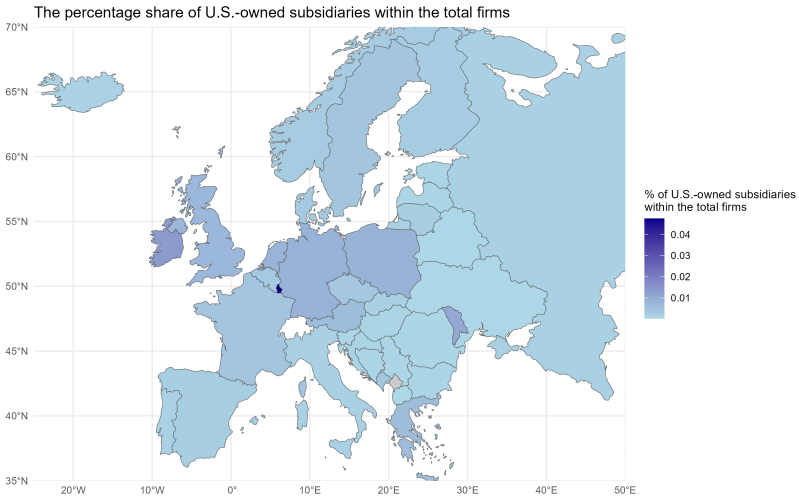
(**A**) AI Employment of U.S. Parent Firms by European Countries with U.S. Subsidiaries



(**B**) U.S.-owned Subsidiaries (Total)



(**C**) U.S.-owned Subsidiaries (% of all firms)



Notes: This figure displays heatmaps illustrating the distribution of U.S.-owned subsidiaries and U.S. AI investment across Europe. Panel A visualizes the aggregated amount of AI employees as of 2021 of all U.S. firms with at least one subsidiary in the respective country. Panel B shows the total number of U.S.-owned subsidiaries as of 2010. Figure C depicts the share of U.S.-owned subsidiaries as percentage of the overall number of firms in each country as of 2010.

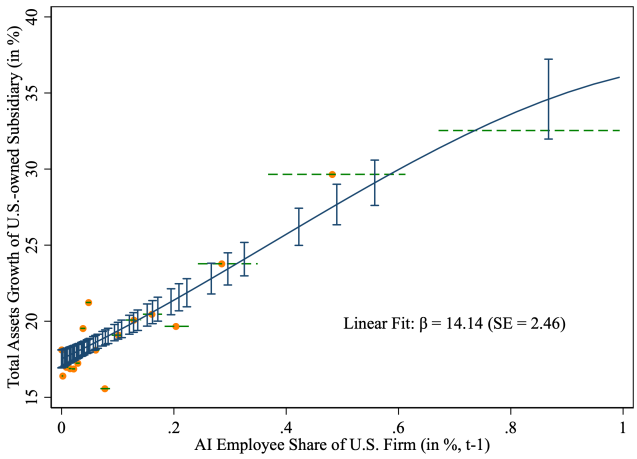
Table 1: Summary Statistics

	N	Mean	SD	P25	P50	P75
Panel A: Subsidiary Sample						
Share of U.S. AI Employees$_{p,t-1}$ (in %)	325,713	0.13	0.25	0.00	0.03	0.13
Number of U.S. AI Employees$_{p,t-1}$	325,713	75.11	473.37	0.00	2.00	13.00
Number of Total U.S. Employees$_{p,t-1}$	325,713	26367.37	64019.74	1768.00	5717.00	21804.00
Total Assets$_{s,t}$	325,713	181.07	626.76	1.73	10.53	60.05
Number of Employees$_{s,t}$	183,610	185.28	1481.99	8.00	33.00	116.00
Operating Revenue$_{s,t}$	204,940	70.41	194.21	2.00	10.82	45.07
Labor Productivity$_{s,t}$	147,274	0.94	2.42	0.17	0.31	0.66
R&D Expenses$_{s,t}$/Total Assets$_{s,t-1}$	8,735	0.05	0.15	0.00	0.00	0.03
R&D Subsidy Rate$_{c,t}$	325,286	0.15	0.14	0.09	0.11	0.20
CIT Rate$_{c,t}$ (in %)	325,713	25.10	5.90	20.00	25.00	29.94
R&D Tax Incentive$_{c,t}$	325,713	0.44	0.50	0.00	0.00	1.00
Profit Tax Incentive$_{c,t}$	325,713	0.43	0.50	0.00	0.00	1.00
R&D and Profit Tax Incentive$_{c,t}$	325,713	0.17	0.38	0.00	0.00	0.00
GDP$_{c,t}$	325,713	1809.66	1240.41	527.85	2144.94	2784.85
Panel B: Country-Industry Sample						
U.S. AI$_{c,i,t-1}$	18,486	6.48	21.83	0.01	0.42	2.61
U.S. Empl.$_{c,i,t-1}$	18,486	3.38	6.75	0.17	1.07	3.31
U.S. Capex$_{c,i,t-1}$	18,316	168.24	383.02	5.76	42.08	150.58
Agg. Total Assets$_{c,i,t}$	18,486	66,184.80	417,975.46	1,524.90	6,358.89	26,537.31
Agg. Number of Employees$_{c,i,t}$	18,316	52,483.59	111,231.77	4,638.50	16,154.00	53,269.00
Agg. Operating Revenue$_{c,i,t}$	18,486	17,578.42	50,455.54	951.76	3,930.68	14,493.29
Agg. Total Assets (ex. U.S. AI)$_{c,i,t}$	18,130	60,763.24	368,344.54	1,419.44	5,974.27	24,862.50
Agg. Number of Employees (ex. U.S. AI)s$_{c,i,t}$	18,446	50,739.17	106,311.08	4,477.00	15,759.00	51,381.00
Agg. Operating Revenue (ex. U.S. AI)$_{c,i,t}$	18,474	16,349.37	47,351.01	872.68	3,626.30	13,461.12
R&D Subsidy Rate$_{c,t}$	18,109	0.14	0.14	0.00	0.12	0.22
CIT Rate$_{c,t}$ (in %)	18,425	23.08	6.57	19.00	22.00	28.00
R&D Tax Incentive$_{c,t}$	18,314	0.50	0.50	0.00	0.00	1.00
Profit Tax Incentive$_{c,t}$	18,486	0.50	0.50	0.00	1.00	1.00
R&D and Profit Tax Incentive$_{c,t}$	18,486	0.23	0.42	0.00	0.00	0.00

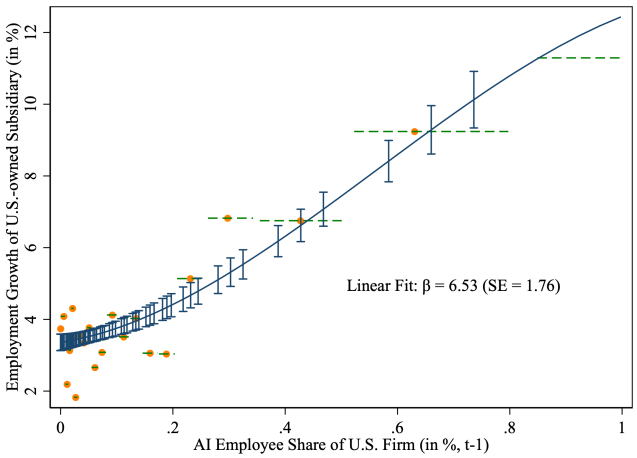
Notes: This table reports summary statistics for the subsidiary sample (Panel A) and the country-industry sample (Panel B). The variable indices refer to U.S. parent firm p, European subsidiary s, country c, industry i and year t. Financial variables are reported in USD million. U.S. firm-level AI investment data is from Babina et al. (2024*a*). Financial variables at the subsidiary level as well as on all country-industries' firms are retrieved from Orbis. Data on R&D subsidy rates and CIT rates is taken from the OECD and Tax Foundation, respectively. The R&D tax incentive dummy equals one for country-years with above-median R&D tax subsidy rates. The profit tax incentive dummy equals one for country-years with either a preferential tax regime (Cyprus, Ireland, Luxembourg, Malta, the Netherlands, Switzerland) or a CIT rate below 21%. The combined dummy equals one when both incentives apply. GDP information is from the Worldbank, denoted in current USD in billions.

Figure 3: U.S. Firm AI Investment and Growth at U.S. Firms' Subsidiaries in Europe

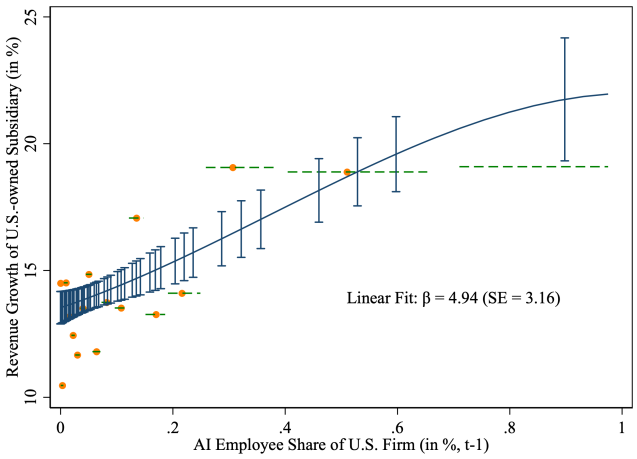
(**A**) U.S. Firm AI Investment and Subsidiary-level Total Assets Growth



(**B**) U.S. Firm AI Investment and Subsidiary-level Employment Growth



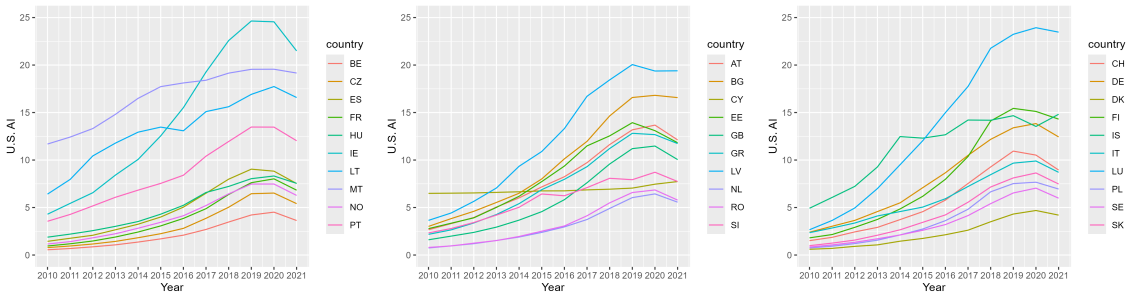
(**C**) U.S. Firm AI Investment and Subsidiary-level Revenue Growth



Notes: Panel A illustrates the correlation between the growth in total assets of U.S. firms' European subsidiaries and the share of AI employees in the parent U.S. firms from the previous year. Specifically, the figure presents a binscatter visualization of the relationship between the subsidiary's change in total assets (scaled by lagged total assets) and the U.S. firms' lagged AI employment share, controlling for subsidiary country and year fixed effects, following the binscatter method recommended by Cattaneo et al. (2024). Additionally, the text in the graph shows the results of a standard OLS regression for comparison to the data-driven estimation of conditional means with optimal binning as in Cattaneo et al. (2024). Panels B and C show equivalent results with subsidiary-level employment and revenue outcomes, respectively

Figure 4: Exposure to U.S. AI Investment across European Economies in 2010-2021

(**A**) Most Favorable R&D Tax (**B**) Next 10 Countries (**C**) Least Favorable R&D Tax



Notes: This figure presents the European country-industry-year level exposure variable $U.S.\ AI_{c,i,t-1}$, averaged by country over the years. The countries are grouped into three categories based on the generosity of their R&D tax incentives as of 2010, where the countries displayed in (A) provide the most favorable and the countries shown in (C) the least favorable R&D tax incentives.

Table 2: The Effect of U.S. AI Investment and Taxes on European Business Production Inputs and Output

	(1)	(2)	(3)	(4)
Panel A	ln(Total Assets)			
	Baseline	R&D Tax	Profit Tax	R&D and Profit Tax
U.S. AI	0.0027**	0.0014	0.0006	0.0014
	(0.0011)	(0.0010)	(0.0017)	(0.0010)
*U.S. AI * Tax Incentive*		0.0025**	0.0029*	0.0051***
		(0.0011)	(0.0018)	(0.0017)
U.S. Empl.	0.0011	0.0059	0.0027	0.0039
	(0.0102)	(0.0108)	(0.0098)	(0.0104)
*U.S. Empl. * Tax Incentive*		-0.0070*	-0.0038	-0.0113**
		(0.0037)	(0.0044)	(0.0052)
U.S. Capex	0.0002**	0.0002**	0.0003***	0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
*U.S. Capex * Tax Incentive*		-0.0000	-0.0001	-0.0001
		(0.0000)	(0.0001)	(0.0001)
N	18,316	18,316	18,316	18,316
R2 Within Adj.	0.007	0.008	0.008	0.010
Country-Industry FE	X	X	X	X
Country-Year FE	X	X	X	X

Table 2: The Effect of U.S. AI Investment and Taxes on European Business Production Inputs and Output (*continued*)

	(1)	(2)	(3)	(4)
Panel B	ln(Number of Employees + 1)			
	Baseline	R&D Tax	Profit Tax	R&D and Profit Tax
U.S. AI	0.0010	0.0011	-0.0005	0.0006
	(0.0011)	(0.0010)	(0.0020)	(0.0012)
*U.S. AI * Tax Incentive*		-0.0000	0.0022	0.0016
		(0.0013)	(0.0019)	(0.0017)
U.S. Empl.	0.0000	0.0020	0.0003	0.0014
	(0.0128)	(0.0124)	(0.0127)	(0.0126)
*U.S. Empl. * Tax Incentive*		-0.0036	-0.0010	-0.0056
		(0.0037)	(0.0054)	(0.0055)
U.S. Capex	0.0002*	0.0002*	0.0002*	0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
*U.S. Capex * Tax Incentive*		0.0000	-0.0000	0.0000
		(0.0001)	(0.0001)	(0.0001)
N	17,966	17,966	17,966	17,966
R2 Within Adj.	0.002	0.002	0.003	0.002
Country-Industry FE	X	X	X	X
Country-Year FE	X	X	X	X

Table 2: The Effect of U.S. AI Investment and Taxes on European Business Production Inputs and Output textit(continued)

	(1)	(2)	(3)	(4)
Panel C	ln(Operating Revenue)			
	Baseline	R&D Tax	Profit Tax	R&D and Profit Tax
U.S. AI	0.0017	0.0016	-0.0018	0.0010
	(0.0010)	(0.0011)	(0.0016)	(0.0010)
*U.S. AI * Tax Incentive*		0.0002	0.0047***	0.0026
		(0.0012)	(0.0018)	(0.0017)
U.S. Empl.	0.0101	0.0106	0.0093	0.0095
	(0.0113)	(0.0115)	(0.0107)	(0.0116)
*U.S. Empl. * Tax Incentive*		-0.0004	0.0006	0.0016
		(0.0036)	(0.0043)	(0.0050)
U.S. Capex	0.0003**	0.0003**	0.0003***	0.0003**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
*U.S. Capex * Tax Incentive*		-0.0001	-0.0001	-0.0001**
		(0.0001)	(0.0001)	(0.0001)
N	18,269	18,269	18,269	18,269
R2 Within Adj.	0.007	0.007	0.009	0.008
Country-Industry FE	X	X	X	X
Country-Year FE	X	X	X	X

Notes: This table reports the results of estimating the effect of U.S. AI exposure on European country-industry outcomes using the following OLS regression equation (equ. 3): $Y_{c,i,t} = \beta_0 + \beta_1 U.S.\,AI_{c,i,t-1} + \beta_2 U.S.\,AI_{c,i,t-1} * Tax\,Incentive_{c,t} + \gamma_{c,i} + \delta_{c,t} + \epsilon_{c,i,t}$. The outcome variables are the natural logarithm of total assets (Panel A), number of employees (Panel B) and operating revenue (Panel C) of all European firms, aggregated at the country-industry-level with industry being defined as two-digit NACE code. The variable $U.S.\,AI_{c,i,t}$ is a instrument capturing a country-industry's exposure to U.S. AI investment, defined as: $U.S.\,AI_{c,i,t-1} = \frac{\sum_{f=1}^{F}(U.S.\,Subs_{f,c,i,2010} * AI\,Empl._{f,t-1})}{\sum_{f=1}^{F}(MNE\,Subs_{f,c,i,2010})}$. Column (1) shows baseline results without tax interactions. The specifications also includes alternative measures of European country-industry's exposure to U.S. firms'. Specifically, **U.S. Empl.** is the exposure to total U.S. employment on European country-industry outcomes, and *U.S. Capex* is the exposure to U.S. firms' worldwide consolidated capital expenditures (Capex). Compared to the *U.S. AI* exposure measure, these alternative exposure measures are calculated analogously but using U.S. firms' total U.S. employees from Cognism, as provided by Babina et al. (2024*a*), or using U.S. firms' Capex from Compustat, as the shift term discussed in Section 3.2.1. Columns (2) – (4) interact U.S. AI exposure as well as the alternative U.S. firm exposure measures with dummies for R&D tax incentives and profit tax incentives. The R&D tax incentive dummy equals one for country-years with above-median R&D tax subsidy rates. The profit tax incentive dummy equals one for country-years with either a preferential tax regime (Cyprus, Ireland, Luxembourg, Malta, the Netherlands, Switzerland) or a CIT rate below 21%. The combined dummy equals one when both incentives apply. We include country-industry and country-year fixed effects. Robust standard errors are clustered at the country-industry level. Standard Errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

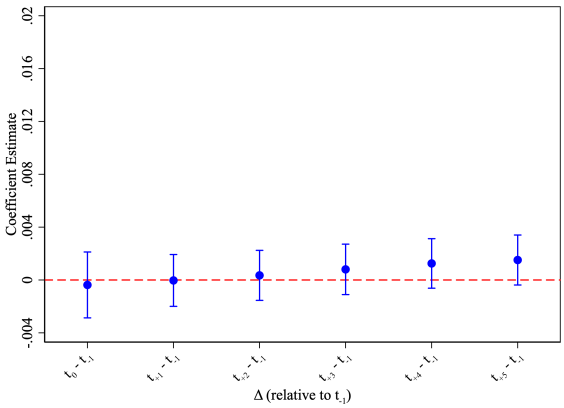
Table 3: Within vs Cross-firm Spillover Effects of U.S. AI Investment and Taxes on European Business Production Inputs and Output

	(1)	(2)	(3)	(4)
Aggregated Sample:	All Firms		Excluding U.S. AI Firm Subsidiaries	
Panel A	ln(Total Assets)		ln(Total Assets)	
	Baseline	R&D and Profit Tax	Baseline	R&D and Profit Tax
U.S. AI	0.0032***	0.0023**	0.0022**	0.0017*
	(0.0009)	(0.0009)	(0.0010)	(0.0010)
*U.S. AI * Tax Incentive*		0.0035**		0.0019
		(0.0015)		(0.0017)
N	18,486	18,486	18,474	18,474
R2 Within Adj.	0.005	0.006	0.002	0.002
Panel B	ln(Operating Revenue)		ln(Operating Revenue)	
	Baseline	Profit Tax	Baseline	Profit Tax
U.S. AI	0.0028***	-0.0009	0.0021**	-0.0012
	(0.0010)	(0.0017)	(0.0010)	(0.0017)
*U.S. AI * Tax Incentive*		0.0048***		0.0044**
		(0.0018)		(0.0018)
N	18,439	18,439	18,418	18,418
R2 Within Adj.	0.003	0.006	0.002	0.002
Country-Industry FE	X	X	X	X
Country-Year FE	X	X	X	X

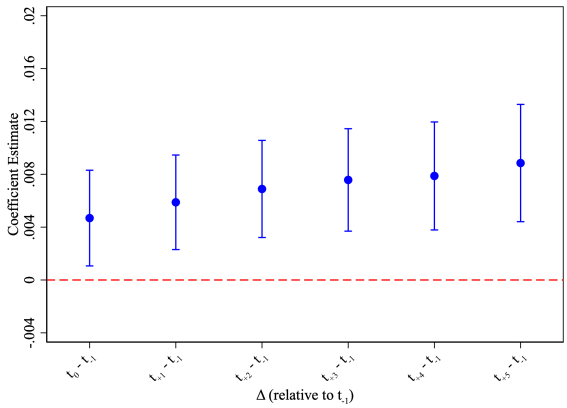
Notes: This table reports the results of estimating the effect of U.S. AI exposure on European country-industry outcomes using the following OLS regression equation (equ. 3): $Y_{c,i,t} = \beta_0 + \beta_1 U.S.AI_{c,i,t-1} + \beta_2 U.S.AI_{c,i,t-1} * TaxIncentive_{c,t} + \gamma_{c,i} + \delta_{c,t} + \epsilon_{c,i,t}$. Columns (1) and (2) show results for the outcome variables natural logarithm of total assets (Panel A) and operating revenue (Panel C) of all European firms, aggregated at the country-industry-level with industry being defined as two-digit NACE code. Columns (3) and (4) show results of estimating the pure spillover effect of U.S. AI exposure on European country-industry outcomes using also using aggregated total assets and operating revenue but after excluding European firms held by U.S. parents with AI investment from the aggregation. The variable $U.S.\ AI_{c,i,t}$ is a instrument capturing a country-industry's exposure to U.S. AI investment, defined as: $U.S.\ AI_{c,i,t-1} = \frac{\sum_{f=1}^{F}(U.S.\ Subs_{f,c,i,2010} * AI\ Empl._{f,t-1})}{\sum_{f=1}^{F}(MNE\ Subs_{f,c,i,2010})}$. Columns (1) and (3) show baseline results without tax interactions. Columns (2) and (4) interact U.S. AI exposure with dummies for R&D tax incentives and profit tax incentives as defined above (see Table 2). We include country-industry and country-year fixed effects. Robust standard errors are clustered at the country-industry level. Standard Errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 5: Effect of Taxes and U.S. AI Investment on European Economies: Dynamics

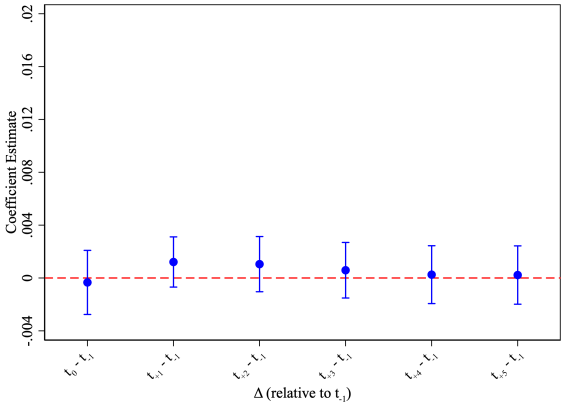
(**A**) Total Assets - ***Low*** Tax Attractiveness



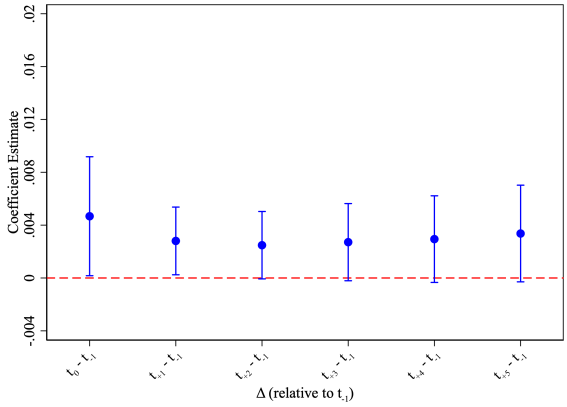
(**B**) Total Assets - ***High*** Tax Attractiveness



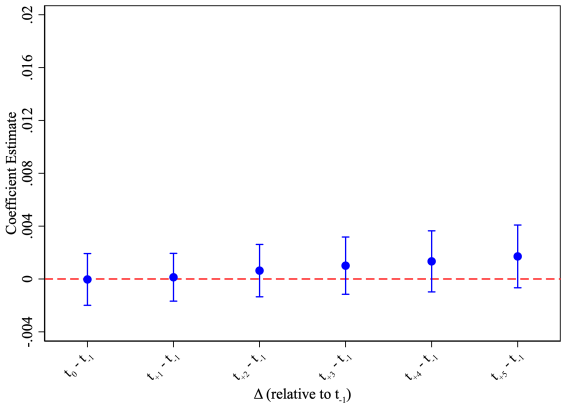
(**C**) Employees - ***Low*** Tax Attractiveness



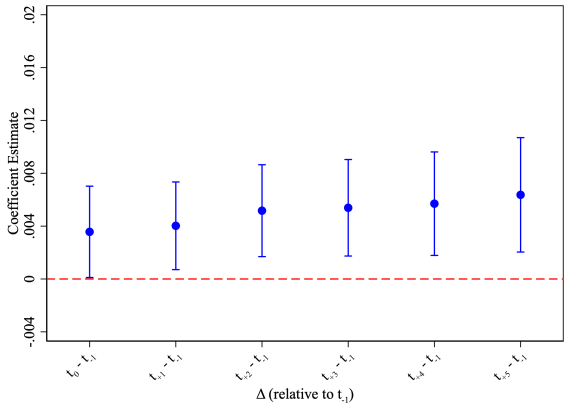
(**D**) Employees - ***High*** Tax Attractiveness



(**E**) Revenues - ***Low*** Tax Attractiveness



(**F**) Revenues - ***High*** Tax Attractiveness



Notes: This figure illustrates the dynamic effects of U.S. AI exposure on aggregated total assets, employment, and revenues of European country-industry firms, based on a long-differences estimation. The x-axis represents the number of years over which the difference in outcomes and lagged AI investment is measured. The y-axis shows the estimated coefficients and confidence intervals from the long-differences model. The model estimates the difference in the natural logarithm of aggregated total assets, employment, or revenues between $t-1$ and the respective year on the y-axis at the country-industry level, using the corresponding difference in $U.S.\ AI_{c,i,t-1}$ as the key regressor. Panels A, C, and E report results for countries with relatively low tax attractiveness, while Panels B, D, and F present estimates for countries with high tax attractiveness. The sample split is based on the median R&D tax subsidy rate and whether a country offers a corporate income tax rate below 21% or a preferential tax regime in a given year.

Table 4: U.S. Firm AI Investment, Taxes, and European Subsidiary Input and Output

	(1)	(2)	(3)
Panel A	ln(Total Assets)		
	R&D Tax	Profit Tax	R&D and Profit Tax
*U.S. Firm AI Share * Tax Incentive*	-0.14	0.36***	0.37**
	(0.20)	(0.13)	(0.16)
Tax Incentive	-0.01	-0.04	-0.16***
	(0.04)	(0.05)	(0.06)
ln(GDP)	0.19	0.13	0.14
	(0.12)	(0.13)	(0.12)
N	317,255	317,255	317,255
R2 Within Adj.	0.16	0.16	0.16
Panel B	ln(Number of Employees)		
	R&D Tax	Profit Tax	R&D and Profit Tax
*U.S. Firm AI Share * Tax Incentive*	0.04	0.21**	0.26**
	(0.08)	(0.10)	(0.11)
Tax Incentive	-0.11***	-0.22***	-0.22***
	(0.02)	(0.03)	(0.03)
ln(GDP)	-0.15*	-0.09	-0.14
	(0.09)	(0.09)	(0.09)
N	173,874	173,874	173,874
R2 Within Adj.	0.27	0.27	0.27
Panel C	ln(Operating Revenue)		
	R&D Tax	Profit Tax	R&D and Profit Tax
*U.S. Firm AI Share * Tax Incentive*	0.03	0.37***	0.41***
	(0.11)	(0.09)	(0.13)
Tax Incentive	-0.13***	-0.01	-0.29***
	(0.03)	(0.04)	(0.05)
ln(GDP)	0.32***	0.25**	0.32***
	(0.11)	(0.11)	(0.11)
N	189,214	189,214	189,214
R2 Within Adj.	0.25	0.25	0.25
Firm-Year FE	X	X	X
Country FE	X	X	X
Industry-Year FE	X	X	X

Notes: This table reports the results of estimating the effect of U.S. parent firms' AI investments on their European subsidiaries' outcomes using equation 4. The outcome variables are the natural logarithm of total assets (Panel A), number of employees (Panel B), and operating revenue (Panel C) at the subsidiary level. The variable $U.S.\ Firm\ AI\ Share_{p,t-1}$ captures a U.S. firm's AI investment in the prior year. The key coefficient of interest, β_1, measures the extent to which the response of a U.S.-owned subsidiary to its parent firm's AI investment is amplified in countries with more attractive tax environments. Column (1) interacts U.S. AI investment with a dummy for R&D tax incentives. The R&D tax incentive dummy equals one for country-years with above-median R&D tax subsidy rates. Column (2) interacts U.S. AI investment with a dummy for profit tax incentive, equal to one for country-years with either a preferential tax regime (Cyprus, Ireland, Luxembourg, Malta, the Netherlands, Switzerland) or a corporate income tax (CIT) rate below 21%. Column (3) includes the interaction of both tax incentives. We include U.S. firm-by-year fixed effects ($\alpha_{p,t}$), country fixed effects (γ_c), and industry-by-year fixed effects ($\delta_{i,t}$). The European country-level GDP control variable is the natural logarithm of the gross domestic product in current USD. Standard errors are clustered at the U.S. firm level. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: U.S. Firm AI Investment, Taxes, and European Subsidiary Productivity and R&D

	(1)	(2)	(3)
Panel A	Labor Productivity		
	R&D Tax	Profit Tax	R&D and Profit Tax
*U.S. Firm AI Share * Tax Incentive*	0.13**	0.32***	0.48***
	(0.06)	(0.05)	(0.10)
Tax Incentive	-0.08***	-0.02	-0.21***
	(0.01)	(0.02)	(0.03)
$ln(GDP)$	0.17**	0.14*	0.13*
	(0.07)	(0.07)	(0.08)
N	144,795	144,795	144,795
R2 Within Adj.	0.29	0.29	0.29
Firm-Year FE	X	X	X
Country FE	X	X	X
Industry-Year FE	X	X	X

Panel B	R&D Expenses / Total Assets$_{t-1}$		
	R&D Tax	Profit Tax	R&D and Profit Tax
*U.S. Fim AI Share * R&D Subsidy Rate*	1.23***		-20.23**
	(0.44)		(10.23)
*U.S. Fim AI Share * CIT Rate*		0.02	-0.04**
		(0.01)	(0.02)
*U.S. Fim AI Share * R&D Subsidy Rate * CIT Rate*			0.28**
			(0.13)
R&D Subsidy Rate	-0.18*		2.09
	(0.09)		(2.19)
CIT Rate		-0.00	0.01
		(0.00)	(0.00)
*R&D Subsidy Rate * CIT Rate*			-0.03
			(0.03)
$ln(GDP)$	0.01	0.06	0.02
	(0.13)	(0.13)	(0.16)
N	6,421	6,421	6,421
R2 Within Adj.	0.38	0.37	0.38
Firm-Year FE	X	X	X
Country FE	X	X	X
Industry-Year FE	X	X	X

Notes: Panel A presents the results of estimating the model from Table 4, using labor productivity as the dependent variable. Labor productivity is defined as the natural logarithm of operating revenue per employee. Panel B uses a subsample for which unconsolidated financial information on subsidiaries' R&D expenses is available. This subsample includes 1,356 unique subsidiaries of 274 unique U.S. firms, incorporated in the following countries: Denmark, Germany, Luxembourg, Sweden, and the United Kingdom. Due to the limited number of countries, we do not use the tax incentive indicator variables but instead employ continuous measures of R&D subsidy rates and the corporate income tax rate (CIT) for the included country-year observations. To ease the interpretation of regression coefficients, we use the net-of-tax rate for CIT (higher values indicate a greater tax incentive). Standard errors are clustered at the U.S. firm level. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: U.S. Firm AI Investment, Taxes, and European Subsidiary Market Presence

	(1)	(2)	(3)
	Subsidiary Count in Country		
	R&D Tax	Profit Tax	R&D and Profit Tax
*U.S. Firm AI Share * Tax Incentive*	0.06**	0.09**	0.14***
	(0.03)	(0.04)	(0.04)
Tax Incentive	0.00	-0.08***	-0.04***
	(0.01)	(0.02)	(0.02)
$ln(GDP)$	0.24***	0.24***	0.22***
	(0.04)	(0.04)	(0.04)
N	101,600	101,600	101,600
Pseudo R2	0.71	0.71	0.71
Firm-Year FE	X	X	X
Country FE	X	X	X

Notes: This table presents the results of estimating a model similar to Table 4, but using the U.S. firm-by-European country-by-year level as the unit of observation. The dependent variable is the number of majority-owned subsidiaries in a given country and year. The reported results are estimated using a Poisson maximum likelihood model, and the model includes U.S. firm-by-year as well as firm-country fixed effects. Standard errors are clustered at the U.S. firm level. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix

Taxes and the Global Spillovers of AI Investments

Emilia Gschossmann
Marcel Olbert

This version: March 20, 2025

Table A-1: U.S. AI Firm's Subsidiaries by European Country and Industry

Industry Section	Austria	Belgium	Bulgaria	Croatia	Cyprus	Czech Republic	Denmark	Estonia	Finland	France	Germany	Greece	Hungary	Iceland	Ireland	**Total**	**Total** (%)
A - Agriculture (	11	12	0	0	0	0	12	0	0	18	9	0	11	0	18	**281**	**0.1%**
B - Mining and quarrying	12	12	11	0	3	0	46	0	0	51	143	0	11	0	18	**1,773**	**0.5%**
C - Manufacturing	820	2,769	149	75	2	1,440	855	147	736	5,430	7,335	82	700	44	1,651	**53,108**	**16.3%**
D - Electricity, gas, steam (supply	0	22	48	0	3	12	0	0	0	644	34	0	36	0	36	**2,865**	**0.9%**
E - Water supply	6	51	12	0	0	6	0	0	0	19	48	0	0	0	12	**643**	**0.2%**
F - Construction	77	241	8	44	4	11	47	24	24	196	166	19	22	0	146	**4,213**	**1.3%**
G - Wholesale and retail	3,018	3,247	386	343	29	1,794	2,407	146	1,260	7,110	6,572	526	1,206	15	783	**63,198**	**19.4%**
H - Transportation and storage	96	343	31	0	0	106	63	11	35	765	580	19	53	15	103	**5,305**	**1.6%**
I - Accommodation/food service	76	122	12	25	7	2	20	20	0	4,280	323	27	36	0	63	**8,306**	**2.6%**
J - Information and communication	626	923	355	204	3	691	903	93	594	2,491	3,105	131	384	97	1,340	**35,482**	**10.9%**
K - Financial and insurance	464	734	43	15	33	103	1,169	41	160	4,282	2,510	59	228	75	1,823	**56,146**	**17.2%**
L - Real estate activities	154	266	82	40	0	511	164	17	77	978	1,204	15	66	0	148	**11,518**	**3.5%**
M - Professional, sci., and techn. act.	875	1,290	285	274	5	809	566	193	542	3,540	6,206	241	448	49	2,178	**47,966**	**14.7%**
N - Admin and support service	399	288	101	28	0	153	265	41	151	1,469	1,981	101	270	8	1,262	**23,984**	**7.4%**
O - Public admin and defence	0	2	0	0	0	0	0	0	0	0	22	0	0	0	22	**269**	**0.1%**
P - Education	0	12	0	0	0	24	0	0	8	263	53	11	3	0	1	**1,434**	**0.4%**
Q - Human health and social work	0	47	23	0	2	19	0	0	29	82	381	0	0	0	100	**3,965**	**1.2%**
R - Arts, entertainment and rec.	12	37	0	0	0	15	47	12	21	117	32	0	22	1	18	**1,731**	**0.5%**
S - Other service activities	16	29	12	12	0	10	0	0	0	72	525	0	8	0	273	**3,425**	**1.1%**
T - Activities of households	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**76**	**0.0%**
U - Eextraterritorial organisations	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**25**	**0.0%**
Total	6,662	10,447	1,558	1,060	91	5,706	6,564	745	3,637	31,807	31,229	1,231	3,504	304	9,995	**325,713**	**100.0%**
Total (%)	2.0%	3.2%	0.5%	0.3%	0.0%	1.8%	2.0%	0.2%	1.1%	9.8%	9.6%	0.4%	1.1%	0.1%	3.1%	**100.0%**	

This table reports the number of U.S. firms' subsidiaries by European country and NACE Rev. 2 Industry Section during the sample period 2010–2021. The sample is restricted to U.S. firms with at least one AI-skilled employee during the sample period, as measured in Babina et al. (2024*a*). The dataset includes 1,898 unique U.S. firms and 43,049 unique majority-owned subsidiaries with non-missing unconsolidated financial information across European countries.

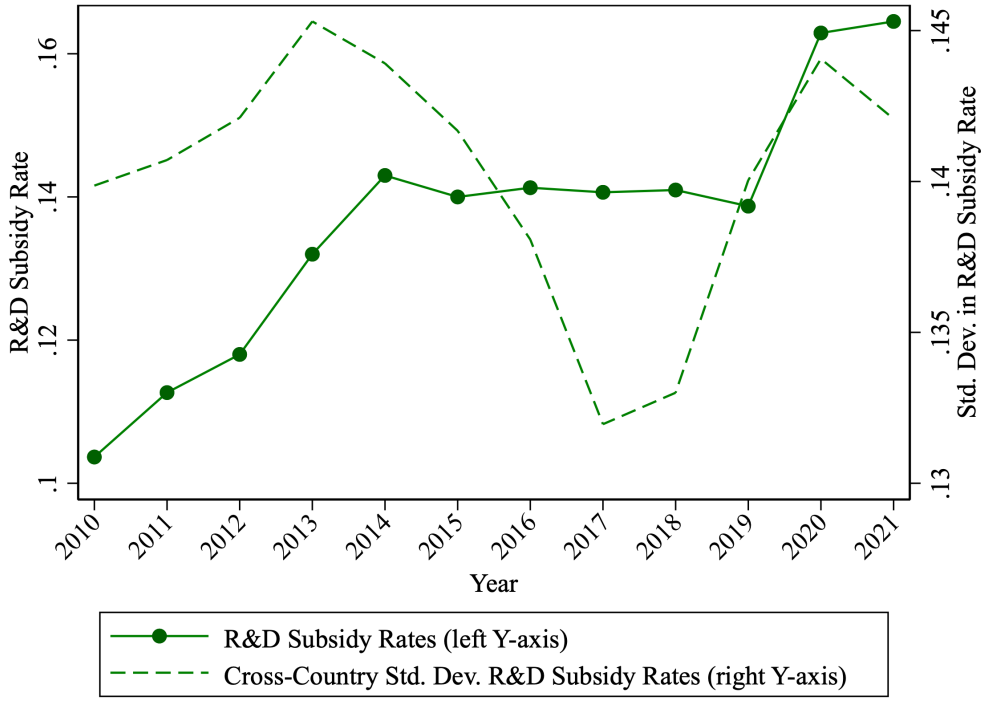
Table A-1: U.S. AI Firm's Subsidiaries by European Country and Industry (*continued*)

Industry	Italy	Latvia	Lithuania	Luxembourg	Malta	Netherlands	Norway	Poland	Portugal	Romania	Slovak Republic	Slovenia	Spain	Sweden	Switzerland	U.K.	**Total**	**Total** (%)
A	36	0	0	0	0	1	12	16	9	11	0	0	7	12	0	86	**281**	**0.1%**
B	38	0	0	0	0	178	198	82	0	25	0	0	6	0	0	939	**1,773**	**0.5%**
C	5,026	24	54	98	77	3,351	609	1,960	558	443	440	156	2,721	1,426	6	13,924	**53,108**	**16.3%**
D	464	0	0	0	0	48	12	106	0	0	0	0	572	1	0	827	**2,865**	**0.9%**
E	4	0	0	0	0	52	0	9	46	12	2	0	80	15	0	269	**643**	**0.2%**
F	829	15	2	12	0	120	126	131	85	64	12	10	220	47	0	1,511	**4,213**	**1.3%**
G	4,753	78	101	262	22	5,527	1,941	2,185	2,179	613	737	277	4,539	3,632	4	7,506	**63,198**	**19.4%**
H	205	10	13	35	4	398	192	190	74	70	53	20	226	55	7	1,533	**5,305**	**1.6%**
I	229	0	0	1	20	129	17	126	113	12	12	10	865	48	0	1,711	**8,306**	**2.6%**
J	1,765	94	69	174	48	2,048	780	908	469	622	207	112	1,534	1,519	0	13,193	**35,482**	**10.9%**
K	883	31	29	9,980	177	19,248	184	206	182	10	11	18	948	1,241	0	11,259	**56,146**	**17.2%**
L	704	3	0	52	8	918	267	740	218	22	245	0	549	492	0	3,578	**11,518**	**3.5%**
M	2,315	161	68	160	7	3,775	883	1,039	582	493	308	134	1,667	1,540	2	17,331	**47,966**	**14.7%**
N	902	0	20	224	15	885	555	340	338	166	210	23	775	379	0	12,635	**23,984**	**7.4%**
O	11	0	0	0	0	8	0	0	0	0	0	0	0	0	0	204	**269**	**0.1%**
P	47	0	0	0	0	87	19	14	7	0	10	0	75	37	0	763	**1,434**	**0.4%**
Q	49	0	0	0	0	63	7	25	166	12	0	0	129	31	0	2,800	**3,965**	**1.2%**
R	96	0	9	0	32	142	6	35	0	12	12	0	74	36	0	943	**1,731**	**0.5%**
S	12	0	0	0	0	62	0	69	20	0	22	12	52	16	0	2,203	**3,425**	**1.1%**
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	76	**76**	**0.0%**
U	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	20	**25**	**0.0%**
Total	18,368	416	365	10,998	410	37,045	5,808	8,181	5,046	2,587	2,281	772	15,039	10,527	19	93,311	**325,713**	**100.0%**
Total (%)	5.6%	0.1%	0.1%	3.4%	0.1%	11.4%	1.8%	2.5%	1.5%	0.8%	0.7%	0.2%	4.6%	3.2%	0.0%	28.6%	**100.0%**	

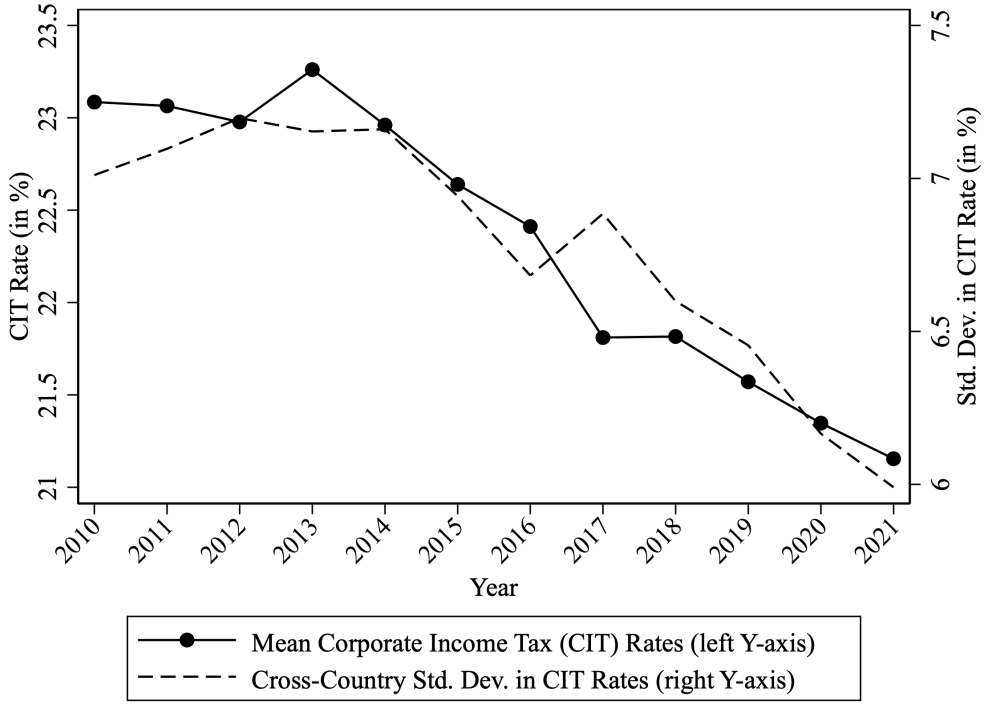
This table reports the number of U.S. firms' subsidiaries by European country and NACE Rev. 2 Industry Section during the sample period 2010–2021. The sample is restricted to U.S. firms with at least one AI-skilled employee during the sample period, as measured in Babina et al. (2024*a*). The dataset includes 1,898 unique U.S. firms and 43,049 unique majority-owned subsidiaries with non-missing unconsolidated financial information across European countries.

Figure A-1: Tax Incentive Policy Variation across European Countries

(**A**) R&D Subsidy Rates



(**B**) Corporate Income Tax Rates



Notes: This figure illustrates the tax policy variation used in our analysis. Panel A plots the average R&D subsidy rate across all countries over time in our sample period (green solid line, left Y-axis). The R&D tax subsidy rate is defined as 1 minus the B-index for large profitable firms. The B-index measures the before-tax income required for a representative firm to break even on USD 1 of R&D spending, accounting for all tax incentives in a given country. We use the measure specifically for large and profitable firms. The green dashed line (right Y-axis) represents the cross-country variation in each year, measured by the standard deviation across countries. Panel B presents the analogous statistics for countries' corporate income tax rates (black lines).

Table A-2: R&D Subsidy Rates across European Countries and Years

ISO2	Country	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
AT	Austria	0.09	0.12	0.12	0.12	0.12	0.12	0.15	0.15	0.17	0.17	0.17	0.17
BE	Belgium	0.15	0.15	0.15	0.16	0.16	0.16	0.16	0.16	0.16	0.15	0.15	0.16
BG	Bulgaria	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CH	Switzerland	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
CY	Cyprus	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
CZ	Czech Republic	0.20	0.20	0.20	0.20	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
DE	Germany	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	0.19	0.19
DK	Denmark	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.07	0.07
EE	Estonia	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ES	Spain	0.35	0.35	0.35	0.35	0.35	0.34	0.33	0.33	0.33	0.33	0.33	0.33
FI	Finland	-0.01	-0.01	-0.01	0.19	0.14	-0.01	-0.01	-0.01	-0.01	-0.01	0.00	0.00
FR	France	0.43	0.44	0.44	0.45	0.45	0.45	0.43	0.43	0.43	0.43	0.39	0.37
GB	United Kingdom	0.11	0.09	0.09	0.09	0.09	0.10	0.10	0.10	0.11	0.11	0.12	0.12
GR	Greece	0.01	0.01	0.01	0.08	0.08	0.10	0.10	0.10	0.10	0.08	0.29	0.26
HR	Croatia	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	0.07	0.07	0.07
HU	Hungary	0.22	0.22	0.22	0.36	0.35	0.35	0.35	0.22	0.21	0.20	0.19	0.19
IE	Ireland	0.26	0.25	0.27	0.26	0.27	0.29	0.29	0.29	0.29	0.29	0.27	0.27
IS	Iceland	-0.01	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.30	0.30
IT	Italy	-0.02	-0.02	-0.02	-0.02	-0.02	0.04	0.04	0.09	0.09	0.07	0.11	0.20
LT	Lithuania	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31	0.31
LU	Luxembourg	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
LV	Latvia	0.00	0.00	0.00	0.00	0.31	0.31	0.31	0.31	0.00	0.00	0.00	0.00
MT	Malta	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	-0.02	-0.02	-0.02
NL	Netherlands	0.09	0.10	0.12	0.14	0.15	0.15	0.15	0.15	0.13	0.15	0.15	0.15
NO	Norway	0.22	0.22	0.22	0.22	0.22	0.22	0.21	0.21	0.21	0.21	0.22	0.22
PL	Poland	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	0.04	0.09	0.22	0.22	0.22	0.22
PT	Portugal	0.41	0.41	0.41	0.41	0.40	0.39	0.39	0.39	0.39	0.39	0.39	0.39
RO	Romania	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
SE	Sweden	-0.01	-0.01	-0.01	-0.01	0.05	0.05	0.05	0.05	0.05	0.05	0.11	0.11
SI	Slovenia	0.08	0.08	0.20	0.19	0.19	0.19	0.19	0.21	0.21	0.21	0.21	0.21
SK	Slovak Republic	-0.01	-0.01	-0.01	-0.01	-0.01	0.11	0.11	0.10	0.28	0.41	0.55	0.55

Notes: This table presents the variation in the R&D tax incentive variable used in our analysis. The table reports the tax subsidy rate by country and year, defined as 1 minus the B-index. The B-index measures the before-tax income required for a representative firm to break even on USD 1 of R&D spending, accounting for all tax incentives in a given country. We use the measure specifically for large and profitable firms. Data are sourced from the OECD.

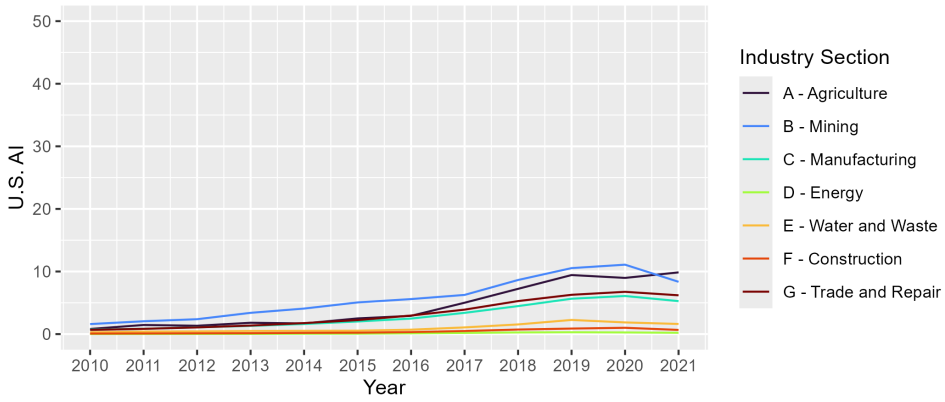
Table A-3: Corporate Income Tax Rates R&D Subsidy Rates across European Countries and Years

ISO2	Country	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
AT	Austria	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0
BE	Belgium	34.0	34.0	34.0	34.0	34.0	34.0	34.0	34.0	29.6	29.6	25.0	25.0
BG	Bulgaria	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0
CH	**Switzerland**	**21.2**	**21.2**	**21.2**	**21.1**	**21.1**	**21.1**	**21.1**	**21.1**	**21.1**	**21.1**	**21.1**	**19.7**
CY	**Cyprus**	**10.0**	**10.0**	**10.0**	**12.5**	**12.5**	**12.5**	**12.5**	**12.5**	**12.5**	**12.5**	**12.5**	**12.5**
CZ	Czech Republic	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0
DE	Germany	30.2	30.2	30.2	30.2	30.2	30.2	30.2	30.2	29.8	29.9	29.9	29.8
DK	Denmark	25.0	25.0	25.0	25.0	24.5	23.5	22.0	22.0	22.0	22.0	22.0	22.0
EE	Estonia	21.0	21.0	21.0	21.0	21.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0
ES	Spain	30.0	30.0	30.0	30.0	30.0	28.0	25.0	25.0	25.0	25.0	25.0	25.0
FI	Finland	26.0	26.0	24.5	24.5	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0
FR	France	34.4	36.1	36.1	38.0	38.0	38.0	34.4	34.4	34.4	34.4	32.0	28.4
GB	United Kingdom	28.0	26.0	24.0	23.0	21.0	20.0	20.0	19.0	19.0	19.0	19.0	19.0
GR	Greece	24.0	20.0	20.0	26.0	26.0	26.0	29.0	29.0	29.0	24.0	24.0	24.0
HR	Croatia	0.0	0.0	0.0	0.0	0.0	20.0	20.0	18.0	18.0	18.0	18.0	18.0
HU	**Hungary**	**19.0**	**19.0**	**19.0**	**19.0**	**19.0**	**19.0**	**19.0**	**9.0**	**9.0**	**9.0**	**9.0**	**9.0**
IE	Ireland	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5	12.5
IS	Iceland	18.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0
IT	Italy	31.4	31.4	31.3	31.3	31.3	31.3	31.3	27.8	27.8	27.8	27.8	27.8
LT	**Lithuania**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**
LU	Luxembourg	28.6	28.8	28.8	29.2	29.2	29.2	29.2	27.1	26.0	24.9	24.9	24.9
LV	**Latvia**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**15.0**	**20.0**	**20.0**	**20.0**	**20.0**
MT	**Malta**	**35.0**	**35.0**	**35.0**	**35.0**	**35.0**	**35.0**	**35.0**	**35.0**	**35.0**	**35.0**	**35.0**	**35.0**
NL	Netherlands	25.5	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0
NO	Norway	28.0	28.0	28.0	28.0	27.0	27.0	25.0	24.0	23.0	22.0	22.0	22.0
PL	Poland	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0	19.0
PT	Portugal	26.5	28.5	31.5	31.5	31.5	29.5	29.5	29.5	31.5	31.5	31.5	31.5
RO	Romania	16.0	16.0	16.0	16.0	16.0	16.0	16.0	16.0	16.0	16.0	16.0	16.0
SE	Sweden	26.3	26.3	26.3	22.0	22.0	22.0	22.0	22.0	22.0	21.4	21.4	20.6
SI	Slovenia	20.0	20.0	18.0	17.0	17.0	17.0	17.0	19.0	19.0	19.0	19.0	19.0
SK	Slovak Republic	19.0	19.0	19.0	23.0	22.0	22.0	22.0	21.0	21.0	21.0	21.0	21.0

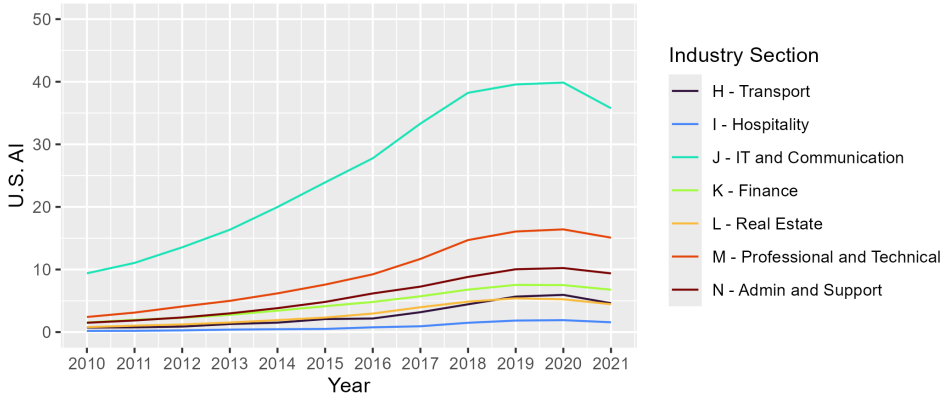
Notes: This table presents the variation in corporate income tax rates used in our analysis. Bolded countries are classified as having favorable corporate tax regimes, accounting for corporate income tax incentives beyond the statutory rate, as identified in prior research (e.g., De Simone and Olbert, 2022).

Figure A-2: Exposure to U.S. AI Investment across Industries in Europe in 2010-2021

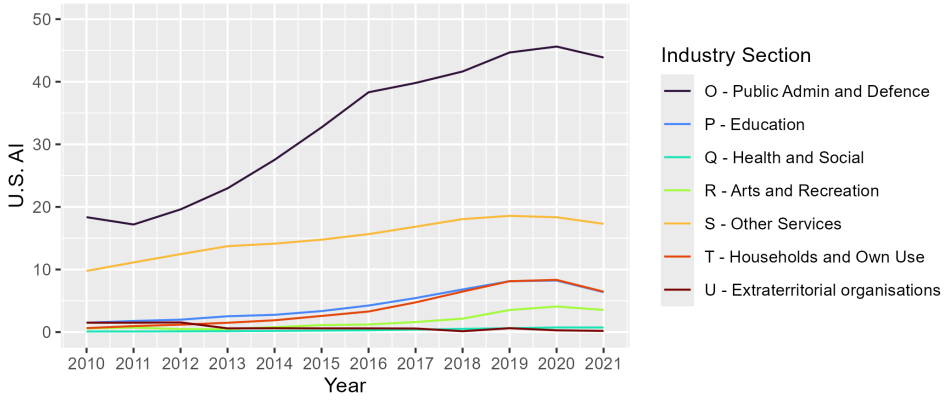
(**A**) Industry Sections A-G



(**B**) Industry Sections H-N



(**C**) Industry Sections O-U



Notes: This figure presents the European country-industry-year level exposure variable $U.S.\ AI_{c,i,t-1}$, averaged by NACE Rev. 2 industry sections over the years.

Table A-4: Robustness of Aggregate Results to Industry-Year Fixed Effects

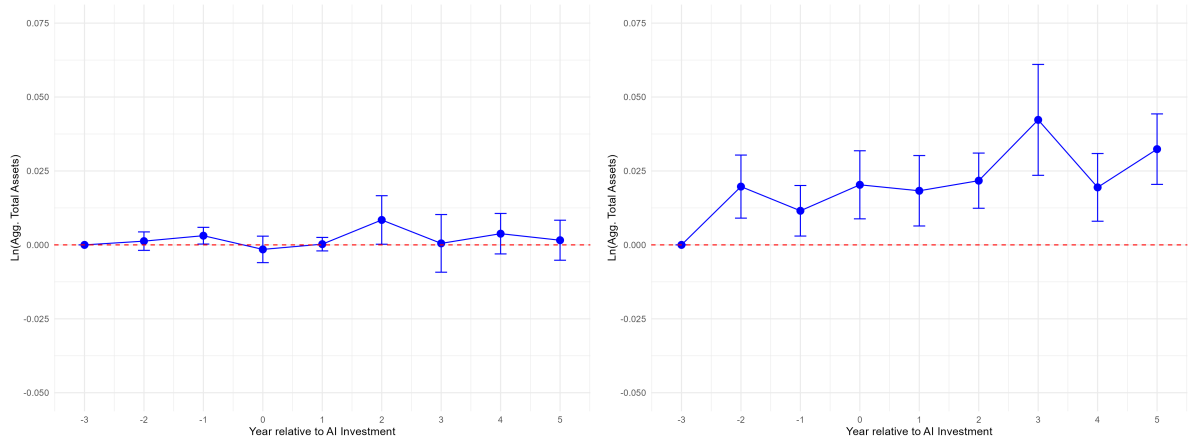
	(1)	(2)	(3)	(4)
Panel A	ln(Total Assets)			
	Baseline	R&D Tax	Profit Tax	R&D and Profit Tax
U.S. AI	0.0029***	0.0022**	0.0011	0.0019**
	(0.0010)	(0.0009)	(0.0016)	(0.0009)
*U.S. AI * Tax Incentive*		0.0014	0.0024	0.0036**
		(0.0010)	(0.0016)	(0.0015)
N	18,486	18,486	18,486	18,486
R2 Within Adj.	0.003	0.004	0.004	0.005
Panel B	ln(Number of Employees + 1)			
	Baseline	R&D Tax	Profit Tax	R&D and Profit Tax
U.S. AI	0.0012	0.0013	-0.0004	0.0007
	(0.0011)	(0.0010)	(0.0020)	(0.0011)
*U.S. AI * Tax Incentive*		-0.0003	0.0020	0.0015
		(0.0011)	(0.0018)	(0.0015)
N	18,132	18,132	18,132	18,132
R2 Within Adj.	0.000	0.000	0.001	0.001
Panel C	ln(Operating Revenue)			
	Baseline	R&D Tax	Profit Tax	R&D and Profit Tax
U.S. AI	0.0030***	0.0031***	-0.0003	0.0023**
	(0.0011)	(0.0011)	(0.0017)	(0.0011)
*U.S. AI * Tax Incentive*		-0.0002	0.0043**	0.0024*
		(0.0011)	(0.0017)	(0.0014)
N	18,439	18,439	18,439	18,439
R2 Within Adj.	0.003	0.003	0.005	0.004
Country-Industry FE	X	X	X	X
Country-Year FE	X	X	X	X
Industry Section-Year FE	X	X	X	X

Notes: This table reports the results of estimating the effect of U.S. AI exposure on European country-industry outcomes using equation 3. In addition to the country-industry and country-year fixed effects as in Table 2, the specifications include NACE Rev. 2 industry section-year fixed effects. Robust standard errors are clustered at the country-industry level. Standard Errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure A-3: Effect of Taxes and U.S. AI Investment on European Economies: Distributed Lead-Lag

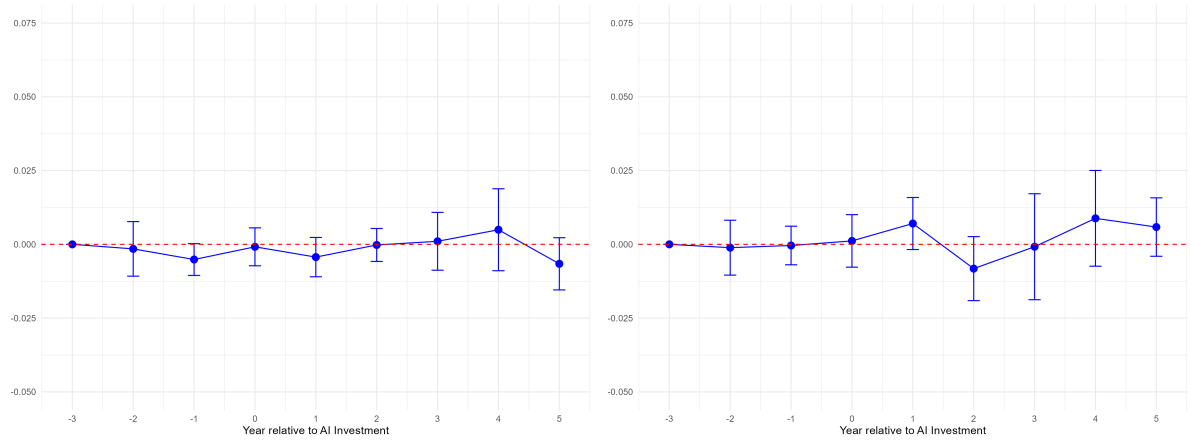
(**A**) Total Assets - ***Low*** Tax Attractiveness

(**B**) Total Assets - ***High*** Tax Attractiveness



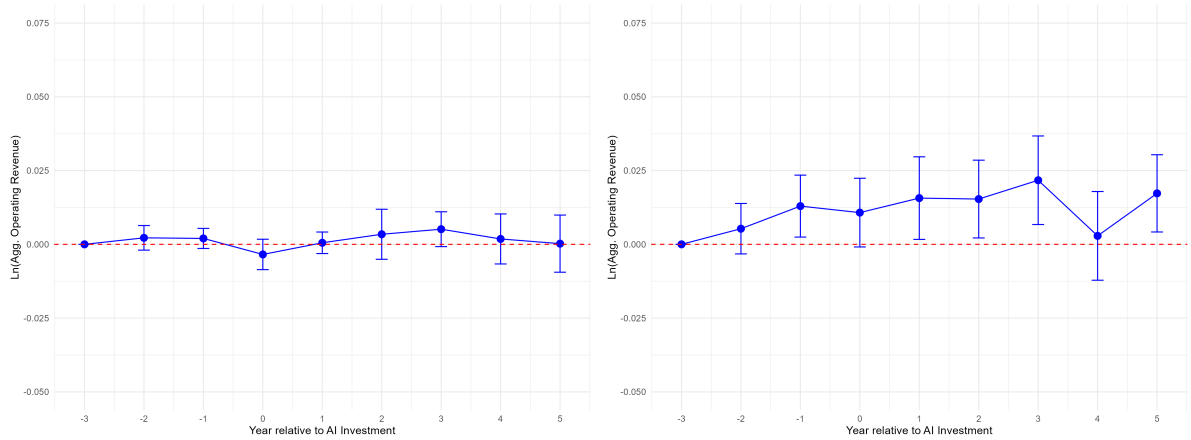
(**C**) Employees - ***Low*** Tax Attractiveness

(**D**) Employees - ***High*** Tax Attractiveness



(**E**) Revenues - ***Low*** Tax Attractiveness

(**F**) Revenues - ***High*** Tax Attractiveness



Notes: This figure illustrates the effect dynamics of U.S. AI exposure on European country-industries using a distributed lead-lag model. The x-axis represents the years relative to AI investment, while the y-axis depicts the coefficients from the distributed lead-lag regression. The model uses the log of aggregated total assets, employees, or revenues at country-industry level as the outcome variable and multiple leads and lags of the $U.S.\ AI_{c,i,t}$ variable as regressors. Panels A, C, and E (B, D, and F) present results for the subsample of countries with a relatively low (high) tax attractiveness, respectively. The sample split is based on the median R&D tax subsidy rate and whether a country offers a corporate income tax rate below 21% or a preferential tax regime in a given year.

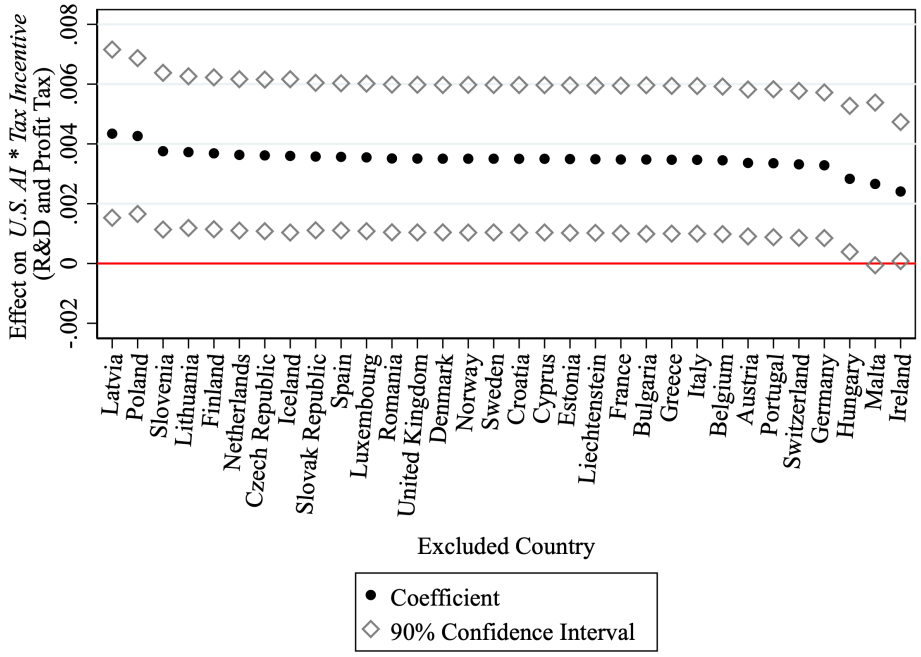
Table A-5: Aggregate Results: Results by Country

		Total Assets		Revenue			R&D Subsidy Rate			CIT Rate		
ISO2	Country	Coeff.	SE	Coeff.	SE	N	Mean	First	2021	Mean	First	2021
CY	Cyprus	0.199	0.058	0.503	0.072	283	-0.01	0.00	-0.01	11.9	10.0	12.5
HU	Hungary	0.019	0.004	0.007	0.005	599	0.26	0.22	0.19	14.9	19.0	9.0
MT	Malta	0.018	0.003	0.008	0.003	228	0.16	0.22	-0.02	35.0	35.0	35.0
IE	Ireland	0.009	0.004	0.008	0.004	760	0.27	0.26	0.27	12.5	12.5	12.5
SK	Slovakia	0.007	0.002	0.002	0.002	544	0.17	-0.01	0.55	20.9	19.0	21.0
DK	Denmark	0.007	0.011	-0.005	0.004	714	0.00	-0.01	0.07	23.3	25.0	22.0
ES	Spain	0.006	0.007	0.001	0.001	873	0.34	0.35	0.33	27.3	30.0	25.0
LV	Latvia	0.006	0.001	0.004	0.001	287	0.10	0.00	0.00	16.6	15.0	20.0
SE	Sweden	0.004	0.006	-0.003	0.004	754	0.04	-0.01	0.11	22.9	26.3	20.6
IS	Iceland	0.004	0.002	0.002	0.002	173	0.23	-0.01	0.30	19.8	18.0	20.0
HR	Croatia	0.004	0.006	0.001	0.003	217	0.02	-0.01	0.07	18.6	20.0	18.0
RO	Romania	0.004	0.001	0.005	0.001	611	0.08	0.08	0.08	16.0	16.0	16.0
GB	U. K.	0.003	0.003	0.008	0.004	996	0.10	0.11	0.12	21.4	28.0	19.0
NO	Norway	0.003	0.002	0.003	0.002	720	0.22	0.22	0.22	25.3	28.0	22.0
LU	Lux.	0.003	0.003	0.010	0.004	392	-0.01	-0.01	-0.01	27.6	28.6	24.9
FI	Finland	0.003	0.001	0.001	0.002	632	0.02	-0.01	0.00	21.7	26.0	20.0
EE	Estonia	0.002	0.003	0.003	0.003	360	0.00	0.00	0.00	20.4	21.0	20.0
SI	Slovenia	0.002	0.001	0.003	0.001	359	0.18	0.08	0.21	18.4	20.0	19.0
BG	Bulgaria	0.002	0.002	0.004	0.002	506	0.00	0.00	0.00	10.0	10.0	10.0
CZ	Czech Rep.	0.002	0.004	0.003	0.001	660	0.21	0.20	0.21	19.0	19.0	19.0
FR	France	0.001	0.003	0.004	0.003	863	0.43	0.43	0.37	34.9	34.4	28.4
GR	Greece	0.001	0.001	0.002	0.001	416	0.10	0.01	0.26	25.1	24.0	24.0
PL	Poland	0.001	0.001	0.001	0.001	828	0.08	-0.01	0.22	19.0	19.0	19.0
IT	Italy	0.000	0.003	-0.003	0.003	827	0.04	-0.02	0.20	29.9	31.4	27.8
LT	Lithuania	-0.001	0.005	0.002	0.003	338	0.31	0.31	0.31	15.0	15.0	15.0
AT	Austria	-0.001	0.006	-0.008	0.008	649	0.14	0.09	0.17	25.0	25.0	25.0
NL	Netherlands	-0.002	0.004	0.009	0.006	884	0.14	0.09	0.15	25.0	25.5	25.0
PT	Portugal	-0.002	0.002	-0.001	0.002	582	0.40	0.41	0.39	30.3	26.5	31.5
DE	Germany	-0.003	0.007	-0.005	0.006	915	0.01	-0.02	0.19	30.1	30.2	29.8
CH	Switzerland	-0.007	0.008	-0.011	0.011	467	-0.01	-0.01	-0.01	21.0	21.2	19.7
BE	Belgium	-0.015	0.007	-0.004	0.010	820	0.16	0.15	0.16	31.8	34.0	25.0

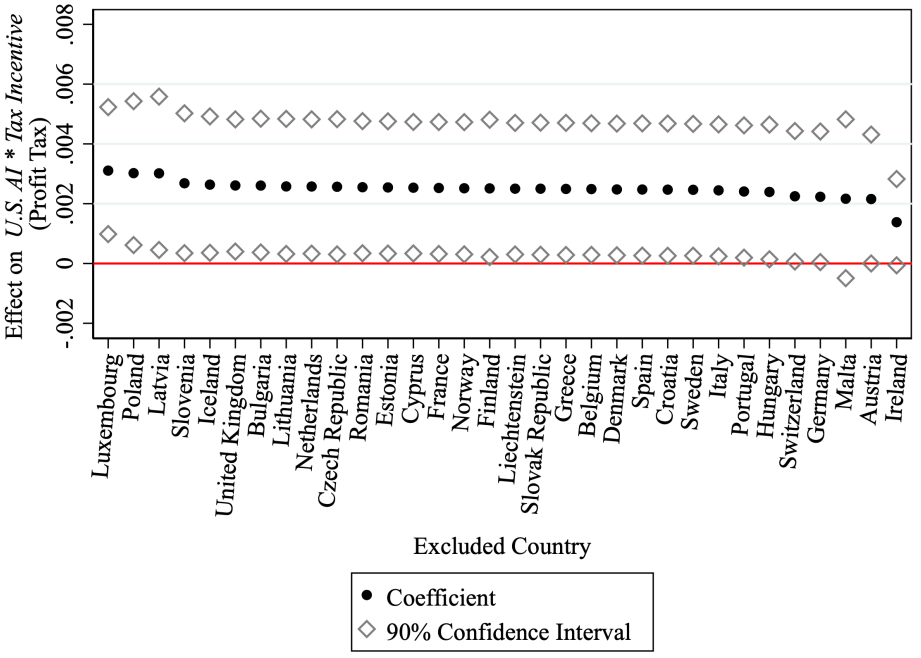
Notes: This table reports the results of estimating the effect of a European country-industry's exposure to U.S. firms' AI investment on European country-industry total assets and revenues, based on equation 3, estimated separately for each country in the sample. After the country names on the left, the table first presents the coefficient estimate (Coeff.) on *U.S. AI* and the corresponding standard error (SE) when ln(Total Assets) and ln(Operating Revenue) are the outcome variables at the aggregate level. This is followed by the number of country-industry observations used in the country-by-country regressions (N)). For each country, we also report key tax policy parameters, including the RD tax subsidy rate and the corporate income tax rate. We show the mean during the sample period, as well as the values for the first year the country has usable observations as well as the last sample period year (2021).

Figure A-4: Robustness of Aggregate Results to Excluding Specific Countries

(**A**) Total Assets



(**B**) Revenues



Notes: Panel A presents the results of estimating the effect of U.S. AI exposure and R&D and profit tax incentives on European country-industry total assets, using the baseline version of equation 3, as in Column (4) of Table 2, Panel A, while excluding one sample country at a time. Panel B presents the results of estimating the effect of U.S. AI exposure and profit tax incentives on European country-industry revenues, using the baseline version of equation 3, as in Column (3) of Table 2, Panel C, while excluding one sample country at a time. The markers represent the point estimates on the interaction term *U.S. AI * Tax Incentives*, with the corresponding 90% confidence intervals.