Integrators: The Firm Boundaries of Capital-Skill Complementarity*

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Abstract

Linking Belgian firm-level data on capital investments, buyer–supplier transactions, and worker skills, we show that the skill bias of new capital arises entirely outside the boundaries of investing firms. Following investment spikes in machinery, firms increase their demand for high-skilled STEM workers from external suppliers by 47%, compared with 8–17% for other skills, while in-house employment grows evenly and contributes less than 5%. The external skill bias arises first from machine integration and later from complementary services, and is stronger for smaller firms, lumpy investments, and capital undergoing rapid technological change—consistent with fixed costs of hiring technology-complementary skills. A simple aggregation suggests that skill bias from new machinery can account for a 23% rise in the demand for high-STEM labor between 2003 and 2021. Our findings place specialized supplier skills at the center of technology adoption, reconciling classic theories of capital–skill complementarity with modern firm-level evidence of skill-neutral investment effects.

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How do new machines affect the demand for worker skills? Since the capital–skill complementarity hypothesis of Griliches (1969), economists have argued that new machinery complements skilled labor. As Greenwood and Yorukoglu (1997) note, *"setting up and operating new technologies often involves acquiring and processing information. Skill facilitates this adoption process."*

Yet despite its central role in many macro-labor models (Krusell et al., 2000), recent micro-level evidence of capital–skill complementarities has been elusive. Armed with newly available firm-level data, a growing number of studies document that firms investing in new machinery do not alter their skill mixes (Aghion et al., 2024; Curtis et al., 2022; Hirvonen, Stenhammar and Tuhkuri, 2025), challenging the capital–skill complementarity hypothesis.[1]

In this paper, we argue that it is essential to look *beyond* the boundaries of investing firms to capture the skill bias of new machines. We present novel evidence that the skills required to adopt and deploy new machinery are predominantly sourced from *external* firms. Thus, while new machines may appear skill-neutral for the in-house workforce of adopting firms, they raise the skill demands of supplier firms, generating capital–skill complementarities in the broader labor market.

Robot integration provides a prominent example of the process we have in mind. A common rule of thumb in industrial robotics is that installation and integration services account for roughly two-thirds of the total cost of a robot cell (IFR, 2022). Because many manufacturers lack the in-house expertise to perform this integration, they typically outsource it to specialized external providers. Reflecting this demand, the number of integrator firms in the U.S. increased by about 300% over the past decade (RIA, 2020).[2]

[1] Berlingieri et al. (2024) find modestly positive capital–skill complementarity at the firm level, though still an order of magnitude smaller than what would be required to explain the aggregate rise in skill demand attributed to capital by Krusell et al. (2000).

[2] The central role of external suppliers in technology adoption echoes historical evidence on the emergence of millwrights on the eve of the Industrial Revolution (Mokyr, Sarid and Van Der Beek, 2022).

While recent work emphasizes the importance of integrators for robot adoption (Békés et al., 2025; Brynjolfsson et al., 2023), their implications for skill bias remain unexplored.[3]

To study this process systematically, we link Belgian firm-level data on capital investments, buyer–supplier transactions, and worker skills from 2003 to 2021. This unique combination of data allows us to examine how firms adjust their labor demand around major capital investment events, encompassing both in-house employment and external labor services. To capture skill bias, we classify labor along two dimensions: the *level* of education (low refers to below-tertiary education; high to tertiary or higher) and the *field* of education (STEM vs. non-STEM). Under the capital–skill complementarity hypothesis, capital investment should increase the relative demand for high-STEM labor.

We adopt the "investment spikes" design from recent studies (e.g., Bessen et al. (2025), Aghion et al. (2024), and Hirvonen, Stenhammar and Tuhkuri (2025)), analyzing how firms adjust their labor demand before and after large increases in machinery investment. Reflecting the lumpy nature of capital investment (Cooper and Haltiwanger, 2006), the machinery stock per worker more than triples—from 15 to over 50 thousand euros—around a typical investment spike in our analysis sample. Our empirical strategy uses a difference-in-differences approach, comparing firms that experience an investment spike to similar firms in the same industry that do not.

We establish six key findings on how firms adjust their skill demand around machinery investment spikes.

First, firms that experience spikes show a sharp rise in demand for high-STEM labor. In the year of adoption, total employment (including both in-house and external workers) of high-STEM workers increases by about 51%, compared with only 11–20% for other skill categories. Four years later, demand for high-skilled STEM workers remains 34%

[3]Bilgin, Faia and Ottaviano (2025) study how robot adoption affects the total factor productivity (TFP) of upstream and downstream suppliers. By contrast, our contribution is to identify the skill bias of new capital. Moreover, we examine a much broader set of technologies than industrial robotics, covering multiple capital types and sectors.

above baseline, while employment in other skill categories has grown more modestly by 19–26%.

Second, the shift toward high-skilled STEM workers stems *exclusively* from external labor services. By contrast, in-house employment grows more evenly across skill categories, contributing about 2–4% of total employment in the year of investment and around 8–12% after four years, consistent with existing firm-level studies (Aghion et al., 2024; Curtis et al., 2022; Hirvonen, Stenhammar and Tuhkuri, 2025).

Third, the external skill bias is initially driven by machine suppliers and integrators, temporarily raising total demand for high-STEM workers by 15%. Over time, demand for external skills shifts toward other suppliers complementary to machine-intensive production, such as software providers. Put differently, while machine integration is an important initial source of skill bias, rising machine intensity in production shifts demand toward a broader set of skill-biased external suppliers.

Fourth, external suppliers play a particularly important role in machinery adoption by smaller firms, generating a larger shift toward high-STEM external hires. Larger firms, by contrast, experience a more modest shift in high-STEM demand around investment events, partly because they are more likely to have already employed such workers in-house prior to adoption.

Fifth, the external high-STEM skill bias of new machinery is pervasive across sectors. While machinery investments are most common in manufacturing, they generate even larger relative shifts in external high-STEM labor in services, partly because services firms employ fewer of these workers to begin with. In particular, while industrial robots are a prominent example of capital that generates skill complementarity, the pattern extends to new machinery more broadly.

Finally, the high-STEM skill bias of investment spikes is specific to new machinery. Building investment spikes generate lower skill bias, which also fades over time. Intangible

capital investments are not associated with changes in the skill mix and also rely far less on external suppliers. Moreover, machinery from new suppliers – which is more likely to embody new technologies – exhibits an even stronger skill bias.

We present a conceptual framework for how new machinery affects the demand for worker skills both within and beyond the boundaries of investing firms. A simple extension of the canonical capital–skill complementarity model reconciles our main findings: hiring machine-complementary skills entails fixed costs.

The presence of fixed costs explains why the high-STEM workers needed to deploy new machinery are often concentrated at specialized external suppliers, which can reap scale economies by serving multiple investing firms. It also explains why these suppliers are especially important for smaller firms (for whom fixed costs are harder to absorb), for lumpy investment categories (in contrast to intangibles, which follow a smoother investment path and therefore require more regular labor, often hired in-house), and for technologically advanced capital types (in contrast to buildings, which are more mature capital goods and require less specialized skills to install and deploy). Fixed costs provide a classic rationale for outsourcing (Grossman and Helpman, 2002), and our contribution is to show that these same considerations shape where technology-complementary skills are deployed.

We conduct several robustness checks of our main results. First, they hold under alternative definitions of investment spikes and under a different construction of the comparison ("non-spiking") group in the difference-in-differences design. Second, our findings remain robust when incorporating higher-order links in the supply chain (i.e., suppliers of suppliers).

Using our firm-to-firm transactions data, we evaluate alternative approaches to capturing the skill bias from external suppliers. First, if machine-complementary external services are primarily sourced locally, then aggregating the analysis to local labor mar-

kets (as in Acemoglu and Restrepo (2020); Aghion et al. (2023); Dauth et al. (2021)) would capture the skill bias of new machinery. In practice, however, we find that the skills required to adopt new machinery are often sourced outside the local labor markets of investing firms, so analyses conducted at the local level still miss most of the bias. Second, if indirect employment merely reflects a broad shift toward external services, then applying fixed sectoral input–output matrices (as in Humlum (2022)) could capture the bias. Yet because new machinery shifts the composition of external services toward high-STEM labor, such approaches also fail to capture much of the resulting skill bias.

As a final step, we assess whether the estimated magnitudes are large enough to affect aggregate skill demands. To do so, we scale our micro-level estimates by the aggregate increase in machinery stocks and investments observed between 2003 and 2021. Using this back-of-the-envelope calculation, we find that skill bias from new machinery can account for a 23% increase in the aggregate demand for high-STEM workers, equivalent to about 60% of the total rise in employment over the period.

In summary, our key contribution is to highlight the importance of external skills in the adoption of new machinery—and to bring new data to bear on their role. Our evidence strongly supports the capital–skill complementarity hypothesis (Griliches, 1969), once we recognize that the relevant skills are often sourced from specialized external suppliers. More broadly, our paper bridges both the empirical and theoretical strands of two extensive but largely distinct literatures. Empirically, we combine firm-level data on technology adoption and employment (e.g., Aghion et al., 2024; Berlingieri et al., 2024; Hirvonen, Stenhammar and Tuhkuri, 2025) with firm-to-firm transactions (e.g., Dhyne et al., 2025; Huneeus, Kroft and Lim, 2025) to measure how the skill bias of new capital manifests along the supply chain. Theoretically, we connect models of technology–skill complementarity (e.g., Goldin and Katz, 1998) and make-or-buy decisions (e.g., Grossman and Helpman, 2002) to understand where technology-complementary skills are deployed.

The remainder of the paper is organized as follows. The next section introduces the conceptual framework. Section 2 describes the data and the measurement of new machinery adoption. Section 3 presents the main results. Section 4 examines heterogeneity by firm characteristics. Section 5 reports robustness checks. Section 6 compares our approach with strategies that do not use firm-to-firm transaction data. Section 7 quantifies the aggregate impact of firm-level investments in new machinery on skill demand. Section 8 concludes.

1 Conceptual Framework

This section presents a conceptual framework for how new capital affects the demand for worker skills both within and beyond investing firms. We embed the capital–skill complementarity model of Goldin and Katz (1998) in a dynamic setting where firms jointly choose investment, hiring, and outsourcing. In the model, both skilled and unskilled labor contribute to two stages of manufacturing: integration and production. Deploying new capital requires integration services, while a more capital-intensive production process may have distinct effects on the productivity of skilled versus unskilled production workers. We use this framework to enumerate the variables of interest, motivate our "investment spikes" empirical strategy (implemented in Section 3), and to derive testable predictions about why firms outsource capital-complementary labor services (examined in Section 4).

1.1 Setup

Consider a firm j in year t. Production combines capital K, skilled labor S^P, and unskilled labor U^P:

$$Y_{jt} = F_{jt}(K_{jt}, S^P_{jt}, U^P_{jt}). \tag{1}$$

The deployment of new capital requires physical investment I_{jt} and integration labor services from skilled S^I and unskilled U^I workers:

$$K_{jt+1} = (1-\delta)K_{jt} + G_{jt}(I_{jt}, S^I_{jt}, U^I_{jt}), \tag{2}$$

where G_{jt} is the firm's investment technology and capital features a one-period time-to-build and depreciates at a rate δ.

For each labor category $\mathbf{L} = \{U^P, S^P, U^I, S^I\}$, firms may either hire directly or rely on outsourced services:

$$\mathbf{L}_{jt} = \mathbf{L}_{Hjt} + \mathbf{L}_{Ojt}. \tag{3}$$

Labor services have market prices $(\mathbf{w}_{Ht}, \mathbf{w}_{Ot})$, whereas hiring in-house may involve additional adjustment costs, $c^H(\mathbf{L}_{Hjt}|\mathbf{L}_{Hjt-1})$. Firms also incur investment costs $c^I_{jt}(I_{jt})$, which may include non-convex components, leading them to concentrate investment in infrequent spikes (Cooper and Haltiwanger, 2006).

Firms choose their labor demands (hired and outsourced) and capital investments to maximize the present-discounted sum of profits:

$$\begin{aligned} V_{jt}(K_{jt}, \mathbf{L}_{Hjt-1}) = \max_{\{\mathbf{L}_{Hjt}, \mathbf{L}_{Ojt}, I_{jt}\}} & \underbrace{P_{jt}F_{jt}(K_{jt}, \mathbf{L}^P_{jt})}_{\text{Revenues}} - \sum_{M\in\{H,O\}} \underbrace{\mathbf{w}_{Mt}\cdot\mathbf{L}_{Mjt}}_{\substack{\text{Wage}\\ \text{Costs}}} - \underbrace{c^H(\mathbf{L}_{Hjt}|\mathbf{L}_{Hjt-1})}_{\substack{\text{Hiring}\\ \text{Costs}}} \\ & - \underbrace{c^I_{jt}(I_{jt})}_{\substack{\text{Investment}\\ \text{Costs}}} + \beta\mathbb{E}_t \underbrace{V_{jt+1}\Big((1-\delta)K_{jt} + G_{jt}(I_{jt}, \mathbf{L}^I_{jt}), \mathbf{L}_{Hjt}\Big)}_{\text{Continuation Value}} \end{aligned} \tag{4}$$

where β is the discount factor, and firms face output prices P_{jt}.[4]

[4]Because we allow F to exhibit decreasing returns to scale, assuming a flat demand curve entails no loss of generality for our propositions.

1.2 Model Predictions

The capital–skill complementarity hypothesis describes how capital and investment affect the relative productivity of skilled workers. Griliches (1969) hypothesizes that capital K makes skilled production labor S^P relatively more productive (Equation 1), while Goldin and Katz (1998) posit that the installation of new capital I requires skilled integrators S^I (Equation 2). As shown in Appendix A.1.1, profit-maximizing firms should therefore increase their relative demand for skills S in response to increases in investments I and capital K:

Prediction 1 (Capital investment and the demand for skills)**.** *Under capital–skill complementarity, capital investment raises the relative demand for skills both initially (through integration labor services) and subsequently (through production labor services).*

See Appendix A.1.1 for a formal derivation.

The novel aspect of our analysis is to recognize that firms may either hire or outsource these workers. What drives firms' decisions to outsource capital-complementary services? In Appendix A.1.2, we derive three simple predictions:

Prediction 2 (Fixed costs and outsourcing of capital-complementary skills)**.** *If hiring capital-complementary workers involves fixed costs f_S^H (e.g., indivisibilities of integrator teams or learning across projects), these labor services are more likely to be sourced from specialized external suppliers. Moreover, smaller firms should be more likely to outsource.*

Prediction 3 (Lumpy investments and outsourcing of capital-complementary skills)**.** *If hiring entails adjustment costs, outsourcing should be more prevalent for lumpy investment categories (e.g., buildings versus software).*

Prediction 4 (Advanced capital and outsourcing of capital-complementary skills)**.** *If the skill bias of capital investments reflects the advanced technologies they embody, we*

should expect stronger effects for capital undergoing more rapid technological change (e.g., machinery versus buildings, or machinery from new suppliers).

See Appendix A.1.2 for formal derivations. In Section 4, we test these predictions to shed light on why firms outsource capital-complementary labor services.

1.3 Identification Strategy

The ideal experiment to test our model's predictions would exogenously vary investment costs c^I to induce variation in investment I and capital K, and then trace the resulting effects on labor demand $\mathbf{L}$ for integration and production tasks, both within and outside the investing firm.

Our main empirical strategy follows the "investment spikes" design pioneered by Bessen et al. (2025) and adapted by Aghion et al. (2024), Hirvonen, Stenhammar and Tuhkuri (2025), and others. The idea is to exploit the lumpiness of capital investment—driven by non-convex adjustment costs c^I—to isolate episodes with sharp increases in investment I and capital stock K, and then examine how firms adjust their labor demand around these discontinuities. In Section 3.1.1, we examine threats to this strategy.

2 Data and Measurement

2.1 Data

We use comprehensive administrative data from Belgium that link firms' annual accounts on capital and investment with business-to-business transaction records and employee-level education data from 2003 to 2021. All datasets share consistent firm identifiers over time, allowing us to merge them at the firm level. We briefly describe the datasets below, with a more detailed discussion provided in Appendix B.

Annual accounts and VAT declarations We observe the annual accounts of all firms in Belgium. These accounts disaggregate tangible fixed assets into buildings and land, machinery and equipment, and office and rolling stock. Firms also report the book value of intangible fixed assets. We complement these data with comprehensive Value Added Tax (VAT) records on firms' sales and purchases. Total purchases distinguish between intermediate inputs and investments in tangible and intangible assets. Total sales include both business-to-business (B2B) and business-to-consumer (B2C) transactions, covering domestic sales as well as exports. Purchases include both direct imports and domestic purchases.

Business-to-business transactions. Our data on business-to-business transactions is based on VAT customer listings. By law, all VAT-liable Belgian firms must report their annual sales to each customer firm, provided the value exceeds 250 euros. This requirement allows us to observe the domestic buyer-supplier linkages of all Belgian firms, along with the total value of their transactions on an annual basis. We observe only the aggregate transaction value between each pair of firms, without detail on transaction type (e.g., investment vs. intermediate) or product code.

For details on the construction of the dataset, see Dhyne, Duprez and Komatsu (2023). The dataset has been used in several recent studies, including Bernard et al. (2022), Baqaee et al. (2025), and Bijnens, Jäger and Schoefer (2025).

Education data. We obtain employee-level data from the social security data warehouse (KSZ), which includes information on each worker's highest educational attainment. Specifically, we observe both the education *level* and *field*. Motivated by the technical skills required to integrate and deploy new machinery (see our conceptual framework in Section 1), we classify workers into four categories: high-skill STEM, high-skill non-STEM, and low-skill STEM and low-skill non-STEM. High-skill refers to tertiary edu-

cation or beyond, while STEM fields are defined as "05 Natural Sciences, Mathematics and Statistics," "06 Information and Communication Technology," and "07 Engineering, Manufacturing and Construction." Employees are matched to their employers based on the Social Security declarations. We observe for each firm the number of employees for each education level × field combination as well as their number of hours worked. With this information, we compute the number of workers in each education category for every firm-year, measured in full-time equivalents. We are the first paper to link the employee-level education data with the business-to-business transactions.

2.2 Measurement

2.2.1 Investment Spikes

We leverage the lumpiness of capital investment to study the outcomes of investing firms before and after they undergo a spike in new capital. This "investment spikes" design was pioneered by Bessen et al. (2025) and has been applied in Aghion et al. (2024), Hirvonen, Stenhammar and Tuhkuri (2025), and others. Specifically, we define a firm as experiencing a machinery investment spike if its change in machinery stock per worker exceeds the 90th percentile of its positive changes:

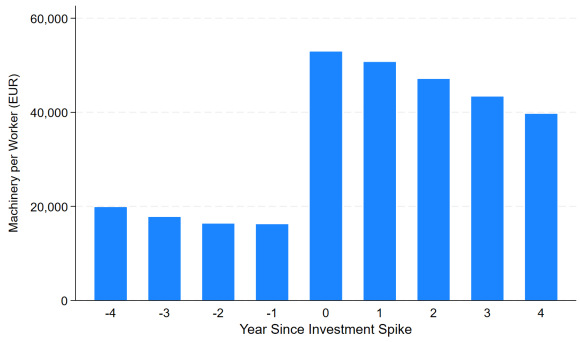
$$\text{Spike}_{jt} = \mathbf{1}[i_{jt} \geq i_{P90|+}] \quad \text{with} \quad i_{jt} = \frac{\Delta\text{Machinery}_{jt}}{\frac{1}{2}(H_{jt} + H_{jt-1})}, \quad I_{P90|+} = \text{€}17,115 \tag{5}$$

where $H_{jt} = \mathbf{1}^T \mathbf{L}_{Hjt}$ denotes in-house employment of firm j and time t.

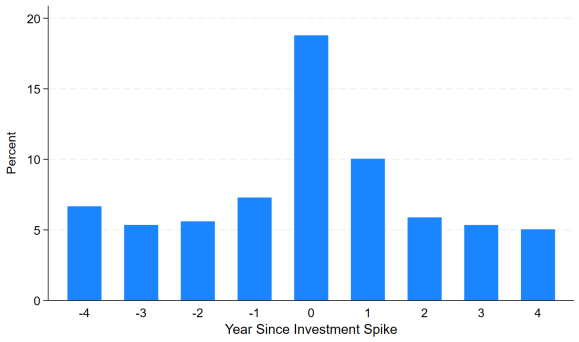
Figure 1 shows that these investment spikes triple the machinery stock per worker, from 16 to 53 thousand euros, with total fixed investment constituting almost 20% of total sales in the spike year. Appendix E.1 demonstrates that our results are robust to alternative percentile thresholds for defining investment spikes.

Figure 1: Machinery Investment Spikes

(a) Machinery Stock per Worker



(b) Investment as a Share of Sales



Notes: This figure shows machinery stocks and capital investment rates around machinery investment spikes. Panel (a) plots the machinery capital stock per worker, and Panel (b) plots the share of investments in total sales. *Sample*: Private sector firms around their first machinery investment spike. Balanced sample for four years before and after the spike.

2.2.2 Machine Supplier Industries

Our study is motivated by the existence of integrator firms that help manufacturers choose, install, and operate robotic systems. In Appendix B.2.1, we describe the industrial organization of machine supply and classify the industry codes in which these suppliers operate. We validate this classification using external lists of robot suppliers in Belgium.

Figure B.1 shows that firms undergoing an investment spike sharply increase their share of purchases from machine supplier industries. On average, total purchases from these external machine suppliers are 1.7 times larger than their direct investment expenditures. This provides the first sign that external suppliers may play a central role in shaping the employment effects of new machinery. Further underscoring the importance of domestic integrators, Appendix B.2.1 show that the machine supplier industries account for the vast majority of industrial robot imports into Belgium. Békés et al. (2025) document a similar pattern in Hungary.

2.2.3 Indirect Employment

To measure firms' indirect employment at external suppliers, we link the firm-to-firm transactions to the payrolls of supplier firms. We rely here on a proportionality assumption common in input-output analysis. For example, if firm j purchases 10% of firm k's sales, we assume firm j indirectly employs 10% of firm k's workers in each skill category.

The first-order indirect employment of skill s by firm j is given by:

$$\mathbf{L}_{Ojt} = \sum_{k} \frac{X_{kjt}}{X_{kt}} \mathbf{L}_{Hkt}, \tag{6}$$

where X_{kjt} denotes the sales of firm k to firm j in year t, and $\mathbf{L}_{Hkt}$ is the in-house employment of firm k. Section 5 shows that our findings are robust to including higher-order linkages (i.e., suppliers of suppliers).

Table 1 reports that the average spiking firm directly employs 40 workers in-house and outsources labor equivalent to 23 full-time workers, including around 4 from machine supplier firms. Notably, the share of high-skill STEM workers among indirectly employed workers at machine suppliers (13.9%) is nearly three times higher than among in-house employees at spiking firms (5.0%). This provides a first indication that these suppliers could be a source of skill bias from new machinery.

Table 1: Firm Employment (Year of Investment Spike)

	Total (FTE)	Share of Total (%)			
		High STEM	High Non-STEM	Low STEM	Low Non-STEM
Direct Employment	39.7	5.0%	14.2%	25.5%	55.3%
Indirect Employment	22.9	6.7%	15.1%	26.8%	51.4%
Machine Suppliers	3.6	13.9%	15.4%	35.9%	34.8%

Notes: This table shows the average direct and indirect employment of spiking firms. *Sample*: Private sector firms in the year of their first machinery investment spike.

3 New Machinery and the Demand for Skills

In this section, we study how firms change their demands for skills around investment spikes in new machinery, analyzing both their direct (in-house) and indirect (outsourced) employment. Section 3.1 describes our empirical strategy and considers threats to identification. Section 3.2 presents our main results.

3.1 Empirical Strategy

Our main empirical strategy follows the "investment spikes" design used by Bessen et al. (2025), Aghion et al. (2024), Hirvonen, Stenhammar and Tuhkuri (2025), among others. The idea is to isolate episodes where firms undergo sharp increases in investment and capital stock, and then examine how they adjust their labor demand around these events.

We make a series of sample cuts to hone in on a well-defined set of spiking firms and events. First, we focus on private sector firms that employ at least five workers (in-house plus indirect) in the year prior to the spike. Second, we focus on firms' first investment spike (65% of spiking firms only experience a single spike). Finally, we study a balanced sample of firms for four years before and after their spikes. Appendix E.1 shows that our results are robust to varying these sample restrictions, including focusing on single-spiking firms or including firm exits. Appendix Table C.1 shows how the restrictions shrink our analysis sample. In total, we retain 3,863 spiking firms in our analysis sample.

Our empirical strategy compares the spiking firms to similar firms that do not experience a spike in the event year. For each spiking firm, we construct a comparison group based on the average of non-spiking firms in the same industry-year that meet the sample criteria (minimum pre-event employment, no previous spikes, and balanced sample) but do not experience a spike in the event year. Table 2 compares the outcomes of spiking and non-spiking firms two years before the spike.[5] Despite not matching on these out-

[5]We choose the two-year pre-spike comparison because investing firms may begin engaging machine

comes, spiking and non-spiking firms are comparable in terms of total employment and skill composition prior to the investment event.

Our main specification is a simple differences-in-differences in outcomes Y between the spiking ($S = 1$) and non-spiking ($S = 0$) firms around a spike-event year, with changes indexed relative to two years before the spike:

$$Y_{it} = \beta_1 S_{ie} + \sum_k \beta_{0k} \mathbf{1}_{\{t=e+k\}} + \sum_{k \neq -2} \beta_{1k} S_{ie} \mathbf{1}_{\{t=e+k\}} + \varepsilon_{it}, \tag{7}$$

where $\mathbf{1}_{\{t=e+k\}}$ are event-time indicators that equal one if year t is k years from the event year e, and β_{1k} are the coefficients of interest, identifying the effect of investment spikes under parallel trends. We estimate Equation (7) by OLS and cluster the standard errors at the event (treated–control pair) level.

integrators (especially for design and advisory services) prior to the physical investment. For example, Figure B.1 shows that purchases from machine suppliers begin to rise modestly in the year preceding the spike.

Table 2: Firm Employment before Machinery Investment Spikes

	Spiking		Non-Spiking		Std. Difference	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
	(1)	(2)	(3)	(4)	(5)	(6)
Total employment	38.8	19.4	43.2	19.2	-0.01	0.00
	(324.0)	(131.9)	(82.3)	(60.9)		
Share of employment (%)						
— High STEM	4.9	5.8	6.0	6.1	-0.11	-0.05
	(10.4)	(5.8)	(6.6)	(3.4)		
— High non-STEM	13.9	16.4	15.1	16.2	-0.06	0.02
	(18.9)	(10.3)	(11.1)	(6.7)		
— Low STEM	26.1	24.8	24.4	23.6	0.08	0.11
	(22.4)	(10.6)	(11.3)	(6.1)		
— Low Non-STEM	55.1	53.0	54.6	54.2	0.02	-0.10
	(25.1)	(11.9)	(13.3)	(6.5)		
Observations	3,863		3,863			

Notes: This table reports direct and indirect employment in treatment (Columns 1-2) and control group (Columns 3-4) in year $t-2$. The table reports total employment in full-time equivalents and the employment share of different skill groups. Columns 5-6 show the standardized difference between the treatment and control group means, calculated in standard deviations of the treatment group, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin, 2008). *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

Our outcomes of interest, Y_{jt}, are firms' total employment—direct plus indirect—by skill group (low non-STEM, low STEM, high non-STEM, and high STEM). We further decompose these outcomes by supplier source, distinguishing between in-house and external labor, as well as across different types of external suppliers (e.g., machine suppliers versus other industries). We focus on employment, measured in full-time equivalents, as earnings are available only in coarse, top-coded bins.

We measure each outcome as a percentage of the skill group's total pre-spike employment, where the pre-spike period is defined as the average over years -3 to -1. Expressing changes relative to *total* group employment (direct plus indirect) has the key advantage of

circumventing issues related to zeros in more disaggregated skill groups (Chen and Roth, 2024), as all firms in our analysis have positive total pre-spike employment in each group. By contrast, 64% of spiking firms have zero direct high-STEM employment prior to the spike, likely reflecting the fixed costs of in-house hiring emphasized in Section 1.2. That said, because direct employment is generally higher than indirect employment in the pre-spike years (Table 2), this *common normalization*—using total group employment as the denominator for all outcomes—works against us in finding that indirect labor is the main driver of total employment changes. Similarly, because machine suppliers constitute a minority of indirect employment (Table 1), the same normalization works against us in finding that machine suppliers are an important driver of indirect employment changes following investment spikes. To clarify the sources of indirect skill bias under this normalization, Appendix C.2 decomposes the contribution of indirect employment to firms' total skill bias into spiking firms' (i) differential increases in direct versus indirect employment and (ii) shifts in indirect employment across skill groups.

3.1.1 Identification Threats and Validity Checks

As discussed in Section 1.3, our ideal experiment would exogenously vary the firm-specific investment cost c_{jt}^I to identify the causal impact of capital investment on labor demand. Of course, as the framework also makes clear, investments are endogenous choices made by firms. In particular, the primary threat to identification is that investment spikes may coincide with other changes in firms' fundamentals, G_{jt} and F_{jt}, causing skill bias even in the absence of capital investments. In this section, we assess this threat to identification.

As a first validity check of the spikes design, Table 2 shows that spiking and non-spiking firms are similar in terms of employment (direct and indirect) and skill shares prior to the spikes. These "balance checks" suggest that investment spikes are not driven by pre-existing technological differences. Moreover, in all figures, we verify that the

spiking and non-spiking follow similar trends prior to the spikes. The flat pre-trends suggest that the underlying fundamentals of the two groups evolve in parallel.[6]

A second piece of supporting evidence comes from prior studies: Hirvonen, Stenhammar and Tuhkuri (2025) and Aghion et al. (2024) show that the spikes design yields similar estimates to those from quasi-experiments based on technology subsidy policies and foreign machine supply shocks, which explicitly vary the firm-specific investment cost c^I_{jt}. Since we closely replicate their design and results for investment spikes, it is plausible that the external validity of their findings extends to our setting.

Third, as emphasized in the "lumpy investment" literature, non-convex adjustment costs for investment c^I naturally give rise to discontinuous jumps in firms' investment and capital; see Cooper and Haltiwanger (2006). Figure 1 confirms that the spike events generate large discontinuities in both investment and capital stocks. Provided that fundamentals evolve smoothly over time, these spikes may be interpreted as a regression discontinuity (RD) design in time. Under this interpretation, we place greater confidence in the short-run responses around the spike years than in the longer-run adaptations to larger capital stocks.[7]

Finally, some of our heterogeneity analyses in Section 4 help strengthen the case that what we identify reflects true capital–skill complementarities rather than confounding shocks. For example, if the skill bias of capital investments reflects the advanced technologies they embody, we should expect weaker effects for mature assets such as

[6]The "balance" and "pre-trend" checks are rationalized by production function estimators that combine time-to-build with a Markov process for firms' technologies, e.g., Olley and Pakes (1996) and Doraszelski and Jaumandreu (2013). Under these assumptions, matching firms on their factor choices before the investment spikes means that the firms also have similar expected technologies in the post-period. Humlum (2022) formalizes this argument when using adoption event studies to identify robot technology among Danish firms.

[7]In particular, it is plausible that investment spikes reflect expectations of future demand. That said, as Lindner et al. (2022) shows, output demand shocks per se do not induce skill bias when production exhibits constant returns to scale. Lashkari, Bauer and Boussard (2024) present a framework in which scale shocks lead firms to invest in IT capital. However, insofar as skill-biased effects operate through capital investment, they continue to identify the capital-skill complementarity of interest.

buildings (Krusell et al., 2000). Consistent with this hypothesis, Section 4.3 shows that building spikes generate weaker skill bias. Moreover, Section 4.4 shows that the skill bias is strongest for machinery purchased from new suppliers. Put differently, these patterns indicate that the skill bias we identify arises from capital–skill complementarities embodied in the capital itself, rather than from confounding shocks associated with investment spikes.

3.2 Main Results

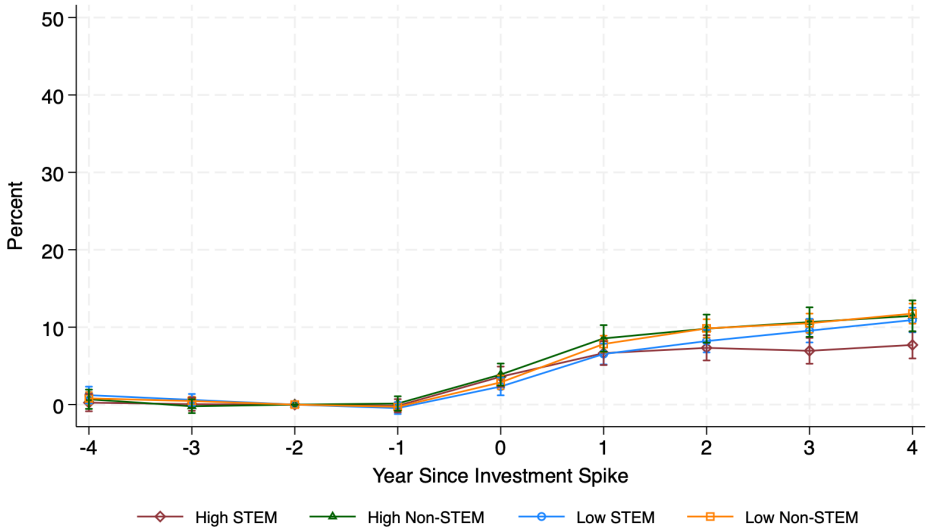
Figure 2 presents our first key result. It plots employment by skill category as a percentage of that category's total pre-spike employment, separating changes into direct employment (Panel (a)) and indirect employment (Panel (b)).

Examining total employment (i.e., the sum of Panels (a) and (b)) shows that firms sharply increase their demand for high-STEM skills. In the year of the investment spike, employment of these workers rises by 51% and remains elevated—at 34%—four years later. By contrast, other skill categories experience more modest increases of 11–20% in the year of the investment spike and 19–26% four years later. Comparing Panels (a) and (b) of Figure 2 reveals that the shift toward high-STEM skills arises *entirely* from external labor services.[8] In-house employment grows more evenly across skill categories, contributing about 2–4% of total employment in the year of the investment spike and around 8–12% after four years.

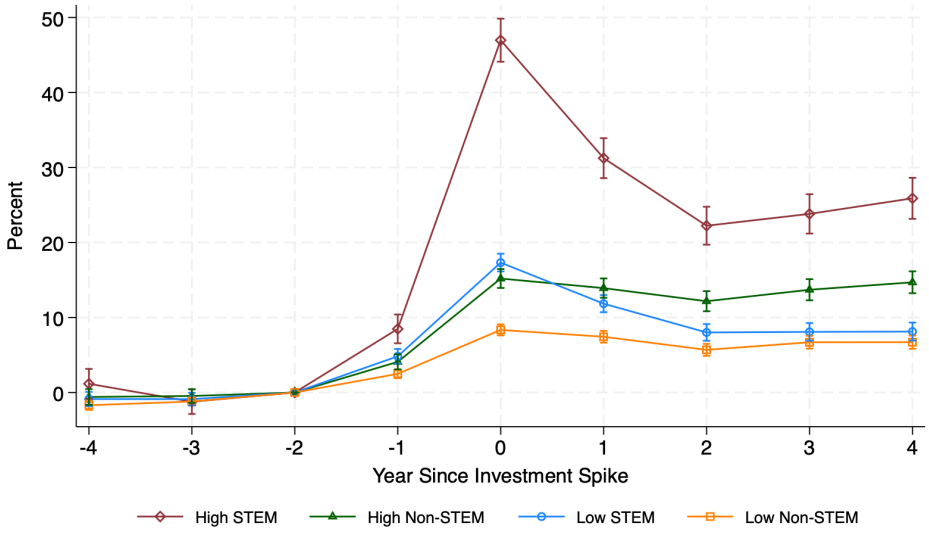
[8]Appendix Figure C.1 shows that the larger effects for external high-STEM labor reflect both that indirect employment increases more than direct employment and that spiking firms shift their indirect employment toward high-STEM skills.

Figure 2: Employment of Skill Groups around Machinery Investment Spikes
(In Percent of Pre-Spike Total Employment by Skill Group)

(a) Direct (In-House)



(b) Indirect (Outsourced)



Notes: This figure shows the employment of high-skilled STEM, high-skilled non-STEM, low-skilled STEM, and low-skilled non-STEM in percent of total pre-spike employment by skill category. Panel (a) considers direct (in-house) employment, while Panel (b) considers indirect employment at supplier firms. Total pre-spike employment is the sum of direct and indirect employment. Pre-spike refers refers to the average over the years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. The estimates are based on the specification in Equation (7), with whiskers representing 95% confidence intervals. *Sample*: Private sector firms around their first machinery investment spikes. Balanced sample for four years before and after the spike.

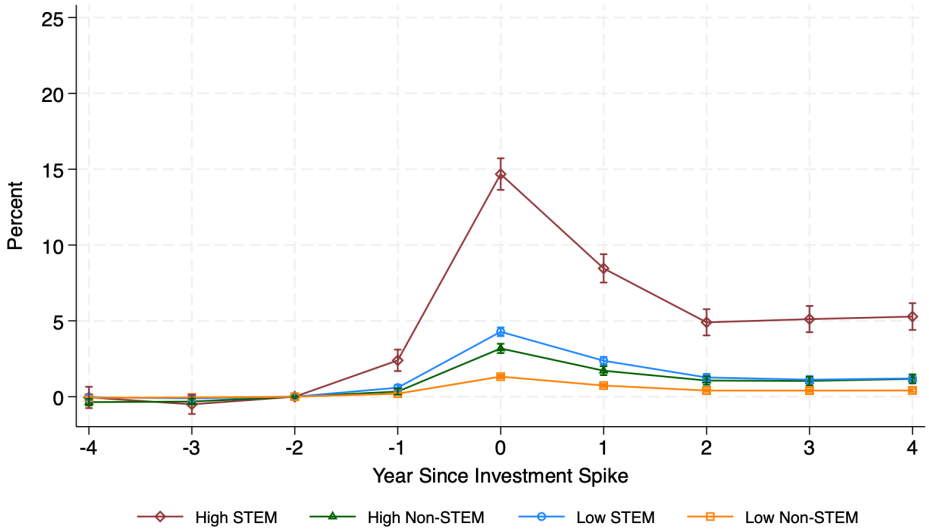
Which supplier industries do these indirect employment effects come from? Figure 3 decomposes indirect employment into "machine suppliers" (Panel (a)) and "other industries" (Panel (b)).

Machine suppliers expand sharply around the investment spike, driving a 15% increase in total demand for high-STEM workers in the year of the spike. Their contribution to the change in total demand then falls to 5%, likely reflecting follow-up replacement and maintenance investments. By contrast, employment of other skill categories through machine suppliers changes little.

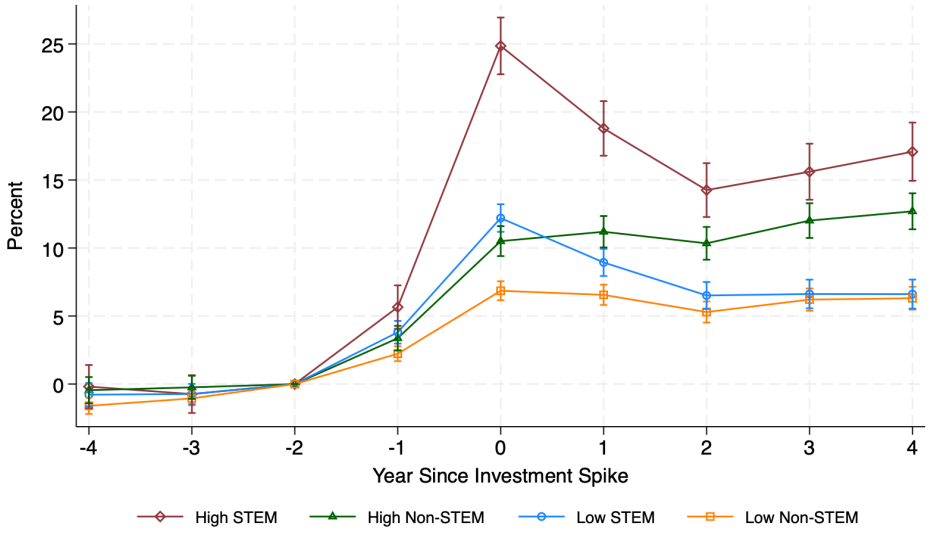
Although machine suppliers are an important source of high-STEM skill bias, Panel (b) shows that most of the indirect employment effects stem from other industries, which generate a 25% increase in total high-STEM employment in the year of the investment spike and a 17% increase four years later. While part of this rise may reflect misclassified "machine suppliers" (see Section 2.2.2), it also indicates that the high-STEM bias extends beyond pure machine supply, reflecting a broader shift in the skill mix of external labor. Other industries are especially important for the persistent increase observed four years later. Appendix C.2.1 shows that this increase in high-STEM skills through "other industries" is widespread across subindustries but is particularly driven by services complementary to automated production, such as computer programming and software development.

Figure 3: Indirect Employment by Supplier Industry
(In Percent of Pre-Spike Total Employment by Skill Group)

(a) Machine Suppliers



(b) Other Industries



Notes: This figure shows the indirect employment of high-skilled STEM, high-skilled non-STEM , low-skilled STEM, and low-skilled non-STEM workers in percent of total pre-spike employment by skill category. Panel (a) considers indirect employment of machine suppliers, while Panel (b) considers indirect employment from all other industries. Total pre-spike employment is the sum of direct and indirect employment, averaged over years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. The estimates are based on the specification in Equation (7), with whiskers representing 95% confidence intervals. *Sample*: Private sector firms around first machinery investment spikes. Balanced sample for four years before and after the spike.

3.3 Connecting Empirics to Theory

Figures 2 and 3 provide clear evidence for the capital–skill complementarity hypothesis developed in Prediction 1 of Section 1.2. As predicted by Goldin and Katz (1998), Figure 3(a) shows that integrating modern machinery raises demand for skilled machinists. Likewise, consistent with Griliches (1969), Figure 2(b) shows that greater capital intensity increases the demand for skilled labor.

The key surprise is that these complementarities operate entirely through external suppliers. The skill-neutral in-house effects in Figure 2(a) reproduce a growing set of firm-level studies showing that new machinery investments increase employment but without a disproportionate rise in skilled labor (Aghion et al., 2024; Curtis et al., 2022; Hirvonen, Stenhammar and Tuhkuri, 2025). Because these studies observe only in-house employment, they conclude that the evidence challenges the capital–skill complementarity hypothesis.[9]

Figure 2(b) resolves this apparent puzzle by showing that external labor services are the missing channel linking capital accumulation to skill demand. This finding is uniquely enabled by the firm-to-firm transaction data available in Belgium. The importance of external suppliers corroborates the anecdotal evidence on robot-integrator firms that initially motivated our study. While Appendix B.2.1 shows that a meaningful share of machine suppliers in Figure 3(a) are robot integrators, our comprehensive evidence reveals that the indirect high-STEM bias of new machinery is pervasive across supplier types.

Moreover, consistent with our theoretical framework featuring both integration and production labor, the indirect employment effects of new capital unfold in two distinct stages: an initial phase around the investment event, driven in part by machine suppliers,

[9]Curtis et al. (2022) conclude that *"our results are not compatible with the capital–skill complementarity hypothesis."* Motivated by the same framework, Hirvonen, Stenhammar and Tuhkuri (2025) write that *"The first part of the paper reports results in sharp contrast with the ideas that technologies necessarily reduce employment or are skill biased."* Aghion et al. (2024) similarly note that their *"…results differ from the estimates of seminal structural models of capital–skill complementarity."*

and a longer-run adjustment driven predominantly by other industries. The somewhat sluggish convergence to long-run employment levels may reflect the costs of identifying and contracting with new suppliers, or the time required to realize the full production benefits of new technologies (McElheran et al., 2025). In Section 7, we exploit this two-stage dynamic to quantify the aggregate skill bias attributable to integration versus production labor.

4 Heterogeneity Analysis

In this section, we characterize how the effects of capital investment vary by the characteristics of the investing firm (Sections 4.1 and 4.2) and the capital type (Sections 4.3 and 4.4). In Section 4.5, we discuss how the effect heterogeneity helps shed light on why firms outsource capital-complementary labor services, tying our evidence to the model predictions from Section 1.2.

4.1 Firm Size

Figure 4 separates spiking firms into small and large firms based on their pre-spike total employment.[10] Small firms rely much more heavily on external high-STEM workers to implement their investment spikes. In the year of the spike, external hires raise high-STEM total employment by 58% in small firms, compared to 36% in large firms. Four years later, these differences persist, with a 35% contribution for small firms compared to 18% for large ones.[11] By contrast, in-house employment expands more similarly across firm sizes, accounting for less than 5% of total employment in the year of the investment spike and roughly 10% after four years, with little difference across skill groups.

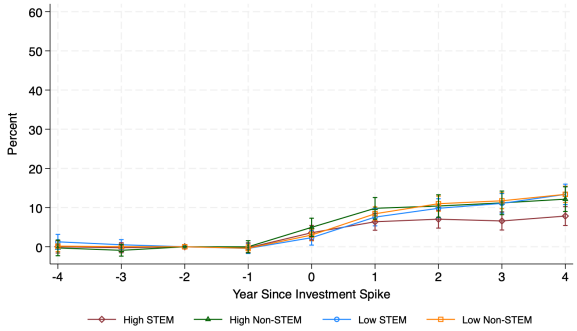
[10]Figure D.1 shows that both small and large spiking firms experience a similar increase of roughly 50 thousand euros in machinery stock per worker. Figure D.2 shows that their difference-in-difference estimates are similar, too.

[11]Consistent with small firms relying more on outsourcing to facilitate their investment spikes, Appendix Figure D.3 shows that their share of machine suppliers in total purchases rises by 6 percentage points in the year of the spike, compared to 4 percentage points for large firms.

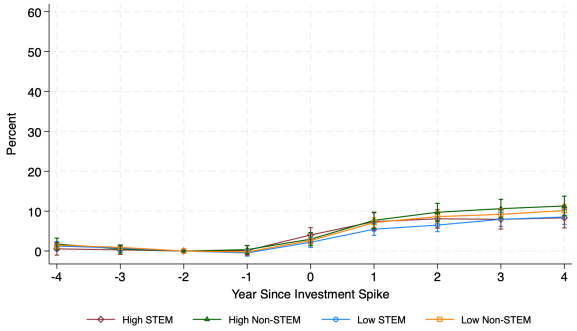
The flip side of the more muted responses from larger firms is that they are more likely to have high-STEM workers employed in-house already before their investment spikes (Appendix D.1). Hence, the differences between small and large firms in Figure 4 partly reflect differences in initial outsourcing strategies. Consistent with this pattern, Békés et al. (2025) show that larger manufacturers are more likely to import robots directly, rather than rely on intermediation by domestic robot integrators, reflecting their greater internal know-how to identify and select appropriate robots.

Figure 4: Employment by Pre-Spike Firm Size
(In Percent of Pre-Spike Total Employment by Skill Group)

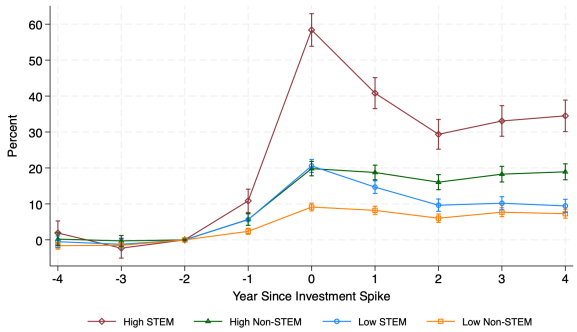
(a) Direct (In-House): Small Firms



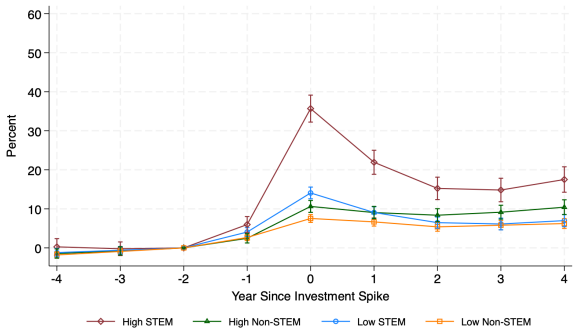
(b) Direct (In-House): Large Firms



(c) Indirect (Outsourced): Small Firms



(d) Indirect (Outsourced): Large Firms



Notes: This figure shows the indirect employment around machinery investment spikes, splitting the effects by the size of the investing firm. Small firms have pre-spike total employment (year −1) below the median (13.1 FTE). Panels (a) and (c) focus on small firms, and Panels (b) and (d) on large firms. Panels (a) and (b) consider the indirect employment of machine suppliers, while Panels (c) and (d) consider the indirect employment from all other industries. The figures show the indirect employment of high-skilled STEM, high-skilled non-STEM, low-skilled STEM, and low-skilled non-STEM workers in percent of total pre-spike employment by skill category. Total pre-spike employment is the sum of direct and indirect employment. Pre-spike refers refers to the average over the years −3 to −1. The estimates are differences-in-differences in outcomes (measured relative to year −2) between the "spiking" and "non-spiking firms" from Table 2. The estimates are based on the specification in Equation (7), with whiskers representing 95% confidence intervals. *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

4.2 Application Sector

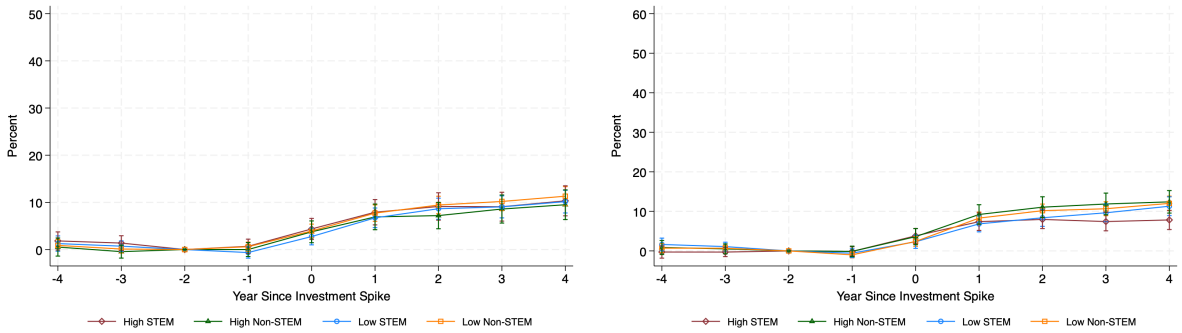
Figure 5 separates spiking firms by sector, with manufacturing firms shown in Panels (a) and (c) and service firms in Panels (b) and (d).[12]

[12]Figure D.4 shows that the remaining private-sector industries (agriculture, utilities, and construction) display similar patterns.

Figure 5: Employment around Machinery Investment Spikes: Sector Heterogeneity
(In Percent of Pre-Spike Total Employment by Skill Group)

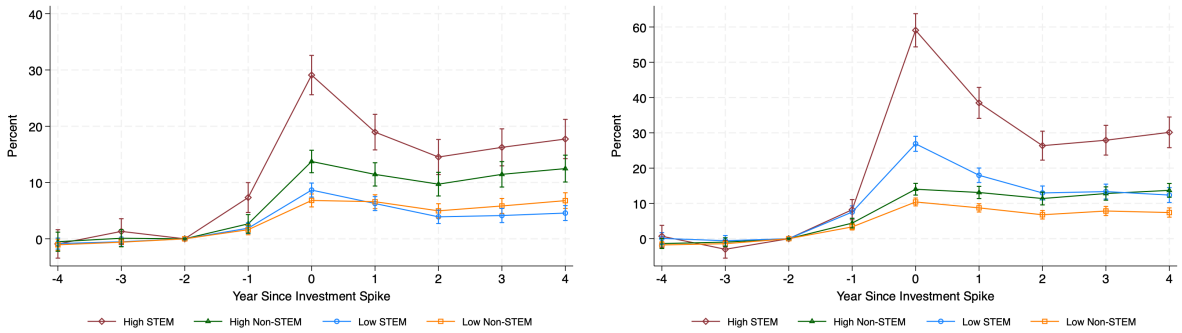
(a) Manufacturing: Direct Employment

(b) Services: Direct Employment



(c) Manufacturing: Indirect Employment

(d) Services: Indirect Employment



Notes: This figure shows the employment around machine investment spikes for manufacturing (Panels (a) and (c)) and Services (Panels (b) and (d)). Panel (a) and (b) consider direct employment, while Panels (c) and (d) consider indirect. The figures show the employment of high-skilled STEM, high-skilled non-STEM, low-skilled STEM, and low-skilled non-STEM workers in percent of total pre-spike employment by skill category. Total pre-spike employment is the sum of direct and indirect employment. Pre-spike refers refers to the average over the years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. The estimates are based on the specification in Equation (7), with whiskers representing 95% confidence intervals. *Sample*: Private sector firms around first investment spike. Balanced sample for four years before and after the spike.

While machinery investments are more prevalent in manufacturing,[13] Panels (c) and (d) show that their skill-biased impacts are pervasive across sectors. If anything, machinery spikes generate even larger relative increases in external high-STEM employment among service-sector firms. Like small firms in Section 4.1, this partly reflects that service firms employ fewer high-STEM workers to begin with (Appendix D.2). Hence, while

[13]Figure F.1 shows that the machinery stock per worker is 90,000 euros in manufacturing, compared to 60,000 in the broader economy.

industrial robots are a prominent example of skill-complementary capital, the skill bias of new machinery extends well beyond robotics and industrial applications.

By contrast, Panels (a) and (b) of Figure 5 show that in-house employment expands more similarly across sectors, accounting for less than 5% of total employment in the year of the investment spike and roughly 10% after four years, again with little difference across skill groups.

4.3 Capital Types

Do other capital types exhibit similar skill bias as machinery? In Figure 6, we replicate the investment spikes design for buildings (Panels (a) and (c)) and intangibles (Panels (b) and (d)). To keep the type of investing firms fixed across panels, we focus on manufacturing firms throughout. [14]

While buildings and intangibles spikes boost employment, these events cause weaker skill bias. For building spikes, indirect high-STEM employment grows roughly two to three times as much as indirect low-STEM and low-non-STEM employment, respectively—compared to three- and four-fold differences for machine spikes in Figure 5. Moreover, this effect quickly dissipates, such that from year two onward, the employment effect for high-STEM is similar to the other skill categories. If anything, high non-STEM sees a somewhat larger increase after building spikes, although the effects are not statistically different.[15] Intangible spikes are associated with smaller employment increases, especially for external hires. These smaller effects partly reflect that intangible capital follows a

[14] Applying the same spike definition for buildings to the full private sector yields an excessively high cutoff, driven by a subset of low-employment service firms undertaking large building investments. Therefore, we focus on the manufacturing sector in this subsection.

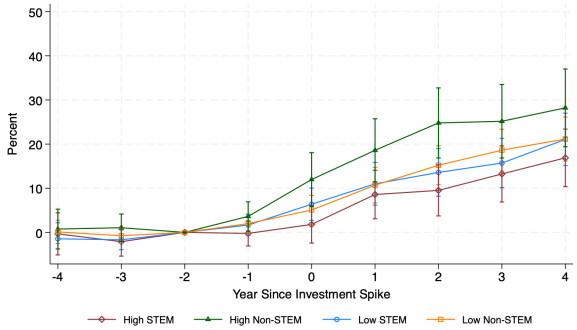
[15] Part of the high-STEM increase at the time of the building spike may reflect simultaneous machinery installation. As shown in Appendix D.3, machinery stock per worker also rises during building spikes. To address this, we exclude spikes where the increase in machinery stock per worker exceeds the 25th percentile. Results are reported in Figure D.7. The skill bias is further reduced but does not disappear completely, which likely reflects the involvement of architects and building engineers in the construction of new buildings. As building investments are highly lumpy, these are not employed in-house. Buildings, however, embody less technological change and therefore generate weaker long-run skill bias, in line with Prediction 4.

much less lumpy investment profile.

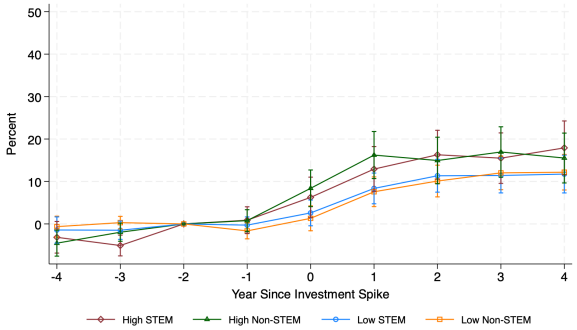
Overall, the distinct skill bias of new machinery—relative to buildings and intangibles—is consistent with the capital-embodied technical change hypothesis, in which the skill bias of new capital reflects the technologies it embodies (Greenwood, Hercowitz and Krusell, 1997; Jones and Liu, 2024).

Figure 6: Employment around Investment Spikes: Heterogeneity by Capital Type (In Percent of Pre-Spike Total Employment by Skill Group)

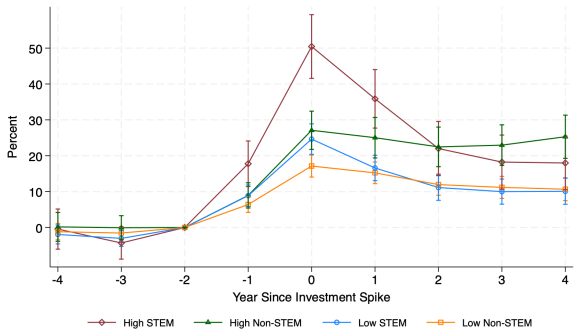
(a) Building Spikes: Direct Employment



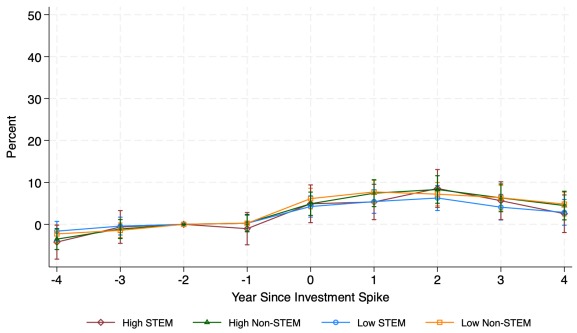
(b) Intangible Spikes: Direct Employment



(c) Building Spikes: Indirect Employment



(d) Intangible Spikes: Indirect Employment



Notes: This figure shows the direct and indirect employment of manufacturing firms around investment spikes in buildings (Panels (a) and (c)) and intangibles (Panels (b) and (d)). Panels (a) and (b) consider direct employment, while Panels (c) and (d) consider indirect. The figures show the indirect employment of high-skilled STEM, high-skilled non-STEM, low-skilled STEM, and low-skilled non-STEM workers in percent of total pre-spike employment by worker types. Total pre-spike employment is the sum of direct and indirect employment. Pre-spike refers to the average over the years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. The estimates are based on the specification in Equation (7), with whiskers representing 95% confidence intervals. Figure 5, Panels (a) and (c) show the corresponding estimates for machinery spikes. *Sample*: Manufacturing firms around first investment spike. Balanced sample for four years before and after the spike.

4.4 New versus Existing Machine Supply

An alternative measure of whether machinery investments embody new technologies—rather than merely replacing existing capital—is whether they are sourced from new suppliers to the firm. For example, Hubmer and Restrepo (2024) show that innovation in new capital types, as opposed to marginal improvements in existing capital, can have distinct effects on labor demand by enabling the automation of new tasks rather than further capital deepening in tasks that are already automated. Consistent with this idea, Appendix D.4 shows that the skill bias of machinery investments is particularly strong when they are sourced from new suppliers to the investing firm.

4.5 Connecting Empirics to Theory

Through the lens of the conceptual framework in Section 1.2, the heterogeneity analyses help shed light on why firms may outsource capital-complementary labor services.

Following Prediction 2, if hiring machine-complementary high-STEM workers entails fixed costs, this can explain why such workers are often concentrated at specialized external suppliers, which achieve scale economies by serving multiple investing firms.[16]

Moreover, following Predictions 2–4, it also clarifies why these suppliers play a particularly important role for smaller firms (for whom fixed costs are harder to absorb), for lumpy investment categories (as opposed to intangibles, which follow smoother investment paths and therefore require more regular labor, often hired in-house), and for technologically advanced capital types (as opposed to buildings, which are more mature capital goods and require less specialized skills to install and deploy).

Differences across capital types further support theories of capital-embodied technical change, in which the skill bias of investments reflects the technologies embodied in the capital. In particular, Krusell et al. (2000) argue that machinery investments—but

[16] In a similar vein, Graff (2025) provides a microfoundation for scale economies in machine repair by allowing repairers to spread their labor across multiple machines with unpredictable breakdowns.

not buildings or structures—generate skill-biased technical change, and Goldin and Katz (1998) emphasize that these capital-skill complementarities are specific to modern manufacturing machinery (as opposed to 19th-century mass production).

Taken together, our evidence strongly aligns with theories of capital-embodied, skill-biased technical change—once we recognize that the fixed costs of hiring the requisite skills often lead investing firms to rely on external suppliers to meet these labor demands.

5 Robustness

This section conducts various robustness checks of our main results. Taken together, these checks confirm that our main result—that machinery investments mainly increase the demand for high-STEM skills through external suppliers—is robust and does not depend on the precise implementation of our empirical design.

Investment Spikes. While our investment-spike strategy follows the literature, Appendix E.1 shows that our results are robust to how we define the investment spikes. In particular, while our baseline specification defines spikes at the 90th percentile, our key patterns are highly similar when using either the 85th or 95th percentiles. Likewise, Appendix E.2 findings are robust to focusing on single-spiking firms.

Unbalanced Panel. While our main results focus on a balanced sample of firms that exists four years before and after the event year, Appendix E.3 shows that our findings are robust to including firm exits as zero employment.

Control Group. Our findings are robust to how we construct the comparison group of "non-spiking" firms. While our baseline specification uses the simple average of non-spiking firms in the same industry (meeting the other pre-sample criteria), Appendix E.4 shows that the results remain virtually unchanged when we instead apply one-to-one

matching.

Higher-Order Links. Our main analysis focuses on first-order indirect employment—that is, the external labor firms employ through their direct suppliers. These suppliers, in turn, also have their own suppliers, and so on. Appendix E.5 shows that our main results are robust to including such higher-order links in the calculation of indirect employment.

6 Accounting for Indirect Employment

The importance of indirect employment for skill bias raises the question of whether alternative approaches, which do not rely on firm-to-firm transactions data, can account for these effects. Using our firm-to-firm transactions data, we evaluate two approaches commonly used in the literature: aggregating the analysis to local labor markets (as in Acemoglu and Restrepo (2020); Aghion et al. (2023); Dauth et al. (2021), among others) or applying fixed sectoral input-output matrices to firm-level effects on total input purchases (as in Humlum (2022), among others). In summary, we find that both approaches miss most of the skill bias from new machinery, because the effects primarily reflect a shift toward suppliers, which are more skill-intensive than the sector average and are most often located outside the investing firm's local labor market.

6.1 Local Labor Markets

A local labor market analysis will capture the indirect employment effects if the machine-complementary services are sourced within the local labor market. Using our firm-to-firm transactions data, we can assess this assumption directly.[17] In particular, we follow Persyn (2011) and split Belgium into 11 functional labor markets, similar or larger in size

[17]Local labor markets capture additional spillovers across firms not considered in this analysis, including competition in product markets (especially for non-tradables) and poaching in labor markets. Hence, this assessment should not be viewed as a comprehensive test of the validity of the local labor markets strategy.

than the commuting zones (CZs) used by papers in the US and elsewhere (Acemoglu and Autor, 2011; Aghion et al., 2023; Dauth et al., 2021).[18]

Figure 7 splits the indirect employment by whether the external suppliers are located inside or outside the local labor markets of investing firms. Most of the indirect employment effects from machinery investment spikes are generated outside the local labor market, especially for high-STEM skills and at machine supplier firms. For example, while indirect employment of machine suppliers increases total high-STEM employment by around 12%, only one-third of this effect is captured within local labor markets.

Why don't local labor markets have more bite for the machine-complementary skilled labor services? First, machine investments are often lumpy and expensive events, making it worthwhile for an integrator to travel across commuting zones to meet these demands. Second, as Appendix C.2.1 showed, the increases in "other industries" often reflect tradable services, e.g., computer programming or software, where providers can often meet demand without traveling to the client facilities. Dhyne and Duprez (2016) documents how firm-to-firm flows in Belgium decrease with the distance between the supplier and buyer, showing important heterogeneity across sectors that align with our findings.

6.2 Sectoral Input-Output

Another common strategy in the literature is to apply sectoral input–output matrices (e.g., from the National Accounts) to firm-level changes in total input purchases. This approach will capture the indirect employment effects if these reflect a general shift toward the typical suppliers of the firm's industry. Figure 8 evaluates this method by scaling firms'

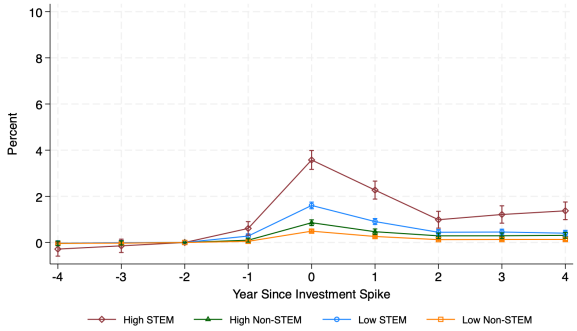
[18] Acemoglu and Restrepo (2020) use 722 CZs, with an average population around 0.5 million people. Dauth et al. (2021) use 402 CZs in Germany, with an average of 0.2 million people (the authors show robustness to making the boundaries broader, increasing the average local population to 0.5 million people). Aghion et al. (2023) use 287 CZs in France, with an average population of 0.24 million. By comparison, the 11 Belgium commuting zones have an average population of 1 million people. The broader boundaries and fewer numbers of the Belgium commuting zones will tend to increase the importance of local labor markets. Hence, we view our conclusion about the minor importance of local labor markets as conservative in this regard.

intermediate input purchases using sectoral input–output tables.[19] While this approach captures some of the indirect employment effects of investment spikes, it still misses most of the high-STEM skill bias associated with new machinery. This shortfall arises because, around machinery investment spikes, investing firms shift toward suppliers that are more high-STEM-intensive than the industry average.

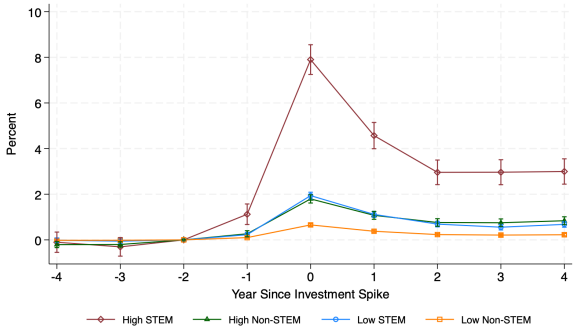
[19]To ensure consistency with our previous analysis, we construct the sectoral input–output tables directly from our firm-to-firm transaction data, ensuring that differences relative to the main analysis reflect only the level of aggregation of input–output relationships.

Figure 7: Indirect Employment by Local Labor Markets (LLM)
(In Percent of Pre-Spike Total Employment by Skill Group)

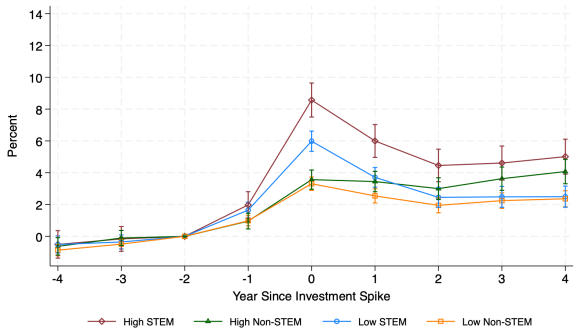
(a) Machine Suppliers: Inside LLM



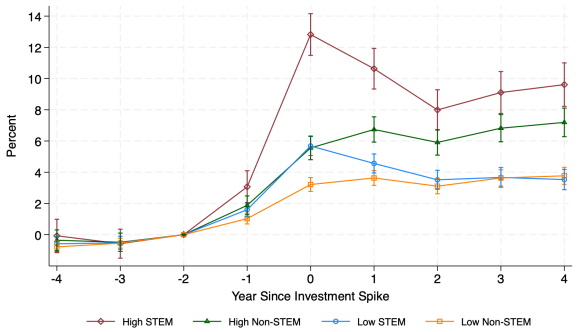
(b) Machine Suppliers: Outside LLM



(c) Other Industries: Inside LLM



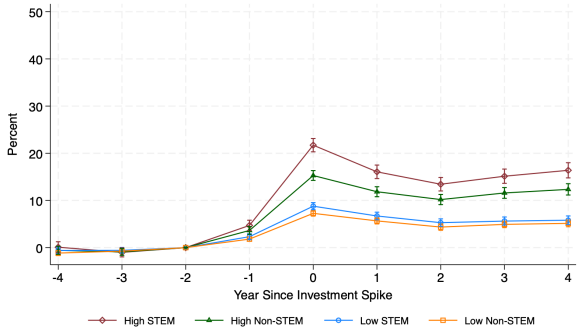
(d) Other Industries: Outside LLM



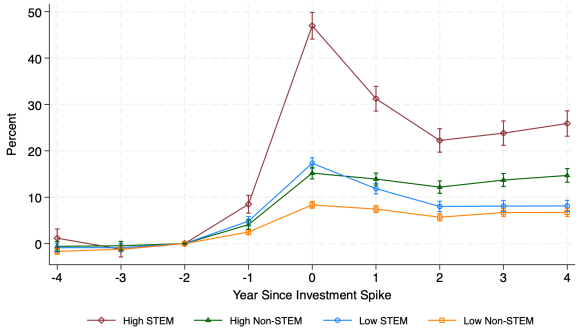
Notes: This figure splits the indirect employment by whether the suppliers are located inside (Panels (a) and (c)) or outside (Panels (b) and (d)) the local labor markets of the firm. Panels (a) and (b) consider the indirect employment of machine suppliers, while Panels (c) and (d) consider the indirect employment from all other industries. The figures show the indirect employment of high-skilled STEM, high-skilled non-STEM, low-skilled STEM, and low-skilled non-STEM workers in percent of total pre-spike employment by skill category. Total pre-spike employment is the sum of direct and indirect employment. Pre-spike refers refers to the average over the years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. The estimates are based on the specification in Equation (7), with whiskers representing 95% confidence intervals. *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

Figure 8: Indirect Employment by Measurement Method
(In Percent of Pre-Spike Total Employment by Skill Group)

(a) Sectoral Input-Output



(b) B2B Transactions (Figure 2(b))



Notes: This figure shows the indirect employment of high-skilled STEM, high-skilled non-STEM, low-skilled STEM, and low-skilled non-STEM in percent of total pre-spike employment by skill category. Panel (a) uses sectoral input-output tables to calculate indirect employment, while Panel (b) uses the business-to-business transactions (as in Figure 2). The estimates are differences-in-differences in outcomes (measured relative to year −2) between the "spiking" and "non-spiking firms" from Table 2. The estimates are based on the specification in Equation (7), with whiskers representing 95% confidence intervals. *Sample*: Private sector firms around their first machinery investment spikes. Balanced sample for four years before and after the spike.

7 Aggregate Implications

A key finding in this study is that investments in new machinery increase the demand for high-STEM workers through external suppliers. While our preceding analysis pertained to the firm level, we now go one step further and ask whether the estimated effects are large enough to potentially matter for the aggregate demand for skills.

To evaluate this question, we conduct a back-of-the-envelope aggregation exercise as in Autor, Dorn and Hanson (2013); Mian and Sufi (2014). This strategy simply scales our firm-level difference-in-difference estimates with the aggregate increase in machine stocks and investments. Notably, because this calculation abstracts from spillovers between spiking and non-spiking firms, we use it merely as a simple and transparent way to illustrate the aggregate potential of our estimated magnitudes.[20]

[20]The back-of-the-envelope calculation will tend to overstate the aggregate impacts if, for example, spiking firms grow by stealing output market shares or poaching workers from their competitors. These

Figure F.1 shows that the machinery stock per worker in Belgian manufacturing grew from €19,500 EUR in 2001 to €57,500 in 2021. We scale these aggregate increases with our firm-level difference-in-difference estimates from Section 3.2. Appendix F details our method. As in our conceptual framework in Section 1, we include both the skills needed to integrate new machinery (reflected in the temporary effects during years 0–2) and to operate a more machine-intensive production (reflected in the stable effect by year 4).

Table 3 reports results for the direct, indirect, and total employment effects by skill group, distinguishing between integration and production labor. To isolate skill bias, we focus on differential impacts relative to the low non-STEM group.[21] The table yields two main takeaways.

First, the aggregate potential of our estimated effects is substantial. Skill bias from the rise of machinery between 2003 and 2021 increased the demand for high-STEM workers by 23% (Column 3). For comparison, aggregate employment of high-STEM workers rose by about 37% over the same period.

Second, accounting for indirect employment (Column 2) is crucial for reaching this conclusion—focusing only on direct employment (Column 1) would misleadingly suggest that machinery biased labor demands slightly *away* from high-STEM workers.

product and labor market spillovers are examples of the "missing intercept" problem that arises when aggregating cross-sectional comparisons; see Moll (2021) for a thoughtful treatment. Moreover, if the supply of skills is inelastic, the labor demand impacts we estimate may manifest in changed wages rather than employment of skills groups. For a more extensive treatment of how to aggregate firm-level capital–skill complementarities, see Berlingieri et al. (2024).

[21] By focusing on differential impacts relative to the non-STEM group, we remove bias in the investment-spike estimates from skill-neutral demand shocks that cause firms to grow evenly across all skill categories.

Table 3: Aggregate Skill Bias from New Machinery
(Differences to Low Non-STEM in Percentage Points)

	Direct (1)	Indirect (2)	Total (3)
High STEM	**-4.5**	**27.8**	**23.3**
– Integration	-0.3	8.1	7.8
– Production	-4.2	19.7	15.5
High Non-STEM	**-0.1**	**10.2**	**10.1**
– Integration	0.2	2.0	2.2
– Production	-0.3	8.2	7.9
Low STEM	**-1.2**	**3.1**	**1.9**
– Integration	-0.4	1.6	1.3
– Production	-0.9	1.5	0.6

Notes: This table reports the impact of new machinery on the aggregate demand for skills, following the back-of-the-envelope calculation detailed in Appendix F. The effects are shown separately for direct employment (Column 1), indirect employment (Column 2), and their total (Column 3), distinguishing between the integration and production labor. All effects are expressed as differences in percentage points relative to the low non-STEM group.

8 Conclusion

The capital–skill complementarity hypothesis is a cornerstone of a large literature on technological change and labor market inequality (Krusell et al., 2000). In this paper, we show that the skill bias of new machinery arises chiefly through external suppliers. This pattern is widely understood among industry practitioners—illustrated by the rise of robot integrators and computer consultants—yet has been largely overlooked in the academic literature.

Our findings have implications for both measurement and theory. On the measurement side, they underscore that capturing the skill bias of new machinery requires looking *beyond* the payrolls of investing firms. In particular, this perspective helps reconcile recent firm-level evidence of skill-neutral investment effects on in-house employment with

classic theories of capital-skill complementarity.

On the theory side, our paper emphasizes the central role of external suppliers in facilitating technology adoption. We propose a conceptual framework that embeds capital–skill complementarities into firms' joint decisions to invest in capital and to hire or outsource the necessary skills. We welcome further research on the causal role of external suppliers in shaping the speed and magnitude of technology diffusion.

Finally, our findings raise a broader question about which other phenomena may be poorly captured by in-house employment alone. Our theoretical framework suggests that whenever the complementary (substitutable) labor exhibits scale economies, the positive (negative) employment effects are likely to materialize at specialized suppliers, outside the boundaries of the directly affected firms. While capital-complementary skills provide a clear example, investigating whether similar dynamics arise in other contexts—such as firms engaging in globalization, the green transition, or remote work—constitutes a promising avenue for future research.

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Online Appendix

Integrators: The Firm Boundaries of Capital-Skill Complementarity

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A Conceptual Framework

A.1 Model Predictions

A.1.1 Capital Investment and the Demand for Skills

This section shows that, under the capital-skill complementarity hypothesis, profit-maximizing firms should increase their relative demands for skilled workers S in response to increases in investments I and capital K:

Prediction 1 (Capital investment and the demand for skills)**.** *Under capital–skill complementarity, capital investment raises the relative demand for skills both initially (through integration labor services) and subsequently (through production labor services).*

In its simplest form, the capital–skill complementarity hypothesis pertains to the functional form of the production and investment functions, F and G. Griliches (1969) specifies that capital is a stronger Q-complement for skilled than for unskilled labor in production F. Goldin and Katz (1998) posits that G relies on skilled "machinists" to integrate new capital. To distill the implications of these properties for the demand for skills, we make several simplifying assumptions. First, we abstract from the decision to hire or outsource labor services (Section A.1.2 introduces the outsourcing decision). Second, we assume that labor costs are linear and static. Finally, to focus on complementarities with capital, we assume that F and G exhibit Q-neutrality between skilled and unskilled labor, $F_{S_P U_P} = G_{S_I U_I} = 0$.

Under these assumptions, the firm's profit-maximization problem reads:

$$V(K) = \max_{\{I,L\}} PF(K, L_P) - w_S(S_P + S_I) - w_U(U_P + U_I) - c_I(I) + \beta \mathbb{E}V((1-\delta)K + G(I, L_I)), \tag{8}$$

where $L_K = (S_K, U_K)$, $K \in \{P, I\}$, denotes production and integration labor. In this setup, we can prove two predictions that substantiate Prediction 1.

Prediction 1(a) (Capital and the demand for production skills)**.** *Capital increases the demand for skilled production workers if it is a Q-complement for skilled labor, and it induces skill bias whenever its curvature-adjusted complementarity is stronger for skilled than for unskilled labor.*

Proof. The first-order condition for production labor is

$$P\,F_{S_P}(K, S_P, U_P) = w_S, \qquad P\,F_{U_P}(K, S_P, U_P) = w_U.$$

Differentiating w.r.t. K (holding P, w_S, w_U fixed) and writing $' \equiv \partial/\partial K$,

$$F_{S_PS_P}\,S'_P + F_{S_PU_P}\,U'_P + F_{S_PK} = 0, \qquad F_{U_PS_P}\,S'_P + F_{U_PU_P}\,U'_P + F_{U_PK} = 0.$$

Under Q-neutrality, $F_{S_PU_P} = F_{U_PS_P} = 0$, the system decouples:

$$S'_P = -\frac{F_{S_PK}}{F_{S_PS_P}}, \qquad U'_P = -\frac{F_{U_PK}}{F_{U_PU_P}}.$$

with $F_{S_PS_P} < 0$ and $F_{U_PU_P} < 0$ under strict concavity of the production function.

Level effects. The impact of capital on the demand for skills is governed by their cross-partials in F:

$$\operatorname{sign}(S'_P) = \operatorname{sign}(F_{S_PK}), \qquad \operatorname{sign}(U'_P) = \operatorname{sign}(F_{U_PK}).$$

In particular, if capital is a (weak) Q-complement for skilled and a (weak) Q-substitute for unskilled production labor, i.e. $F_{S_PK} \geq 0 \geq F_{U_PK}$, then $S'_P \geq 0 \geq U'_P$.

Skill bias. The impact of capital on the relative demand for skilled workers is:

$$\frac{d}{dK}\log\!\left(\frac{S_P}{U_P}\right) = \frac{S'_P}{S_P} - \frac{U'_P}{U_P} = \frac{F_{S_PK}}{-F_{S_PS_P}} \cdot \frac{1}{S_P} - \frac{F_{U_PK}}{-F_{U_PU_P}} \cdot \frac{1}{U_P}.$$

Hence, increased capital will raise the relative demand if the curvature-adjusted complementarity with capital is stronger for skilled labor than for unskilled labor:

$$\frac{F_{S_PK}}{-F_{S_PS_P}} \cdot \frac{1}{S_P} > \frac{F_{U_PK}}{-F_{U_PU_P}} \cdot \frac{1}{U_P}.$$

□

Prediction 1(b) (Investment and the demand for integration skills)**.** *Investment increases the demand for skilled integration workers if it is a Q-complement for skilled labor in integration, and it induces skill bias whenever its curvature-adjusted complementarity is stronger for skilled than for unskilled labor.*

Proof. The proof follows a similar argument as for Prediction 1(a). The first-order conditions for integration labor follow from the continuation value of capital accumulation:

$$\beta \frac{\partial \mathbb{E}V}{\partial K} G_{S_I}(I, S_I, U_I) = w_S, \qquad \beta \frac{\partial \mathbb{E}V}{\partial K} G_{U_I}(I, S_I, U_I) = w_U.$$

Differentiating with respect to investment I (holding β, w_S, w_U fixed) and writing $' \equiv \partial/\partial I$, we obtain

$$G_{S_IS_I} S_I' + G_{S_IU_I} U_I' + G_{S_II} = 0, \qquad G_{U_IS_I} S_I' + G_{U_IU_I} U_I' + G_{U_II} = 0.$$

Under Q-neutrality between skilled and unskilled integration labor, $G_{S_IU_I} = G_{U_IS_I} = 0$, the system decouples:

$$S_I' = -\frac{G_{S_II}}{G_{S_IS_I}}, \qquad U_I' = -\frac{G_{U_II}}{G_{U_IU_I}},$$

with $G_{S_IS_I} < 0$ and $G_{U_IU_I} < 0$ under strict concavity of the integration function G.

Level effects. The impact of investment on the demand for integration skills is governed by their cross-partials in G:

$$\text{sign}(S_I') = \text{sign}(G_{S_II}), \qquad \text{sign}(U_I') = \text{sign}(G_{U_II}).$$

In particular, if investment is a (weak) Q-complement for skilled integration labor and a (weak) Q-substitute for unskilled integration labor, i.e. $G_{S_I I} \geq 0 \geq G_{U_I I}$, then $S_I' \geq 0 \geq U_I'$.

Skill bias. The effect of investment on the relative demand for skilled integration workers is

$$\frac{d}{dI}\log\Big(\frac{S_I}{U_I}\Big) = \frac{S_I'}{S_I} - \frac{U_I'}{U_I} = \frac{G_{S_I I}}{-G_{S_I S_I}} \cdot \frac{1}{S_I} - \frac{G_{U_I I}}{-G_{U_I U_I}} \cdot \frac{1}{U_I}.$$

Hence, investment increases the relative demand for skilled integration workers if the curvature-adjusted complementarity with investment is stronger for skilled than for unskilled labor:

$$\frac{G_{S_I I}}{-G_{S_I S_I}} \cdot \frac{1}{S_I} > \frac{G_{U_I I}}{-G_{U_I U_I}} \cdot \frac{1}{U_I}.$$

□

A.1.2 Outsourcing of Labor Services

In this section, we extend the model to incorporate firms' decisions to either hire or outsource their labor services. We show how fixed and sunk costs of hiring impact firms' optimal outsourcing decisions. While we focus our analysis on integration labor, similar arguments hold for production labor.

Firms hire or outsource worker to minimize their employment costs

$$c_L(E) = \min_{\{L^H, L^O\}} \Big\{ c(L^H, L^O) \quad \text{s/t} \quad L^H + L^O = E \Big\} \tag{9}$$

Prediction 2 (Fixed costs and outsourcing of capital-complementary skills)**.** *If hiring capital-complementary workers involves fixed costs f_S^H (e.g., indivisibilities of integrator teams or learning across projects), these labor services are more likely to be sourced from specialized external suppliers. Moreover, smaller firms should be more likely to outsource.*

Proof. Suppose hiring involves fixed costs:

$$c(L^H, L^O) = \sum_{M \in \{P,I\}} (c_M^H(L_M^H) + c_M^O(L_M^O)), \quad \text{with} \tag{10}$$

$$c^H(S_I) = w_S^H S_I + f_S^H \tag{11}$$

$$c^O(S_I) = w_S^O S_I \tag{12}$$

with $w_S^H < w_S^O$ and $f_S^H > 0$. Firms will hire their skilled integrators if their demand exceeds:

$$c^H(S_I) \leq c^O(S_I) \iff S_I \geq S_I^* = \frac{f_S^H}{w_S^O - w_S^H}. \tag{13}$$

Equation (13) shows that fixed costs of hiring skilled integrators (f_S^H) lead investing firms to outsource these services. In particular, smaller firms—those with integration labor demands below S_I^*—will rely on specialized external suppliers for skilled integration. □

In the next proposition, we show that if hiring of skilled integration labor entails adjustment costs, outsourcing should be more prevalent for lumpy investment categories.

Prediction 3 (Lumpy investments and outsourcing of capital-complementary skills)**.** *If hiring entails adjustment costs, outsourcing should be more prevalent for lumpy investment categories (e.g., buildings versus software).*

Proof. Suppose hiring involves adjustment costs:

$$c^H(S_{It}|S_{It-1}) = w_S^H S_{It} + \alpha_S^H (S_{It} - S_{It-1})^2 \tag{14}$$

$$c^O(S_{It}) = w_S^O S_{It}, \tag{15}$$

with $w_S^H < w_S^O$ and $\alpha_S^H > 0$.

For simplicity, assume investments and skilled integrators are perfect complements as

in Goldin and Katz (1998):

$$G(I, L_I) = \min\{I, S_I\} \tag{16}$$

Compare two capital types. Type A has a perfectly smooth investment profile:

$$I_{At} = I/2, \forall t. \tag{17}$$

Type B has a lumpy investment profile with zeros every second year:

$$I_{Bt} = \begin{cases} I & \text{for } t \text{ even} \\ 0 & \text{for } t \text{ odd .} \end{cases} \tag{18}$$

For the smooth type A, firms will hire $S_{It}^H = I/2$ integrators in every period at costs

$$c^H(S_{It}|S_{It-1}) = w_S^H I/2 + \alpha_S^H (I/2 - I/2)^2 = w_S^H I/2 < w_S^O I/2 \tag{19}$$

For the lumpy type B, firms will hire $S_{It}^H = I$ in investment years (when t is even). However, because of adjustment costs, firms will keep some of their integrators onboard in years of inaction (when t is odd):

$$S_{it} = \min_{S_I}\{w_S^H S_{It} + \alpha_S^H (S_{It} - I)^2 + \beta\alpha_S^H (I - S_{It})^2\} \implies \tag{20}$$

$$S_{it}^* = I - \frac{w_S^H}{2\alpha_S^H(1+\beta)} \text{ for } t \text{ odd} \tag{21}$$

The cost of hiring skilled integrators is:

$$c^H(S_I) = w_S^H I + \alpha_S^H (I - S_{it}^*)^2 + \beta w_S^H S_{it}^* + \beta\alpha_S^H (S_{it}^* - I)^2 \tag{22}$$

$$= (1+\beta) w_S^H I + \frac{(1-2\beta)(w_S^H)^2}{4(1+\beta)\alpha_S^H}. \tag{23}$$

The firm will outsource its skilled integrator services iff

$$w_S^O I \leq (1+\beta) w_S^H I + \frac{(1-2\beta)(w_S^H)^2}{4(1+\beta)\alpha_S^H} \iff \tag{24}$$

$$I \geq I^* = \frac{(2\beta-1)(w_S^H)^2}{4(1+\beta)\alpha_S^H (w_S^H(1+\beta) - w_S^O)} \tag{25}$$

Hence, even if hiring in-house is statically cheaper $w_S^H < w_S^O$, firms will outsource the integration when investment is sufficiently lumpy. □

Prediction 4 (Advanced capital and outsourcing of capital-complementary skills)**.** *If the skill bias of capital investments reflects the advanced technologies they embody, we should expect stronger effects for capital undergoing more rapid technological change (e.g., machinery versus buildings).*

Proof. If the features of F, G, and c^H reflect the technologies embodied in the capital, the comparative statics in Predictions 1–3 will be starker for more advanced forms of capital. □

B Data and Measurement

B.1 Data

We link the following firm-level datasets for the period 2003-2021:

Annual Accounts. We obtain annual accounts for all incorporated non-financial firms in Belgium from the National Bank of Belgium. The dataset includes standard balance-sheet and profit-and-loss items, along with five-digit NACE industry codes. Crucially for our analysis, the book value of tangible fixed assets is disaggregated into (i) land and buildings, (ii) machinery and equipment, and (iii) rolling stock and office machinery. We retain firms that report positive employment in at least one year, yielding 2.7 million firm-year observations on 327,000 firms spanning 2003–2021.

VAT Declarations. All VAT-liable firms in Belgium are required to report their annual totals for sales, investment, and intermediate inputs to the tax authorities. We use these VAT declarations to measure sales, since the annual accounts report sales figures only for large firms. These sales include both sales to consumers and businesses as well as exports. The data on investment referts to total investment and is not split by type of investment (machines, buildings, ...)

Business-to-Business (B2B) Transactions. The VAT customer listings record domestic buyer–supplier links. Every VAT-liable firm must file an annual report listing the aggregate value of invoices issued to each customer. Imports and exports are not covered. To keep the dataset manageable and focus on economically meaningful transactions, we restrict the sample to pairs in which both firms file an annual account and the annual transaction value exceeds €1,000. The resulting dataset contains 115.6 million transactions for 2003–2021. Our data construction follows Dhyne, Duprez and Komatsu (2023) and updates the dataset used by, among others, Bernard et al. (2022) and Baqaee et al. (2025).

Employee-Level Social-Security Data. We obtain worker-level information from the Crossroads Bank for Social Security (KSZ). Employees are linked to their employers' social-security declarations, and each worker is assigned the level and field of their highest diploma.[22]

Tables B.1 and B.2 list the education categories by level and field.[23] For each firm-year, we observe both the headcount and average full-time-equivalent (FTE) hours for every education level-by-field cell, allowing us to construct FTE employment by education category.

[22]Education information is sourced from the Belgian population census; hence, only employees residing in Belgium are included.

[23]A sizable share of low-education records is coded as "not specified," whereas the corresponding share among tertiary academic degrees is only 5.9%.

We classify degrees into four categories based on their level and field:

- **High STEM**: workers with tertiary education or higher (codes 55, 64, 65, 74, or 84) in "05 Natural Sciences, Mathematics and Statistics," "06 Information and Communication Technologies," or "07 Engineering, Manufacturing and Construction."
- **High Non-STEM**: workers with tertiary education or higher in non-STEM fields (including "not specified").
- **Low STEM**: workers with less than tertiary education in STEM fields.
- **Low Non-STEM**: workers with less than tertiary education in non-STEM fields (including "not specified").

Table B.1: Levels of Education

Code	Description	Category	Share of Employment
0	Pre-primary education / less than primary education	Low	1.1%
02	Limited pre-primary education	Low	0.0%
10	Primary education	Low	5.9%
24	Lower secondary education – General	Low	9.0%
25	Lower secondary education – Vocational	Low	9.7%
34	Upper secondary education – General	Low	22.4%
35	Upper secondary education – Vocational	Low	13.3%
40	Post-secondary non-tertiary education	Low	2.6%
44	Post-secondary non-tertiary education – General	Low	0.4%
45	Post-secondary non-tertiary education – Vocational	Low	2.6%
55	Higher education – Short cycle – Vocational	High	0.2%
64	Higher education – Bachelor's or equivalent – Academic	High	0.1%
65	Higher education – Bachelor's or equivalent – Vocational	High	14.8%
74	Higher education – Master's or equivalent – Academic	High	9.1%
84	Doctorate or equivalent – Academic	High	0.3%
98	Highest degree not determined for persons younger than 15	Low	0.0%
99	Highest education level could not be determined	Low	5.1%
.	Missing	Low	3.3%

Notes: This table shows how we classify education levels as "low" or "high." The last column reports each level's share of total full-time-equivalent employment in 2012.

Table B.2: Fields of Education

Code	**Description**	Category	Share of Employment
00	Generic programmes and qualifications	Non-STEM	11.3%
01	Education	Non-STEM	1.0%
02	Arts and humanities	Non-STEM	3.9%
03	Social sciences, journalism and information	Non-STEM	2.1%
04	Business, administration and law	Non-STEM	11.3%
05	Natural sciences, mathematics and statistics	STEM	1.6%
06	Information and Communication Technologies	STEM	1.6%
07	Engineering, manufacturing and construction	STEM	26.7%
08	Agriculture, forestry, fisheries and veterinary	Non-STEM	1.1%
09	Health and welfare	Non-STEM	2.3%
10	Services	Non-STEM	3.6%
99	Not specified	Non-STEM	30.2%
NA	Not available	Non-STEM	0.0%

Notes:This table shows how we classify education field as "STEM" or "Non-STEM." The last column reports each level's share of total full-time-equivalent employment in 2012.

B.1.1 Linking Datasets

Linking KSZ and Annual Accounts. We link the datasets using unique firm identifiers. Of the 3.9 million annual account observations, 2.7 million match to KSZ social-security records. The remaining 1.2 million observations almost entirely reflect firms with zero employees and therefore no KSZ record.[24] Restricting attention to firms that report positive employment, we obtain 2,717,110 observations on 326,554 firms for the period 2003–2021. Within manufacturing, the sample comprises 269,556 observations on 30,030 firms.

Linking Annual Accounts and B2B Transactions. We link the annual accounts (complemented with KSZ employment data) to the B2B transactions using the same

[24]Only 83,000 unmatched observations report positive employment. These correspond to firms that file an annual report but lack a social-security number—for example, certain intermunicipal cooperatives.

unique firm identifiers. Among the 116 million transactions in the B2B records, 90.6% of suppliers are matched to firms in our annual accounts dataset, corresponding to 91.8% of total transaction value. The unmatched suppliers are firms with zero employment.[25] Since we use the B2B transaction data only to calculate first-order indirect employment, dropping transactions with suppliers without employment entails no loss of information.

B.2 Measurement

B.2.1 Machine Supplier Industries

The value chain of machine supply includes producers, distributors, installers, and advisors of new machinery. While production is concentrated among a few large suppliers, some of the other stages in the value chain are sometimes vertically integrated. For example, robot integrator firms often combine distribution, installation, and advisory services. Table B.3 lists the industry codes used to classify each of the machine supplier categories.

Table B.3: Machine Supplier Industries

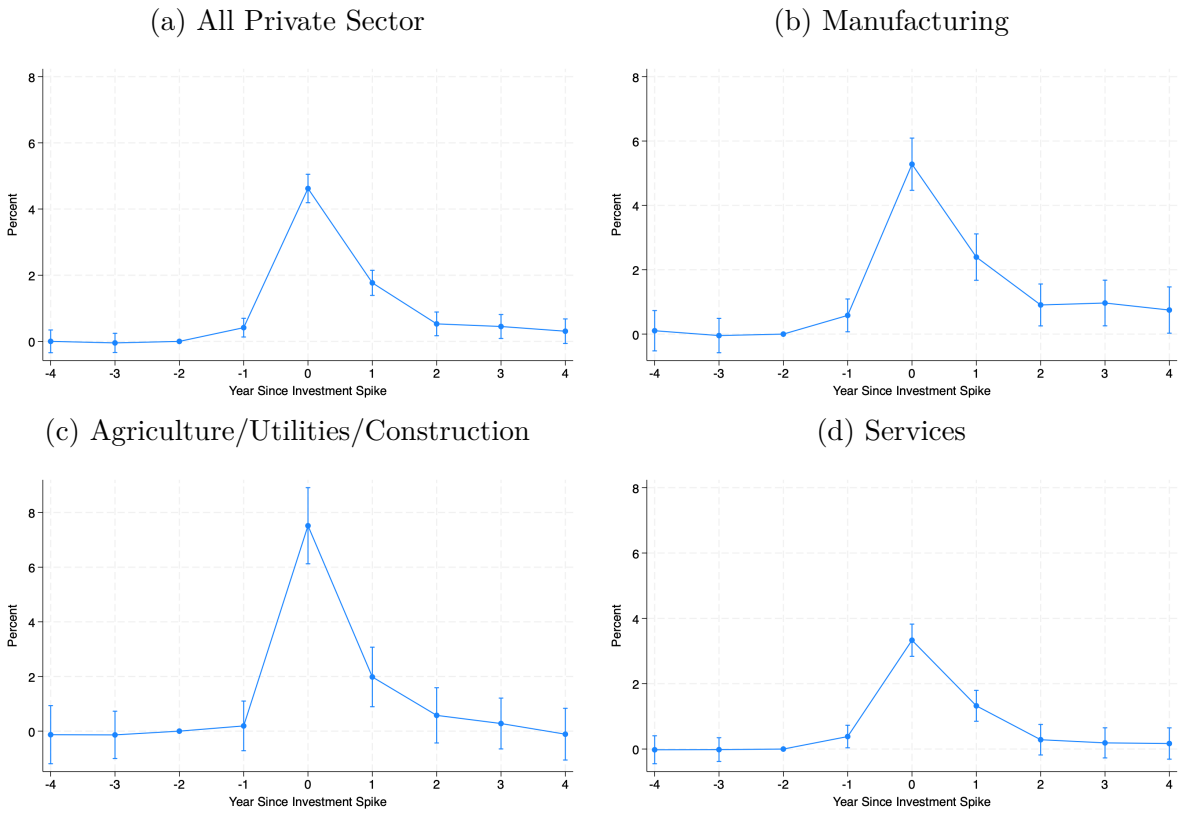
Type	NACE
Builders	2562, 28
Installers	33, 4321
Distributors	4614, 466
Advisors	71, 7022

Notes: This table lists our classification of machine supplier industry codes.

Confirming the relevance of these industries, Figure B.1 shows that firms sharply increase their purchases from them around machinery investment spikes, especially for firms in manufacturing, construction, agriculture, and utilities.

[25]Our annual accounts dataset includes only firms that report positive employment in at least one period, a restriction not applied to the B2B dataset.

Figure B.1: B2B Transactions: Purchases from Machine Supplier Industries



Notes: This figure shows the share of purchases from machine suppliers around machinery investment spikes for all private-sector firms (Panel a) Manufacturing (Panel b), Agriculture/Utilities/Construction (Panel c), and Services firms (Panel d). The estimates are differences-in-differences in outcomes (measured relative to year −2) between the "spiking" and "non-spiking firms" from Table 2. *Sample*: Private sector firms around their first machinery investment spikes. Balanced sample for four years before and after the spike.

We use two external data sources on robot suppliers to validate our industry classification. First, we deploy a market robot on robot suppliers and integrators in Belgium (compiled by `www.HowToRobot.com`, a digital platform that connects manufacturing firms to machine suppliers).[26] Second, we gained access to the Customer Relationship Management (CRM) systems of three of Belgium's largest robot producers and distributors. These lists identify 606 robot supplier firms in 2021.

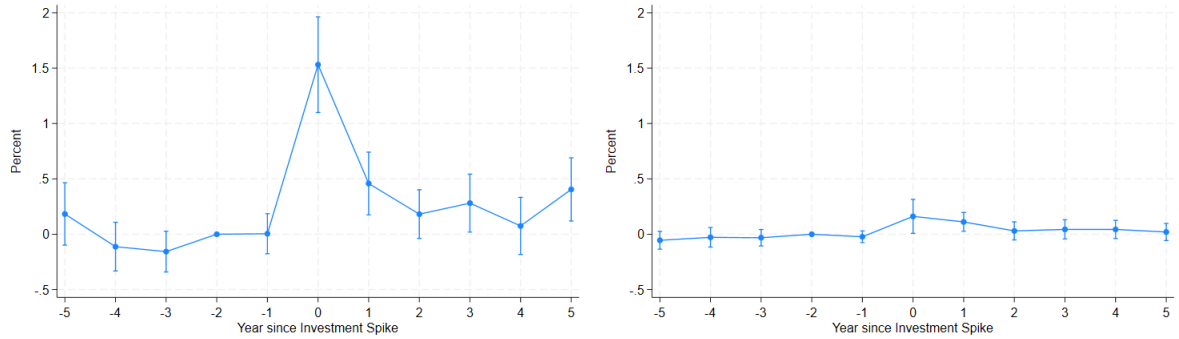
Figure B.2 decomposes the purchases of spiking firms from the external lists according to whether the suppliers are in the machine supplier industry codes. As the figure shows,

[26]Békés et al. (2025) also use the HowToRobot database to identify robot integrators.

our industry classification adequately captures the machine supply from the external lists. Compared to the external lists, the industry code classification has the advantage of being time consistent (the external lists are snapshots from 2021) and comprehensive of all machine supplies (the external lists focus on robot suppliers).

Figure B.2: Share of Purchases from External List of Robot Supplier Firms

(a) Machine Supplier Industries (b) Other Industries

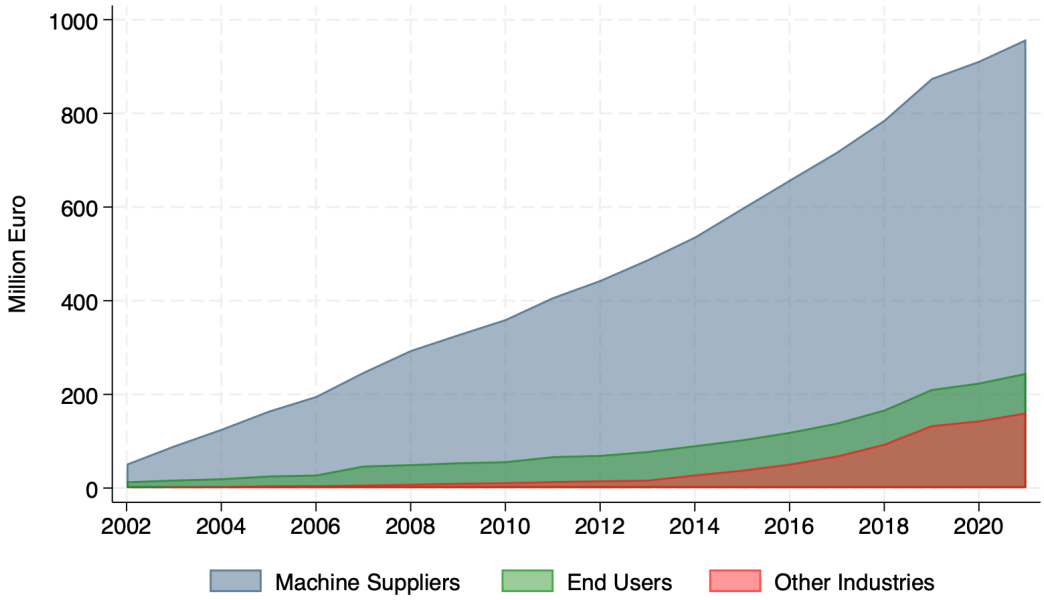


Notes: This figure splits the purchases of spiking firms from the robot supplier firms (in percent of total purchases) according to whether the suppliers are in our classified machine supplier industry codes. The estimates are differences-in-differences in outcomes (measured relative to year −2) between the "spiking" and "non-spiking firms" from Table 2. *Sample*: Manufacturing firms around their first machinery investment spikes. Balanced sample for five years before and after the spike.

To further validate our machine supplier classification and to underscore the importance of domestic integrators, Figure B.3 splits the accumulated imports of industrial robots (HS code 847950) by the industry of the importer. As Belgium does not produce industrial robots, all robots have to be imported from abroad. Indeed, customs records have been a popular source of robot investments at the firm level; see e.g., Acemoglu, Lelarge and Restrepo (2020); Bonfiglioli et al. (2024) in France, Humlum (2022); Mann and Pozzoli (2022) in Denmark, Dixon, Hong and Wu (2021) in Canada, and Acemoglu, Koster and Ozgen (2023) in the Netherlands. However, as the figure shows, end-user industries (that is, manufacturing firms that are not machine suppliers) represent less than 10% of the robot imports in Belgium. By contrast, our machine supplier industries import more than 75% of all industrial robots in Belgium before these are sold to end-

users (usually bundled with integration services). Békés et al. (2025) document a similar pattern in Hungary.[27]

Figure B.3: Accumulated Robot Imports by Sector of Importing Firm



Notes: This figure splits the accumulated aggregate imports of industrial robots (HS code 847950) to Belgium by the industry of the importer.

[27]While Békés et al. (2025) also establish the importance of integrators in facilitating robot adoption, our key contribution is to document that this intermediation is a central mechanism through which new capital generates skill bias. Moreover, we use firms' balance sheets to study a broader set of technologies than industrial robotics, encompassing multiple capital types and sectors.

C New Machinery and the Demand for Skills

C.1 Empirical Strategy

Table C.1: Machinery Investment Spikes Sample Reduction

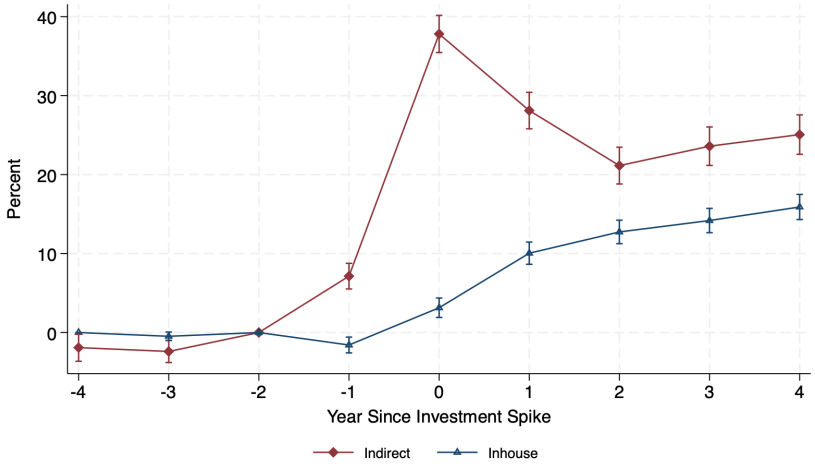
Sample Step	Firms (1)	Investment Spikes (2)
1. Private sector firms with machinery spike	37,379	57,783
2. Pre-spike employment	9,463	15,542
3. First investment spike	9,463	9,463
4. Balanced sample	3,863	3,863

Notes: This table shows how our analysis sample shrinks with the sample criteria listed in Section 3.1. Column (1) shows the number of eligible firms, and Column (2) shows their number of machinery investment spikes.

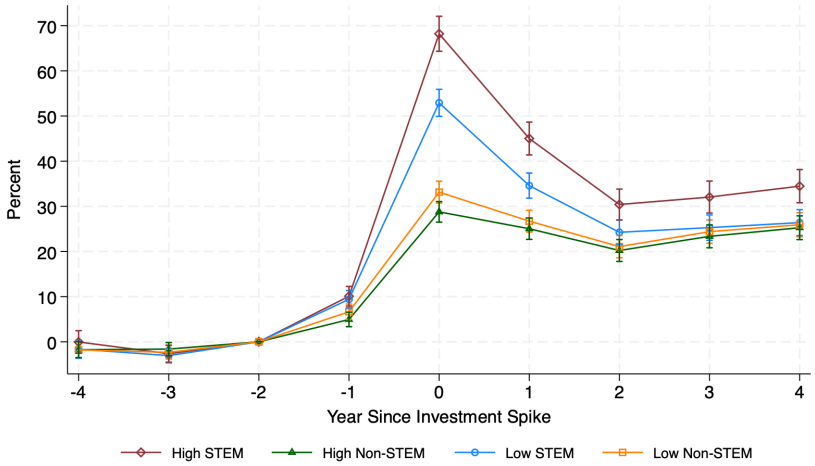
C.2 Main Results

Figure C.1: Drivers of Indirect Skill Bias around Machinery Investment Spikes

(a) In-house and Indirect Employment Growth



(b) Indirect Employment of Skills
(In Percent of Pre-Spike Indirect Employment by Skill Group)



Notes: Panel (a) shows the direct and indirect employment growth around machinery investment spikes. The figure shows in-house employment in percent of pre-spike in-house employment and indirect employment in percent of pre-spike indirect employment (years -3 to -1). The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms". Panel (b) shows the indirect employment of private sector firms around investment spikes in machinery, buildings and intangibles. The figures show the indirect employment of high skilled STEM, high skilled non-STEM, low skilled STEM and low skilled non-STEM workers in percent of pre-spike indirect employment by worker types. Indirect pre-spike employment is the average indirect employment in years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" . *Sample*: Private sector firms around first investment spike. Balanced sample for four years before and after the spike.

C.2.1 Decomposing Other Industries

Table C.2 decomposes the impact of machinery investment spikes on indirect employment (as in Figure 3) across subindustries. The table shows that the high-STEM bias (last column) associated with new machinery is widespread but is particularly pronounced for computer programming.

Table C.2: Decomposing the Impact on Indirect Employment through Other Industries

	Pre-Spike Share	Effect on Indirect Employment (Year 4)				Skill Bias
		High STEM	High Non	Low STEM	Low Non	
	(1)	(2)	(3)	(4)	(5)	$\frac{(2)-(5)}{(1)}$
Machine Suppliers	10.51	5.28	1.17	1.20	0.41	0.46
Other industries						
1-9 Agriculture/Mining	2.05	0.11	0.11	0.09	0.07	0.02
10-12 Food/Beverages	4.35	0.81	0.50	0.27	0.27	0.12
13-15 Textiles/Apparel	1.06	0.09	0.03	0.05	0.03	0.06
16-18 Wood, Paper, Print	3.25	0.33	0.16	0.22	0.17	0.05
19 Coke	0.04	0.00	0.00	0.00	0.00	0.00
20 Chemical and Pharma	1.31	0.29	0.10	0.02	0.03	0.20
22 Rubber-Plastic	1.21	0.25	0.13	0.09	0.06	0.16
23 Non-Metallic	2.54	0.51	0.43	0.21	0.16	0.14
24 Basic Metals	0.48	0.00	0.00	0.00	-0.01	0.02
25 Fabricated Metals	3.25	0.61	0.30	0.22	0.27	0.10
26 Computer, Electronics	0.18	0.01	0.00	0.00	0.00	0.06
27 Electrical Equip.	0.35	0.06	0.00	0.00	0.00	0.17
29-30 Transport Equip.	0.46	0.05	0.02	0.05	0.03	0.04
31-32 Other Manuf.	1.85	0.46	0.14	0.26	0.11	0.19
35-39 Utilities	1.79	0.77	0.42	0.23	0.20	0.32
41-43 Construction	9.09	2.86	0.41	1.42	0.43	0.27
45-47 Wholesale/Retail	24.11	6.23	5.09	2.33	1.74	0.19
49-53 Transport/Storage	6.46	0.21	0.35	0.59	0.56	-0.05
55-56 Hotels & Restaur.	1.13	0.00	0.02	0.02	0.01	-0.01
58-60 Publishing	0.60	0.03	0.12	0.01	0.02	0.02
61 Telecom	0.16	0.04	0.01	0.01	0.00	0.25
62 Computer Program	1.35	1.26	0.22	0.00	0.04	0.90
63 Information Serv.	0.10	0.00	0.00	0.00	0.00	0.00
64-66 Financial Serv.	0.29	0.02	0.02	0.00	0.01	0.03
68 Real Estate	0.42	0.02	0.05	0.00	0.01	0.02
69 Legal Serv.	2.55	0.01	0.20	0.00	0.02	0.00
70 Manag. Consult	0.72	0.19	0.46	0.03	0.07	0.17
72 R&D	0.03	0.00	0.00	0.00	0.00	0.00
73 Advertising	0.59	0.03	0.15	0.01	0.02	0.02
74-75 Other Serv	0.20	0.04	0.03	0.00	0.00	0.20
77 Rental/Leasing	0.63	0.10	0.08	0.04	0.05	0.08
78 Employment Act.	11.99	2.21	3.27	1.90	2.69	-0.04
79 Travel Agency	0.10	0.00	0.00	0.00	0.00	0.00
80 Security	0.38	0.03	0.03	0.04	0.04	-0.03
81 Building Serv.	2.65	0.08	0.19	0.17	0.36	-0.11
82 Administration	0.69	0.02	0.09	0.02	0.02	0.00
84plus Public	1.06	0.03	0.11	0.04	0.07	-0.04

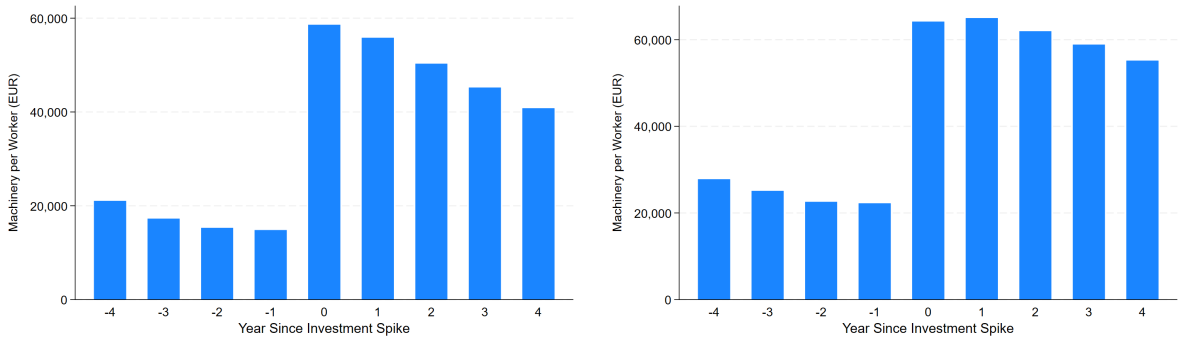
Notes: This table decomposes the impact of machinery investment spikes on indirect employment (as in Figure 3) across two-digit subindustries. Column (1) shows the percent share of the industry in indirect employment in the year before the spike. Columns (2)-(5) show the contribution of this industry to the effect on total employment of each skill group in year 4 after the spike (measured in % of pre-spike total employment). The final column shows the normalized contribution to skill bias, measured as the difference in effects on high-STEM (Column (2)) and Low Non-STEM (Column (5)), relative to the share of the industry in total indirect employment before the spike. *Sample*: Private sector firms around first machinery investment spikes. Balanced sample for four years before and after the spike.

D Heterogeneity Analysis

D.1 Firm Size

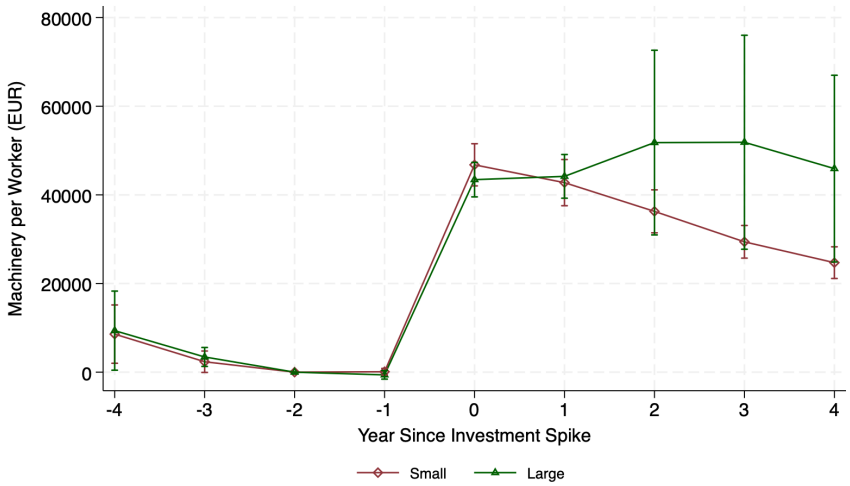
Figure D.1: Machinery Stock per Worker around Spike

(a) Small Firms (b) Large Firms



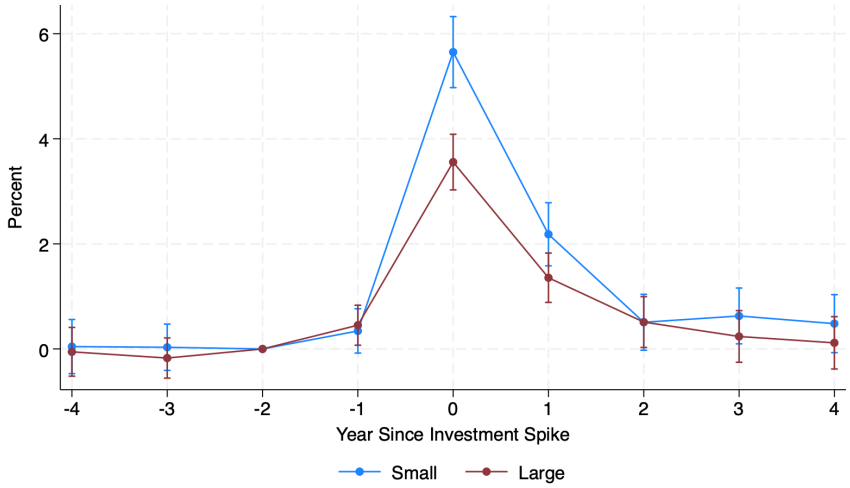
Notes: This figure shows the machinery capital stock per worker around years of machinery investment spikes. Panel (a) focuses on small firms, and Panel (b) on large firms. Small firms have pre-spike employment (year −1) below the median total (in-house + indirect) employment (13.1 FTE). *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

Figure D.2: Machinery per Worker: Large versus Small Firms



Notes: This figure shows the machinery per worker around investment spikes. Small firms have pre-spike employment (year −1) below the median total (in-house + indirect) employment (13.1 FTE). The estimates are differences-in-differences in outcomes (measured relative to year −2) between the "spiking" and "non-spiking firms". *Sample*: Manufacturing firms around first machinery investment spikes. Balanced sample for four years before and after the spike.

Figure D.3: Share of Machine Suppliers in Total Purchases



Notes: This figure shows the share of machine suppliers in total purchases around their first machinery investment spike. Panel (a) focuses on small firms, and Panel (b) on large firms. Small firms have total pre-spike employment (year −1) below the median (13.1 FTE). *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

Table D.1: Small Firms: Firm Employment before Machinery Investment Spikes

	Spiking		Non-Spiking		Std. Difference	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
	(1)	(2)	(3)	(4)	(5)	(6)
Total employment	5.7	2.2	6.2	1.9	-0.09	-0.01
	(5.2)	(2.2)	(.7)	(.6)		
Share of employment (%)						
— High STEM	3.3	5.3	3.5	4.9	-0.02	0.08
	(10.2)	(5.8)	(5.5)	(3.0)		
— High non-STEM	13.4	17.0	13.8	16.3	-0.02	0.06
	(21.3)	(11.3)	(12.0)	(6.5)		
— Low STEM	26.2	25.2	23.8	24.5	0.10	0.07
	(26.1)	(11.5)	(12.8)	(6.3)		
— Low Non-STEM	57.1	52.5	59.0	55.4	-0.07	-0.16
	(28.3)	(12.5)	(12.9)	(6.1)		
Observations	1,926		1,926			

Notes: This table reports direct and indirect employment in treatment (Columns 1-2) and control group (Columns 3-4) in year $t-2$. The table reports total employment in full-time equivalents and the employment share of different skill groups. Columns 5-6 show the standardized difference between the treatment and control group means, calculated in standard deviations of the treatment group, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin, 2008). *Sample*: Small firms around first machinery investment spike. Balanced sample for four years before and after the spike.

Table D.2: Large Firms: Firm Employment before Machinery Investment Spikes

	Spiking		Non-Spiking		Std. Difference	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
	(1)	(2)	(3)	(4)	(5)	(6)
Total employment	71.8	36.5	76.7	35.2	-0.01	0.01
	(455.8)	(183.6)	(117.7)	(87.5)		
Share of employment (%)						
— High STEM	6.5	6.3	6.9	6.5	-0.04	-0.04
	(10.5)	(5.7)	(6.9)	(3.7)		
— High non-STEM	14.4	15.7	15.3	16.0	-0.05	-0.03
	(16.2)	(9.3)	(10.4)	(6.3)		
— Low STEM	25.9	24.4	25.0	23.6	0.05	0.09
	(18.1)	(9.5)	(10.7)	(5.7)		
— Low Non-STEM	57.1	53.5	59.0	53.9	-0.07	-0.03
	(28.3)	(11.4)	(12.9)	(6.5)		
Observations	1,926		1,926			

Notes: This table reports direct and indirect employment in treatment (Columns 1-2) and control group (Columns 3-4) in year $t-2$. The table reports total employment in full-time equivalents and the employment share of different skill groups. Columns 5-6 show the standardized difference between the treatment and control group means, calculated in standard deviations of the treatment group, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin, 2008). *Sample*: Large firms around first machinery investment spike. Balanced sample for four years before and after the spike.

D.2 Application Sector

Table D.3: Manufacturing: Firm Employment before Machinery Investment Spikes

	Spiking		Non-Spiking		Std. Difference	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
	(1)	(2)	(3)	(4)	(5)	(6)
Total employment	63.5	27.3	69.5	28.2	-0.03	-0.01
	(215.6)	(95.8)	(117.4)	(77.7)		
Share of employment (%)						
— High STEM	6.1	6.5	7.2	6.8	-0.11	-0.05
	(9.5)	(5.5)	(5.2)	(2.6)		
— High non-STEM	10.6	14.9	11.4	14.0	-0.06	0.11
	(13.3)	(8.1)	(6.2)	(6.7)		
— Low STEM	32.8	26.3	32.3	25.7	0.03	0.06
	(21.0)	(9.2)	(8.7)	(4.5)		
— Low Non-STEM	50.4	52.3	49.2	53.5	0.05	-0.11
	(22.1)	(10.7)	(9.6)	(5.1)		
Observations	1,226		1,226			

Notes: This table reports direct and indirect employment in treatment (Columns 1-2) and control group (Columns 3-4) in year $t-2$. The table reports total employment in full-time equivalents and the employment share of different skill groups. Columns 5-6 show the standardized difference between the treatment and control group means, calculated in standard deviations of the treatment group, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin, 2008). *Sample*: Manufacturing sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

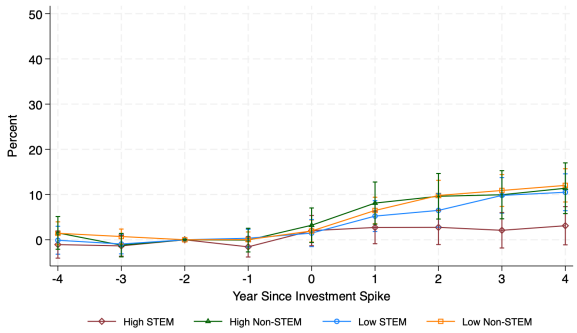
Table D.4: Services: Firm Employment before Machinery Investment Spikes

	Spiking		Non-Spiking		Std. Difference	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
	(1)	(2)	(3)	(4)	(5)	(6)
Total employment	26.1	13.6	30.8	14.0	-0.01	-0.00
	(388.6)	(82.2)	(34.8)	(20.4)		
Share of employment (%)						
— High STEM	4.3	5.6	5.5	5.9	-0.11	-0.05
	(10.9)	(6.3)	(7.8)	(4.1)		
— High non-STEM	18.1	18.4	19.7	19.2	-0.07	-0.07
	(21.9)	(11.6)	(12.5)	(7.3)		
— Low STEM	19.7	22.1	17.8	20.7	0.09	0.13
	(19.6)	(10.4)	(8.4)	(5.1)		
— Low Non-STEM	57.9	53.9	56.9	54.1	0.04	-0.02
	(25.5)	(12.7)	(14.7)	(7.2)		
Observations	2,011		2,011			

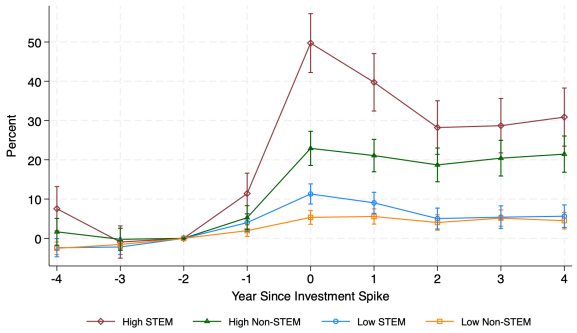
Notes: This table reports direct and indirect employment in treatment (Columns 1-2) and control group (Columns 3-4) in year $t-2$. The table reports total employment in full-time equivalents and the employment share of different skill groups. Columns 5-6 show the standardized difference between the treatment and control group means, calculated in standard deviations of the treatment group, where absolute values above 25% is a standard threshold for assessing imbalance (Stuart and Rubin, 2008). *Sample*: Service sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

Figure D.4: Employment around Investment Spikes: Agriculture/Utilities/Construction

(a) Direct Employment



(b) Indirect Employment



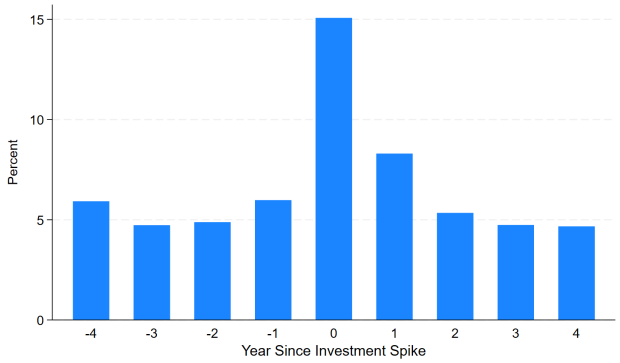
Notes: This figure shows the direct and indirect employment around machine investment spikes for firms in agriculture, construction and utilities. The figures show the indirect employment of high skilled STEM, high skilled non-STEM, low-skilled STEM and low skilled non-STEM workers in percent of total pre-spike employment by skill groups. Total pre-spike employment is the average sum of direct and indirect employment in years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. *Sample*: Private sector firms around first investment spike. Balanced sample for four years before and after the spike.

D.3 Capital Types

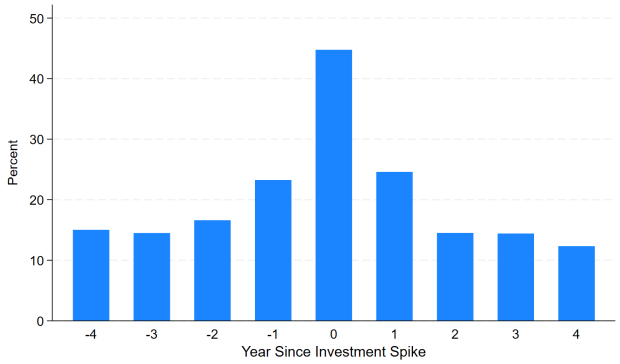
Figure D.5 plots investment as a share of total sales for machinery, building and intagibles spikes. The graphs focus on the 85th percentile cutoff as the 90th percentile cutoff resulted in very high values for the building spikes.

Figure D.5: Investment Shares around Investment Spikes

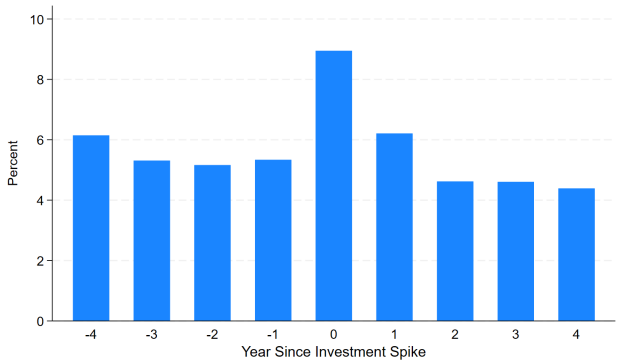
(a) Machine Spikes



(b) Building Spikes



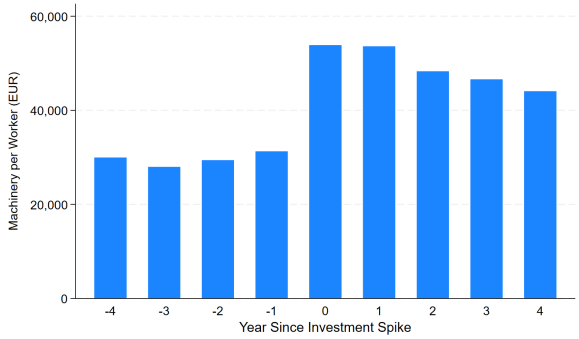
(c) Intangibles Spikes



Notes: *Notes*: Panels (a)–(c) plot the share of investment in total sales around, respectively, machinery, building, and intangible investment spikes. Machinery spikes are defined as years in which the firm's change in machinery stock per worker exceeds the 85th percentile of positive changes (€11k). Building spikes are defined analogously using the change in building stock per worker (85th percentile: €137k). Intangible spikes are defined analogously using the change in intangible capital per worker (85th percentile: €14k). *Sample*: Private-sector firms around their first investment spike, using a balanced panel spanning four years before and after the event.

Figure D.6: Machinery around Building Investment Spikes

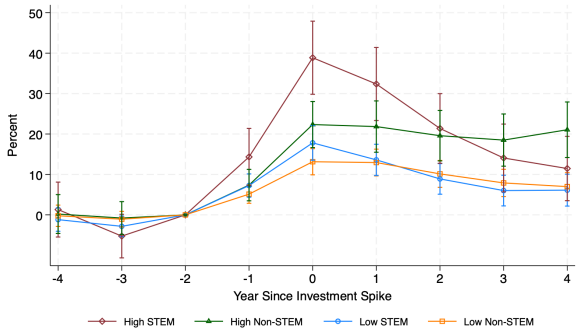
(a) Machinery Stock per Worker around Spike



Notes: The figure plots the machinery capital stock per worker around years of building investment spikes. Building spikes are defined as years when firms' change in building stock per worker exceeds the 90th percentile (€220,195). *Sample*: Private sector firms around first building investment spike. Balanced sample for four years before and after the spike.

Figure D.7: Building Spikes: Excluding Machine Spikes

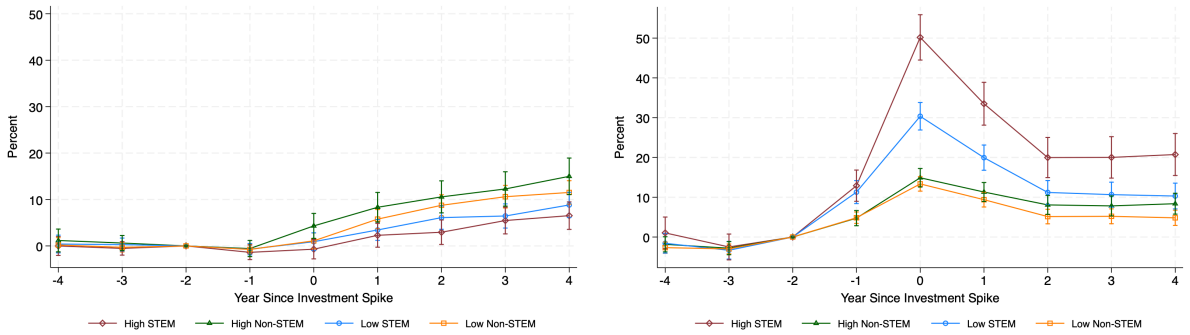
(a) Indirect Employment



Notes: This figure shows the indirect employment of manufacturing sector firms around investment spikes in buildings. The cutoff is defined as the 90th percentile of positive changes in the building stock, excluding the top 25% of increases in machinery per worker at the spike.The figures show the indirect employment of high skilled STEM, high skilled non-STEM, low skilled STEM and low skilled non-STEM workers in percent of pre-spike total employment by worker types. Total pre-spike employment is the average indirect (total) employment in years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms". *Sample*: Manufacturing sector firms around first investment spike. Balanced sample for four years before and after the spike.

Figure D.8: Building Spikes: Cutoff 85th percentile

(a) Direct Employment, 85th percentile cutoff (b) Indirect Employment, 85th percentile cutoff



Notes: This figure shows the indirect employment of private sector firms around investment spikes in buildings. The cutoff is defined as the 85th percentile of positive changes in the building stock (€137k).The figures show the indirect employment of high skilled STEM, high skilled non-STEM, low skilled STEM and low skilled non-STEM workers in percent of pre-spike total employment by worker types. Total pre-spike employment is the average indirect (total) employment in years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms". *Sample*: Private sector firms around first investment spike. Balanced sample for four years before and after the spike.

D.4 New versus Existing Suppliers

In this section, we examine whether the indirect employment from new machinery reflects new or existing suppliers. Moreover, we examine whether the skill bias differs for investment spikes that are driven by new versus new suppliers.

Figure D.9 studies the effects of machine spikes on the indirect employment of existing versus brand-new suppliers.[28] Around 60% of the indirect employment of machine suppliers comes from firms that had sold to the spiking firm already before the spike, with the remaining 40% coming from brand-new suppliers. Investing firms only add suppliers in the year of the spike, with the longer-run increase in indirect employment entirely reflecting a shift in existing suppliers.

Figures D.10 and D.11 compare the employment effects of machinery spikes driven by new and existing suppliers. The figure shows that the indirect skill bias of machinery investments is particularly strong when they are sourced from new suppliers. This is consistent with the idea that new machinery supply may embody new technologies, rather than merely replacing existing capital. By contrast, the direct employment effects (Figure D.10, Panel (i)) are similar for investment events driven by new versus existing suppliers.

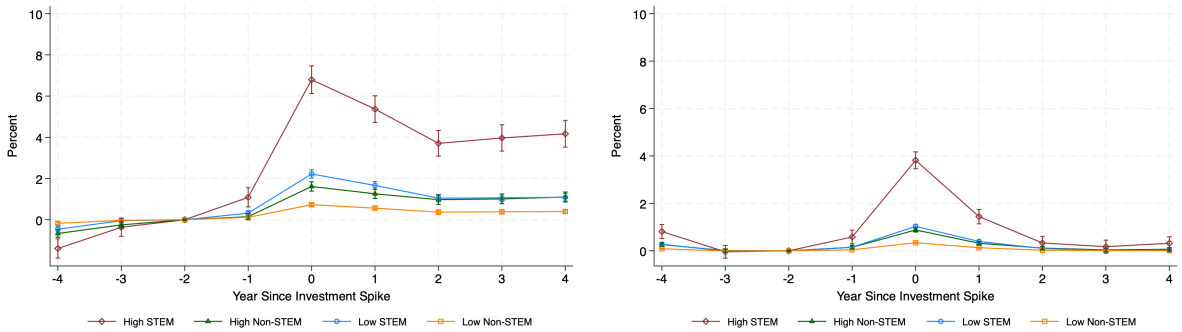
[28] Brand-new suppliers are firms that have not sold to the firm before the year considered.

Figure D.9: Indirect Employment around Machinery Spikes

(i) Machine Suppliers

(a) Existing Suppliers

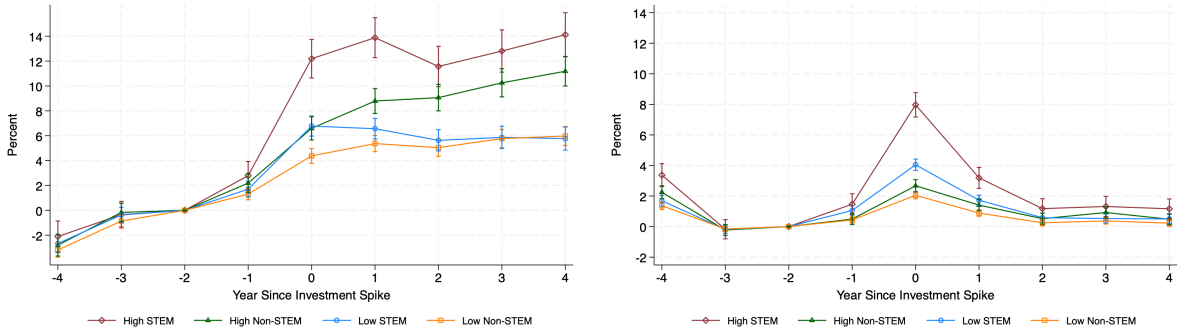
(b) New Suppliers



(ii) Other Industries

(a) Existing Suppliers

(b) New Suppliers

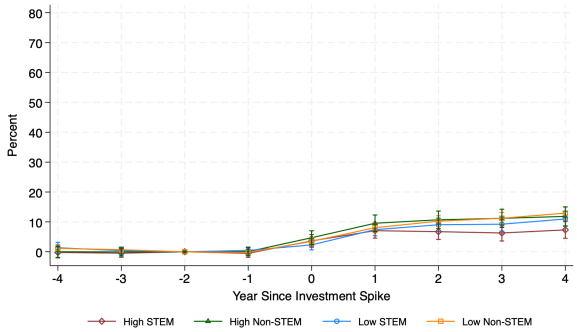


Notes: This figure splits the indirect employment by whether the purchases are from existing suppliers (Panels (a) and (c)) or new suppliers (Panels (b) and (d)). New suppliers are firms that have not sold to the firm before the year considered. Panels (a) and (b) consider the indirect employment of machine suppliers, while Panels (c) and (d) consider the indirect employment from all other industries. The figures show the indirect employment of high skilled STEM, high skilled non-STEM, low skilled STEM and low skilled non-STEM workers in percent of total pre-spike employment by worker types. Total pre-spike employment is the average sum of direct and indirect employment in years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

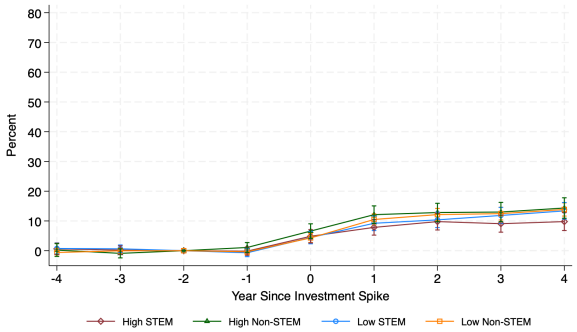
Figure D.10: Employment around Machinery Spikes (In Percent of Total Pre-Spike Employment by Skill Group)

(i) Direct Employment

(a) Spikes Driven by Existing Suppliers

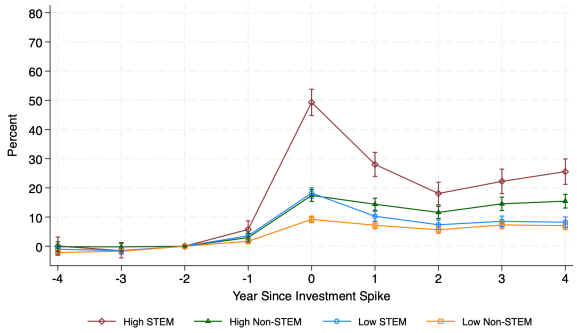


(b) Spikes Driven by New Suppliers

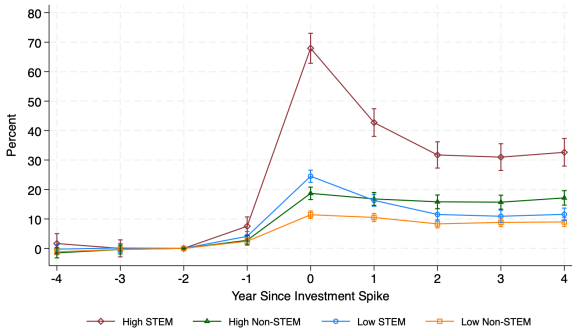


(ii) Indirect Employment

(a) Spikes Driven by Existing Suppliers



(b) Spikes Driven by New Suppliers

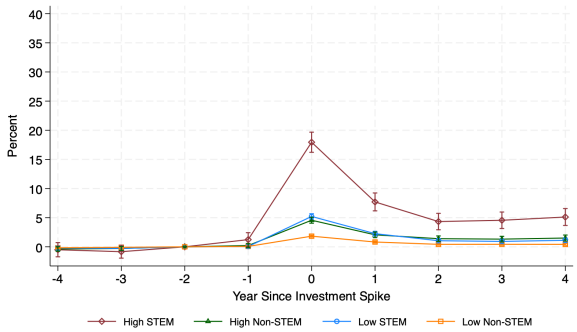


Notes: This figure shows the direct employment (Panel (i)) and indirect employment (Panel (ii)) around machinery investment spikes. Subpanels (a) focus on spikes that are driven by existing suppliers, whereas Subpanels (b) focus on spikes driven by new suppliers. The distinction between spikes driven by new versus existing suppliers is based on the ratio of the change in purchases from new machine suppliers to the sum of the absolute changes in purchases from new and existing machine suppliers at the time of the spike, $S_{\text{new}} = \Delta_{\text{new}}/(|\Delta_{\text{new}}| + |\Delta_{\text{exist}}|)$. Spikes with S_{new} above the sample median (excluding negative changes in total purchases from machine suppliers) are classified as *new-supplier* spikes; the remainder are classified as *existing-supplier* spikes. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. *Sample*: Private sector firms around first machinery investment spikes. Balanced sample for four years before and after the spike.

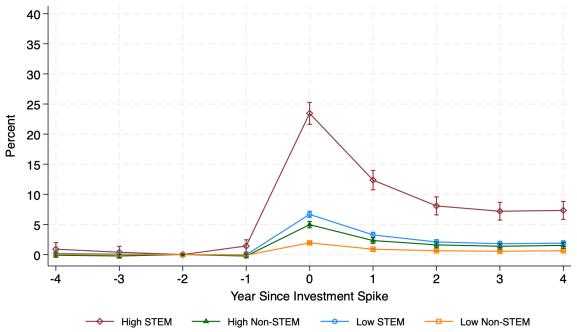
Figure D.11: Indirect Employment around Machinery Spikes

(i) Machine Suppliers

(a) Spikes Driven by Existing Suppliers

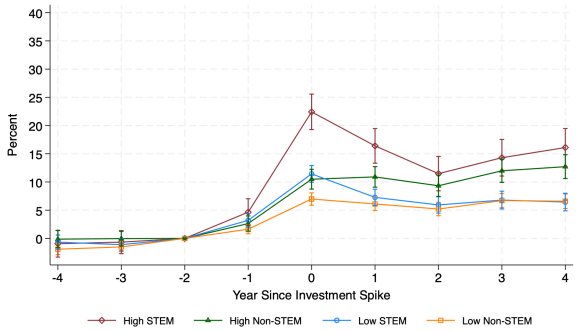


(b) Spikes Driven by New Suppliers

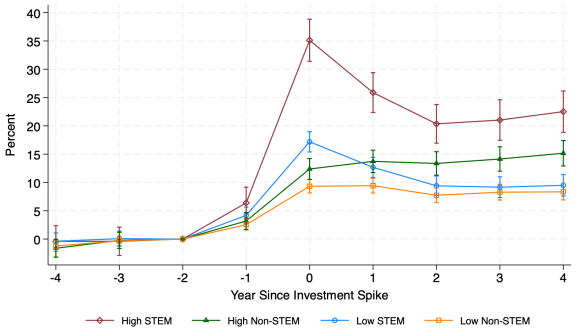


(ii) Other Industries

(a) Spikes Driven by Existing Suppliers



(b) Spikes Driven by New Suppliers)



Notes: This figure shows the indirect employment from machine suppliers (Panel (i)) and other industries (Panel (ii)) around machinery investment spikes. Subpanels (a) focus on spikes that are driven by existing suppliers, whereas Subpanels (b) focus on spikes driven by new suppliers. The estimates are differences-in-differences in outcomes (measured relative to year −2) between the "spiking" and "non-spiking firms" from Table 2. *Sample*: Private sector firms around first machinery investment spikes. Balanced sample for four years before and after the spike.

E Robustness

E.1 Investment Spikes

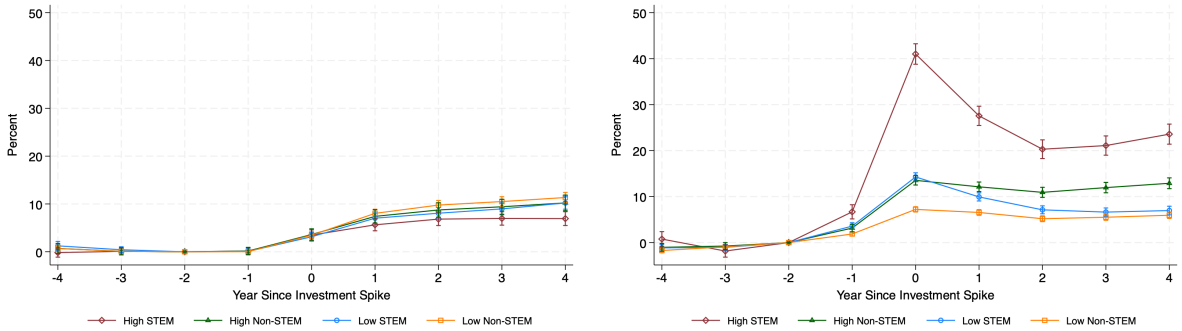
This section shows that our findings are robust to varying the percentile cutoff for defining investment spikes, namely we define the cutoff as the 85th or 95th percentile of positive changes in machinery stock per worker.

The 85th percentile is €10, 611 and results in 5, 539 spikes in the balanced panel. The 95th percentile is €35, 079 and results in 1, 826 spikes in the balanced panel.

Figure E.1: Employment around Machinery Spikes: cutoff 85th percentile

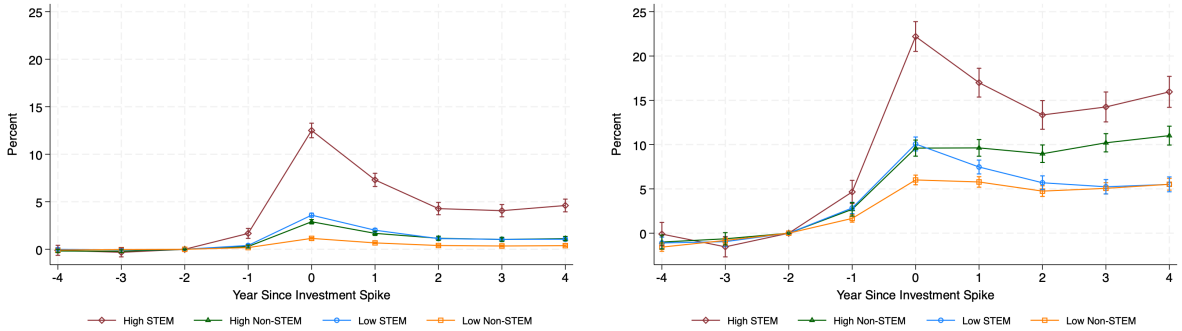
(a) Direct Employment

(b) Indirect Employment



(c) Machine Suppliers

(d) Other Industries

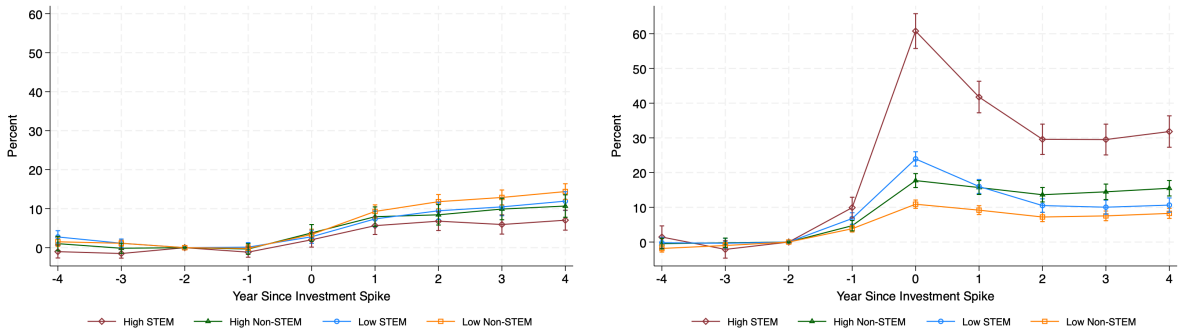


Notes: This figure reproduces the employment effect of machinery investment spikes , but taking the 85th percentile cutoff. This figure shows the employment of high skilled STEM, high skilled non-STEM, low skilled STEM and low-skilled non STEM workers in percent of total pre-spike employment by worker types. Total pre-spike employment is the average sum of direct and indirect employment in years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. *Sample*: Private firms around first and only machinery investment spikes. Balanced sample for four years before and after the spike.

Figure E.2: Employment around Machinery Spikes: cutoff 95th percentile

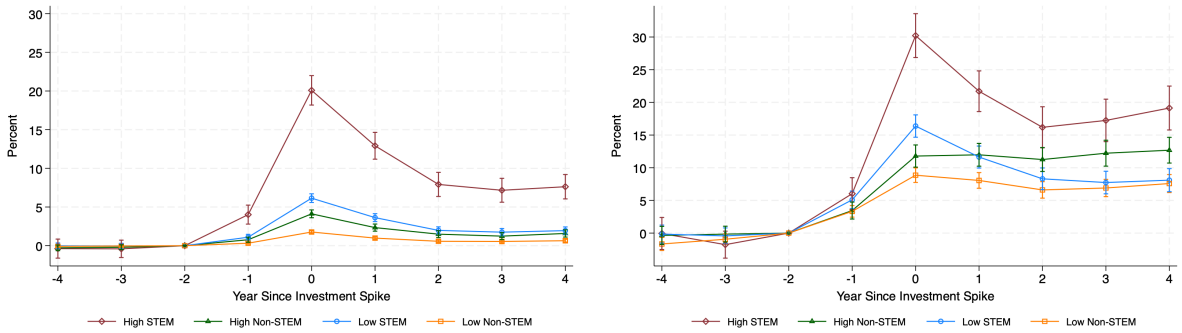
(a) Direct Employment

(b) Indirect Employment



(c) Machine Suppliers

(d) Other Industries



Notes: This figure reproduces the employment effect of machinery investment spikes , but taking the 95th percentile cutoff. This figure shows the employment of high skilled STEM, high skilled non-STEM, low skilled STEM and low-skilled non STEM workers in percent of total pre-spike employment by worker types. Total pre-spike employment is the average sum of direct and indirect employment in years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. *Sample*: Private firms around first and only machinery investment spikes. Balanced sample for four years before and after the spike.

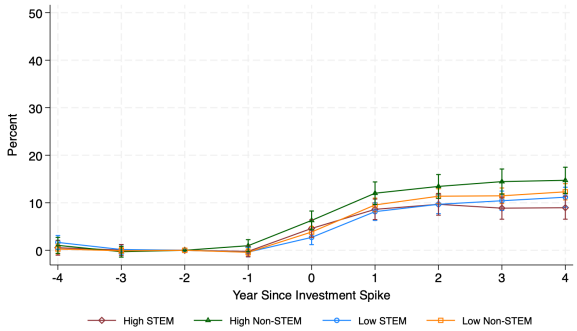
E.2 Single Spiking Firms

Figure E.3 reproduces the employment effect of machinery investment spikes (Figure 2), limiting the sample to the 61% of firms with a single investment spike. Our main conclusions are robust to focusing on these single-spiking firms. In particular, Panels (a)-(b) show machinery investment spikes are skill-neutral for in-house employment but create a gap between the indirect employment of high-s, which Panels (c)-(d) show is driven by machine suppliers initially and other industries eventually. The indirect employment effects are quantitatively smaller for single-spiking firms, reflecting that some spiking

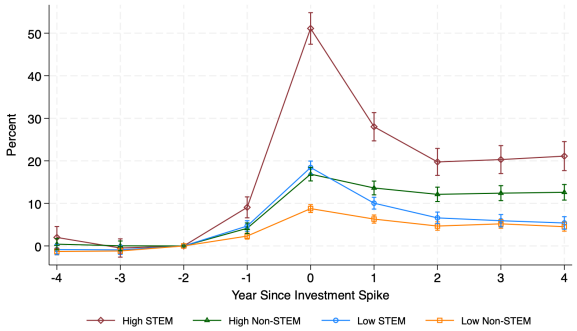
firms make follow-on investments in the post-window, as illustrated in Figure E.4

Figure E.3: Single-Spiking Firms: Employment around Machinery Spikes

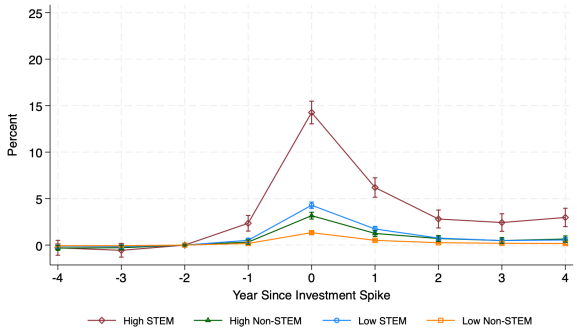
(a) Direct Employment



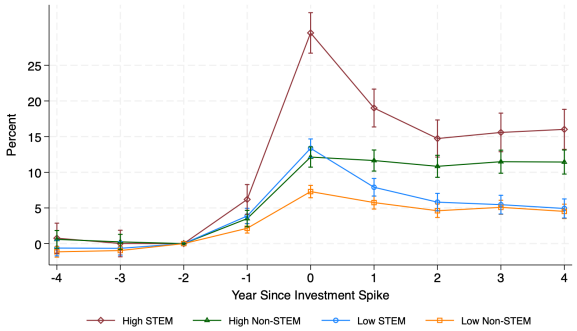
(b) Indirect Employment



(c) Machine Suppliers



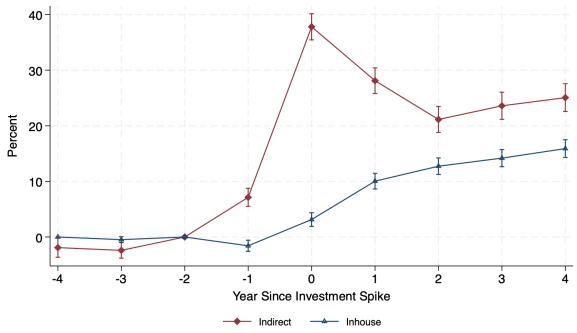
(d) Other Industries



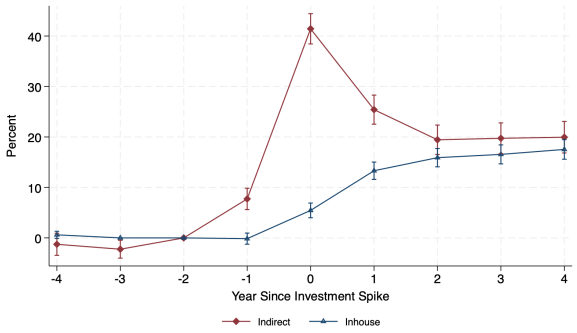
Notes: This figure reproduces the employment effect of machinery investment spikes , limiting the sample to the 61% of firms with a single investment spike. This figure shows the employment of high skilled STEM, high skilled non-STEM, workers in percent of total pre-spike employment by worker types. Total pre-spike employment is the average sum of direct and indirect employment in years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. *Sample*: Private sector firms around first and only machinery investment spikes. Balanced sample for four years before and after the spike.

Figure E.4: Indirect and In-house Employment around Machinery Spikes

(a) All Spikes



(b) Single Spikes



Notes: This figure shows the direct and indirect employment growth of private sector firms around machinery investment spikes. Panel (a) shows results for all spikes and panel (b) limits the sample to single spiking firms. The figure shows in-house employment in percent of pre-spike in-house employment and indirect employment in percent of pre-spike indirect employment. Pre-spike employment is the average sum of direct and indirect employment in years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms". *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

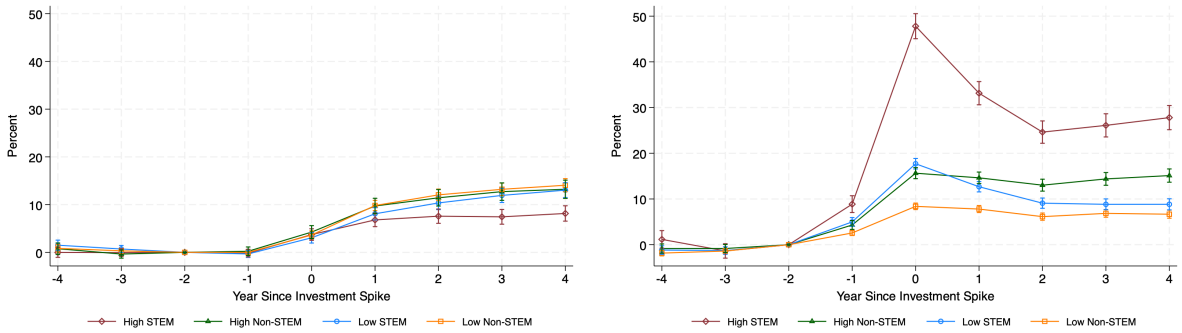
E.3 Unbalanced Panel

Figure E.5 reproduces the employment effect of machinery investment spikes with firm exits included as zero direct and indirect employment.

Figure E.5: Including Exiting Firms: Employment around Machinery Spikes

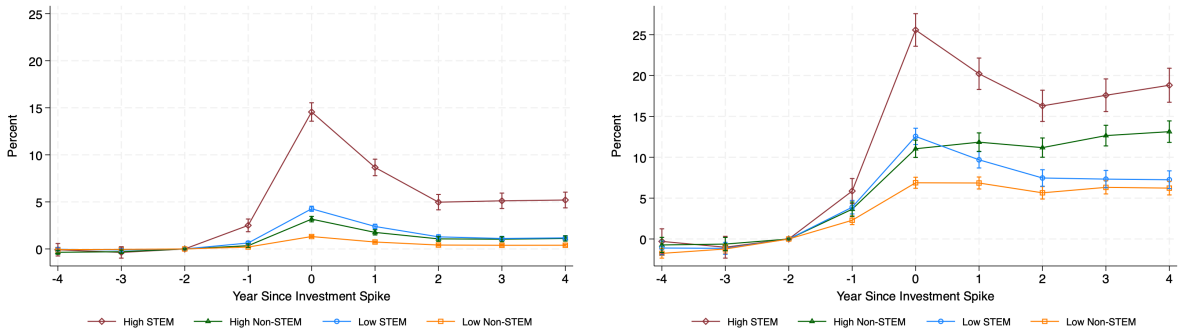
(a) Direct Employment

(b) Indirect Employment



(c) Machine Suppliers

(d) Other Industries



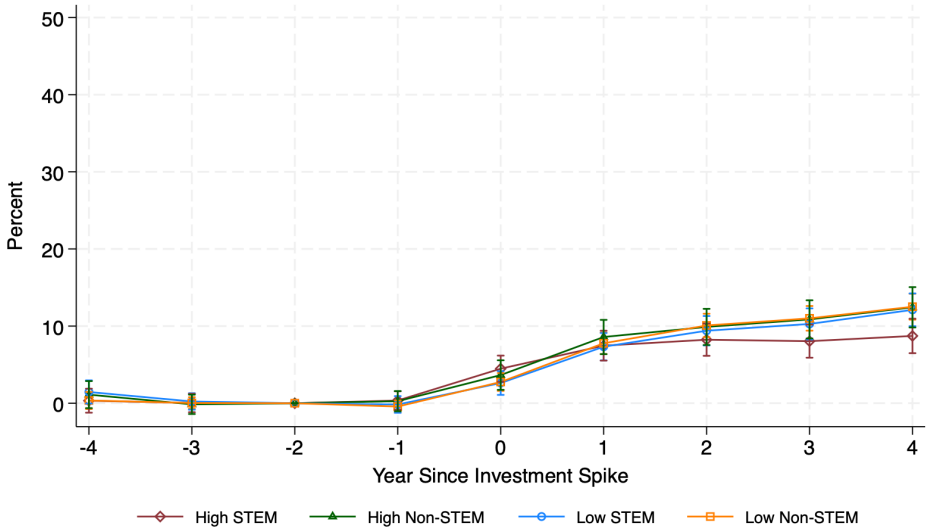
Notes: This figure reproduces the employment effect of machinery investment spikes, assigning zero employment to firm exits. This figure shows the employment of high skilled STEM, high skilled non-STEM, workers in percent of total pre-spike employment by worker types. Total pre-spike employment is the average sum of direct and indirect employment in years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2. *Sample*: Private sector firms around machinery investment spikes. Firm active for four years before the spike.

E.4 Control Group

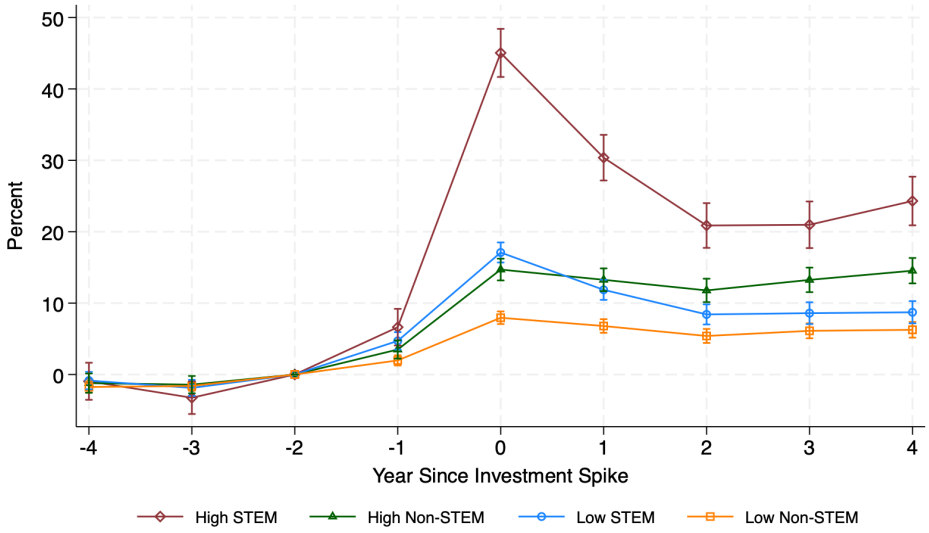
Instead of taking the average firm as our control, we execute a random one-to-one matching within each industry-year cell. More precisely, we select for each firm in spiking year t all firms in the same NACE 3 digit industry that report 4 years before and after t, have at least 5 total employees at $t-1$ and have not spiked before t. Among these firms, we randomly select 1 to include in the control group. Results are reported in Figure E.6. The results are highly similar to the main results, but with slightly larger standard errors.

Figure E.6: Employment of Skill Groups around Machinery Investment Spikes (Random One-to-one Matching)

(a) Direct (In-House)



(b) Indirect (Outsourced)



Notes: This figure shows the employment of high-skilled STEM, high-skilled non-STEM, low-skilled STEM, and low-skilled non-STEM in percent of total pre-spike employment by skill category. Panel (a) considers direct (in-house) employment, while Panel (b) considers indirect employment at supplier firms. Total pre-spike employment is the sum of direct and indirect employment. Pre-spike refers refers to the average over the years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms". The "non-spiking firms" are random 1-to-1 matches within the same industry-year cell. The estimates are based on the specification in Equation (7), with whiskers representing 95% confidence intervals. *Sample*: Private sector firms around their first machinery investment spikes. Balanced sample for four years before and after the spike.

E.5 Higher-Order Links

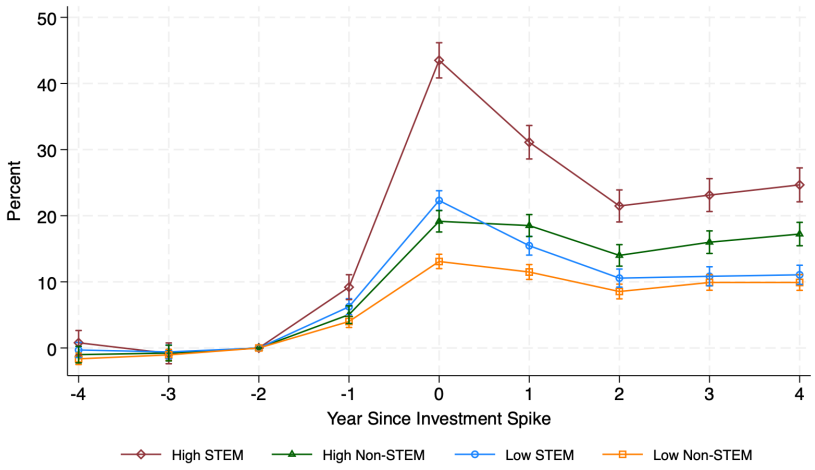
This section shows results when including higher-order links in the computation of indirect employment. More precisely, we compute third-order indirect employment as follows:

$$\mathbf{L}^{3}_{Ojt} = \sum_{k} \frac{X_{kjt}}{X_{kt}} \left(\mathbf{L}_{Hkt} + \sum_{r} \frac{X_{rkt}}{X_{rt}} \left(\mathbf{L}_{Hrt} + \sum_{s} \frac{X_{srt}}{X_{st}} \mathbf{L}_{Hst} \right) \right), \tag{26}$$

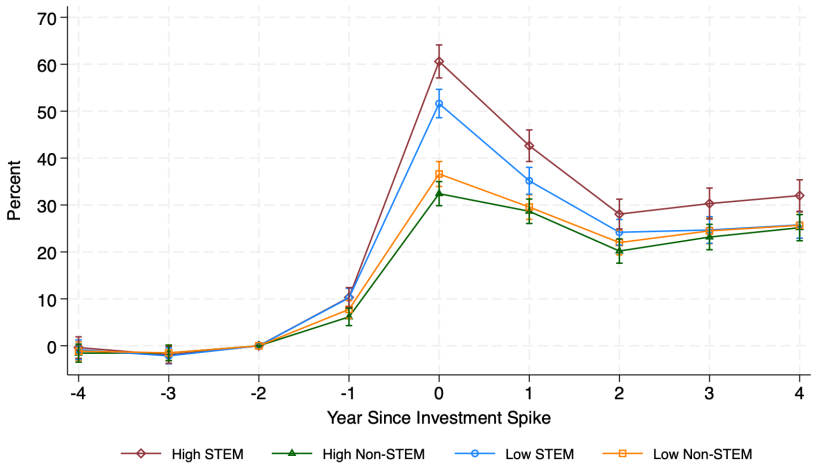
and include it in our analysis as we did with first-order indirect employment. The results are reported in Figure E.7, which shows that our findings are robust to the inclusion of these higher-order supplier links.

Figure E.7: Including Higher Order Links: 3rd Order Included

(a) Indirect Employment in Percent of Pre-Spike *Total* Employment by Skill Group (Higher-Order Version of Figure 2)



(b) Indirect Employment in Percent of Pre-Spike *Indirect* Employment by Skill Group (Higher-Order Version of Figure C.1)



Notes: This figure shows 3rd order indirect employment growth around the machinery investment spikes. Panel (a) shows indirect employment in percent of pre-spike total employment by skill category. Panel (b) shows indirect employment in percent of pre-spike indirect employment by skill category. Pre-spike refers to the average over the years -3 to -1. The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms". *Sample*: Private sector firms around first investment spike. Balanced sample for four years before and after the spike.

F Aggregate Implications

This section describes our approach to quantifying the aggregate potential implied by our estimated firm-level effects. Following Autor, Dorn and Hanson (2013) and Mian and Sufi (2014), we scale the micro-level effects (i.e., our investment-spike difference-in-difference estimates) by the aggregate changes in the treatment variable (i.e., machinery stocks and investments).

Building on our conceptual framework in Section 1, we distinguish between *integration* and *production* labor. Integration labor is employed to install new machinery I, while production labor captures changes associated with the expanded stock of machinery capital K. These two effects are clearly visible in our difference-in-differences estimates on employment (e.g., Figures 2 and 3), which exhibit a sharp increase in the year of investment followed by a gradual convergence to a new, stable level four years later. Specifically, we use the temporary effect around the year of investment to identify effects on integration labor, and the stable effect four years after investment to identify effects on production labor.

Let M_t denote aggregate machinery per worker in period t. Let β_M denote the difference-in-differences estimate for machinery per worker, and let β^u_{ms} denote the estimates for employment of skill group s (low non-STEM, low STEM, high non-STEM, high STEM) in stage u (integration, production) through mode m (direct, indirect). We evaluate the effects of moving from an economy with aggregate machinery per worker M_0 to M_1. Let ΔX denote the change in X between these two periods. Assuming a depreciation rate δ, sustaining the higher machinery stock requires an increase in investment of $\Delta I = \delta \times \Delta M$.

The potential impact on aggregate demand for *production* workers of skill group s

sourced through mode m is:

$$\mathcal{B}^{P}_{ms} = \beta^{P}_{ms} \times \frac{\Delta M}{\beta_M}. \tag{27}$$

The potential impact on aggregate demand for *integration* workers of skill group s sourced through mode m is:

$$\mathcal{B}^{I}_{ms} = \beta^{I}_{ms} \times \delta \times \frac{\Delta M}{\beta_M}. \tag{28}$$

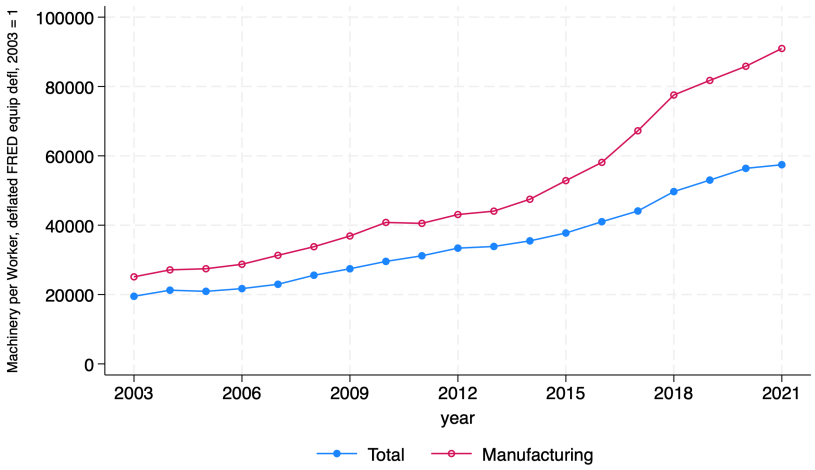
We use the following parameter values:

1. Increase in aggregate machinery per worker ΔM from Figure F.1 (change from 2003 to 2021)
2. Investment-spike effect on machinery per worker β_M from Figure 1 (year 0 effect)
3. Investment-spike effects on employment of skill group s in stage u through mode m from Figure 2 (sum of year 0-2 effects for integration; year 4 effects for production)
4. A depreciation rate δ of 12%, reflecting the typical rate for machinery used by the Bureau of Economic Analysis (Fraumeni, 1997).

Table 3 presents the results obtained by substituting these parameter values into Equations (27)–(28) and expressing effects relative to low non-STEM workers, i.e., $\mathcal{B}^{I}_{m,s} - \mathcal{B}^{I}_{m,\text{Low}-\text{Non}}$.

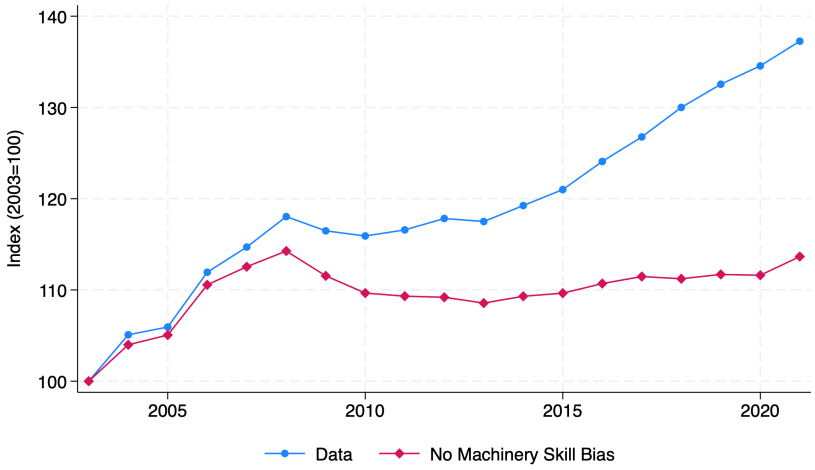
To put these magnitudes in perspective, Figure F.2 plots the counterfactual evolution of high-STEM employment in the absence of skill bias from machinery—that is, setting $\mathcal{B}^{I}_{m,\text{High}-\text{STEM}}$ equal to $\mathcal{B}^{I}_{m,\text{Low}-\text{Non}}$—and assuming the potential effects from Table 3 translate fully into employment. This exercise indicates that skill bias from new machinery can explain up to 60 percent of the observed rise in high-STEM employment since 2003.

Figure F.1: Aggregate Machinery Per Worker



Notes: This figure plots the aggregate machinery stock per worker in the private sector (blue line) and in manufacturing (red line). Machinery capital is deflated using the equipment price deflator from Federal Reserve Bank of St. Louis (2025).

Figure F.2: Aggregate Employment of High-STEM Workers



Notes: This figure shows the growth in employment of high-STEM workers in the private sector (*Data* line). The *No Machinery Skill Bias* line depicts the counterfactual evolution in the absence of skill bias from machinery—that is, setting $\mathcal{B}^I_{m,\text{High+STEM}}$ equal to $\mathcal{B}^I_{m,\text{Low+non-STEM}}$ (see Equation (27))—and assuming the potential effects from Table 3 translate fully into employment.