Integrators: The Firm Boundaries of Capital-Skill Complementarity*

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Abstract

New machinery has long been argued to raise the relative demand for skilled labor — yet modern firm-level evidence finds no such shift for investing firms. We resolve this puzzle by showing that the skills most complementary to new machinery are most often not hired in-house. Linking Belgian firm-level data on capital investments, buyer–supplier transactions, and worker skills, we show that the skill bias of new machinery arises entirely from external suppliers. Following machinery investment spikes, firms' purchases from external suppliers raise total demand for high-STEM workers by 47% (three times the 8–17% rise for other skill groups), while in-house employment grows evenly, contributing less than 5%. The external skill bias comes first from machine integrators and later from complementary services, and is stronger for smaller firms, lumpier investments, and capital undergoing rapid technological change, consistent with fixed and adjustment costs of hiring technology-complementary skills. Our findings reveal that firm boundaries are central to both measuring capital–skill complementarity and understanding technology adoption.

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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., 2025; Curtis et al., 2023; Hirvonen, Stenhammar and Tuhkuri, 2025), challenging the capital–skill complementarity hypothesis.

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 most often not hired in-house but 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 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).

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 through two related channels: installing and integrating new capital requires skilled workers (Goldin and Katz, 1998), as does operating more capital-intensive production (Griliches, 1969).

We adopt the "investment spikes" design from recent studies (e.g., Bessen et al. (2025), Aghion et al. (2025), 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 have not yet done so. While investment spikes are endogenous firm decisions, we conduct several validation checks of our identification strategy. First, the spikes design has been validated against quasi-experiments in prior work (Aghion et al., 2025; Hirvonen, Stenhammar and Tuhkuri, 2025). Second, spiking and non-spiking firms are on similar paths before the spikes, and controlling for their sales growth in the spike year leaves our conclusions intact. Finally, the skill bias of investment spikes is specific to capital embodying advanced technologies (Greenwood, Hercowitz and Krusell, 1997), ruling out generic confounders of large investments.

We establish three main findings on how firms adjust their skill demand around machinery investment spikes.

First, machinery spikes deliver a sharp rise in demand for high-STEM labor — and it comes entirely from outside the firm. Total high-STEM employment (in-house plus

external) rises by 51% in the year of adoption versus only 11–20% for other skill groups, and remains 34% above baseline four years later. The skill-biased shift is delivered entirely by external labor services: in-house employment grows evenly across skill categories, contributing only 2–4% to total employment at the spike and 8–12% after four years, consistent with firm-level studies that observe only in-house payrolls.

Second, the external skill bias unfolds in two stages, corresponding to two distinct theoretical channels. Initially, machine suppliers and integrators drive the shift, raising total high-STEM demand by about 15% in the spike year, the investment-skill complementarity of Goldin and Katz (1998). Over time, the bias persists but migrates to skill-intensive services complementary to capital-intensive production (such as software providers), the capital-skill complementarity of Griliches (1969).

Third, the skill bias of investment spikes varies importantly across investing firms and capital types. The external high-STEM skill bias is stronger for smaller firms, while larger firms are more likely to employ such workers in-house prior to adoption. Similarly, while machinery investments are most common in manufacturing, they generate even stronger external high-STEM bias in services, again partly because services firms employ fewer in-house high-STEM workers to begin with. Importantly, the high-STEM skill bias is specific to new machinery: building spikes generate weaker bias that fades over time, while intangible spikes, with smoother investment profiles, leave the skill mix unchanged and rely far less on external suppliers. Machinery from new suppliers to the firm, which is more likely to embody new technologies, generates the strongest skill bias of all, the capital-embodied technical change of Greenwood, Hercowitz and Krusell (1997).

We present a conceptual framework for how new machinery affects the demand for worker skills both within and beyond the boundaries of investing firms. We explain our findings by combining the canonical model of investment-skill and capital–skill complementarities (Goldin and Katz, 1998; Griliches, 1969) with two classical rationales for

outsourcing: hiring capital-complementary skills entails fixed and adjustment costs (Abraham and Taylor, 1996).

The presence of fixed and adjustment 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 (which entail larger adjustment costs), and for technologically advanced capital types (which require more specialized skills to install and deploy). This mechanism contrasts with the wage-savings motive at the center of the literature on domestic outsourcing (Goldschmidt and Schmieder, 2017): rather than shedding low-pay work to avoid firm wage premia, investing firms outsource their highest-skill work to specialized suppliers that pay a wage premium.

Our estimates also speak to the structural parameters at the heart of the capital–skill complementarity literature. Mapped into the nested-CES framework of Krusell et al. (2000), they imply that machinery substitutes about 1.6 times more easily for low non-STEM labor than for high-STEM labor, confirming capital–skill complementarity at the firm level.

Our main results are robust to the many ways one can construct staggered event studies — the spike threshold, single- versus repeat-spiking treated firms, matched versus cell-average comparison firms, and balanced versus unbalanced panels — as well as to incorporating higher-order links in the supply chain (i.e., suppliers of suppliers). Our stacked difference-in-differences design also addresses concerns with staggered treatments under heterogeneous effects (Roth et al., 2023).

Using our firm-to-firm transactions data, we evaluate alternative approaches to accounting for external employment that do not require such data. Aggregating the analysis to local labor markets (as in Acemoglu and Restrepo (2020); Aghion et al. (2023);

Dauth et al. (2021)) still misses most of the external skill bias, because the skills required to adopt new machinery are often sourced outside the investing firm's local labor market. Applying fixed sectoral input–output matrices (as in Humlum (2022)) also fails to capture the external skill bias, because new machinery shifts the composition of external services toward high-STEM labor.

As a final step, we assess whether the estimated magnitudes are large enough to affect aggregate skill demands. Embedding our micro-level estimates in a calibrated general-equilibrium framework, we find that skill bias from the aggregate rise in machinery stocks and investments between 2003 and 2021 explains about one-quarter of the observed rise in high-STEM employment over the period (10 of 37 percentage points) and a 7 percentage point rise in the high-STEM skill premium.

More broadly, our paper bridges two extensive but largely distinct literatures on capital-skill complementarities and firms' make-or-buy decisions. Empirically, we combine firm-level data on capital investments and employment (e.g., Aghion et al., 2025; Berlingieri et al., 2026; 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 within and outside investing firms. Theoretically, we connect models of investment-skill and capital–skill complementarity (e.g., Goldin and Katz, 1998; Griliches, 1969) and make-or-buy decisions (e.g., Abraham and Taylor, 1996; Grossman and Helpman, 2002) to understand where capital-complementary skills are deployed.

1 Conceptual Framework

To conceptualize our empirical analysis, we embed a canonical model of investment-skill and capital–skill complementarities (Goldin and Katz, 1998; Griliches, 1969) within firms' decision to hire or outsource labor services. We use the framework to derive testable

predictions about investment-skill and capital-skill complementarities and why firms outsource the required labor, and to motivate our "investment spikes" empirical strategy.

1.1 Setup

Consider a firm j in year t. Production combines capital, skilled production labor, and unskilled production labor:

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

Deploying new capital requires physical investment I_{jt} and skilled and unskilled integration labor:

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

where capital depreciates at a rate δ.

For each labor category $\mathbf{L} \in \{U^P, S^P, U^I, S^I\}$, firms can either hire in-house (H) or source from external suppliers (O):

$$\mathbf{L}_{jt} = \mathbf{L}^H_{jt} + \mathbf{L}^O_{jt}. \tag{3}$$

Firms choose investment and labor (in-house and outsourced) to maximize the present-discounted sum of profits. In-house labor may involve fixed and adjustment costs, and investment costs may be non-convex. Appendix A states the firm's full dynamic program.

1.2 Model Predictions

Our first set of predictions relate firms' capital investments to their underlying demand for skills (tested in Section 3). First, following Goldin and Katz (1998), integrating new capital may require skilled workers such as machinists and robot integrators. Second, following Griliches (1969), operating a more capital-intensive production process

may require additional worker skills (for example, programmers and technicians running automated production lines).

Prediction 1 (Capital investment and the demand for skills)**.** *Capital investment raises the relative demand for skills through two channels:*

Prediction 1(a) (Capital-skill complementarity in production)**.** *A larger capital stock K raises the relative demand for skilled production workers S^P (Equation 1).*

Prediction 1(b) (Investment-skill complementarity in integration)**.** *Installing new capital I raises the relative demand for skilled integration workers S^I (Equation 2).*

See Appendix A.1 for formal derivations.

The remaining predictions concern where the capital-complementary skills are hired (in-house or at external suppliers), each highlighting a specific rationale for outsourcing (tested in Section 4). The drivers we examine map to the outsourcing motives identified by Abraham and Taylor (1996).

First, hiring an in-house integrator unit, a team of robot technicians or specialized engineers, may entail fixed costs (indivisibilities, dedicated equipment, learning across projects) that external suppliers can amortize across multiple investing firms (Abraham and Taylor, 1996, § II.C).[1] Second, capital investments often arrive in occasional spikes, generating volatile demand for integration labor; in-house adjustment costs (e.g., hiring or firing costs) may make this difficult to absorb, while suppliers smooth their workload across clients with offsetting demand cycles (Abraham and Taylor, 1996, § II.B). Third, both rationales may be exacerbated for capital undergoing rapid technological

[1]We use fixed costs as one source of scale economies in hiring capital-complementary skills. One such fixed cost is the expertise accumulated by learning across projects, which is visible in how integrators and other machine suppliers market themselves: they compete on portfolios of past installations, showcasing that they have already traveled down the learning curve for a given application — and that they stay current as the underlying technology advances (cf. Prediction 4). The Belgian supplier of machine-tending automation RoboJob, for example, organizes its customer references under the banner of its more than 2,000 installations (RoboJob, 2026); industry bodies collect similar case studies across suppliers (IFR, 2026).

change, where capital-complementary skills are most specialized (Greenwood, Hercowitz and Krusell, 1997).

Prediction 2 (Fixed costs and outsourcing)**.** *If hiring capital-complementary workers involves fixed costs, these labor services are more likely to be sourced from specialized external suppliers. Smaller firms and firms in less capital-intensive sectors (e.g., services) should rely more on outsourcing, as they cannot amortize the fixed costs across enough projects.*

Prediction 3 (Lumpy investments and outsourcing)**.** *If employment entails adjustment costs (e.g., hiring or firing costs), outsourcing should be more prevalent for lumpier investment categories (e.g., machinery versus intangibles).*

Prediction 4 (Advanced capital and outsourcing)**.** *If outsourcing reflects the specialization of capital-complementary skills, the outsourcing rationales should be exacerbated for capital types undergoing rapid technological change (e.g., machinery rather than buildings, or machinery from new rather than existing suppliers).*

See Appendix A.2 for formal derivations.

Beyond Predictions 2 and 3, a final, and perhaps the most commonly considered, motive for outsourcing is to directly save on wages or benefit payments (Abraham and Taylor, 1996, § II.A), e.g. by avoiding firm wage premia (Goldschmidt and Schmieder, 2017). We consider this motive in the analysis below by examining whether high-wage investing firms are more likely to outsource capital-complementary skills than low-wage ones, and by comparing the wages these workers earn at external suppliers versus investing firms.

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, which disaggregate tangible fixed assets into buildings and land, machinery and equipment, and office and rolling stock, along with intangible fixed assets. We complement these with Value Added Tax (VAT) records on firms' sales and purchases (by category and origin).

Business-to-business transactions. Our data on business-to-business transactions come from VAT customer listings: all VAT-liable Belgian firms report annual sales to each customer firm above €250, yielding comprehensive domestic buyer-supplier linkages.[2]

Education data. We obtain employee-level data from the social security data warehouse (KSZ), which records each worker's highest education by *level* (e.g., below-tertiary vs. tertiary or higher) and *field* (e.g., STEM vs. non-STEM).[3] Motivated by the technical skills required to deploy new machinery (Section 1), we classify workers into four categories along these two dimensions: high-STEM, high non-STEM, low STEM, and low

[2]We observe only aggregate transaction values, without detail on transaction type or product code. Data construction follows Dhyne, Duprez and Komatsu (2023); the dataset has been used by Bernard et al. (2022), Baqaee et al. (2025), and Bijnens, Jäger and Schoefer (2025), among others.

[3]STEM comprises ISCED fields 05 (Natural Sciences, Mathematics, Statistics), 06 (Information and Communication Technologies), and 07 (Engineering, Manufacturing, Construction). Appendix Tables B.1 and B.2 provide the full classification.

non-STEM. Employees are matched to their employers via social security declarations, yielding firm-year counts in full-time equivalents for each category.[4] We are the first paper to link these employee-level education data with firm-to-firm transactions.

2.2 Measurement

2.2.1 Investment Spikes

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:

$$\text{Spike}_{jt} = \mathbf{1}[i_{jt} \geq i_{P90|+}] \quad \text{with} \quad i_{jt} = \frac{\Delta\text{Machinery}_{jt}}{\frac{1}{2}(H_{jt} + H_{jt-1})}, \quad i_{P90|+} = \text{€}\,17,115 \tag{4}$$

where $H_{jt} = \mathbf{1}^T \mathbf{L}_{jt}^H$ denotes in-house employment of firm j and time t.[5]

Figure 1 illustrates the lumpiness of machinery investment: these spikes triple the machinery stock per worker (from 16 to 53 thousand euros). The investment flow that produces this step-up is a one-off event, peaking at nearly 20% of sales in the spike year before returning to baseline (Appendix Figure E.1).

2.2.2 Machine Supplier Industries

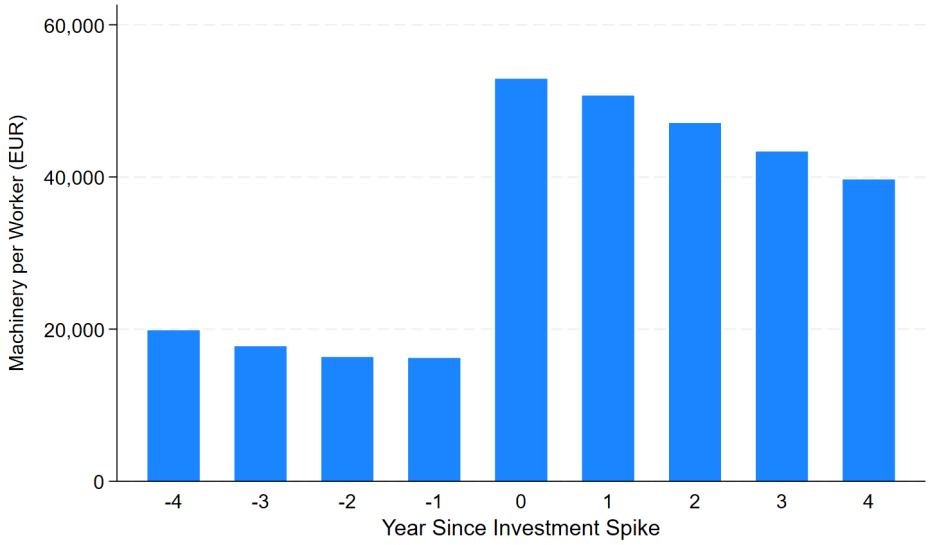
Appendix B.2.2 describes the industrial organization of machine supply, classifies the industry codes for these suppliers, and validates the classification against external lists of robot suppliers in Belgium.

Figure B.1 shows that firms undergoing an investment spike sharply increase their share of purchases from machine supplier industries, with total purchases averaging 1.7

[4]We focus on employment rather than wages due to data limitations: worker-level earnings in the KSZ data are only reported in coarse, top-coded bins, and firm-level wage bills from the annual accounts are not broken down by skill group. That said, because machine suppliers pay higher wages than investing firms (Section 2.2.3), our focus on employment will tend to understate the impact of new machinery on the skill bias in wage bills.

[5]While the specific cutoff at the 90th percentile is arbitrary, Appendix E.1 demonstrates that our results are robust to alternative thresholds. Because spikes are defined in machinery changes per worker, the cutoff also does not mechanically select firms by size; indeed, smaller and larger spiking firms experience similar-sized spikes (Appendix Figures D.1 and D.2).

Figure 1: Machinery Investment Spikes



Notes: This figure plots the machinery capital stock per worker around machinery investment spikes. *Sample*: Private sector firms around their first machinery investment spike. Balanced sample for four years before and after the spike.

times direct investment expenditures, a first sign that external suppliers may shape the employment effects of new machinery.[6]

2.2.3 External Employment

To measure firms' external employment at supplier firms, 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 that firm j externally employs 10% of firm k's workers in each skill category.[7]

[6]Appendix B.2.2 further shows 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. While the physical machines are highly tradable (e.g., Belgium produces no industrial robots), integration is overwhelmingly done locally: domestic integrators import the machines and bundle them with installation and programming services for the end-user firm. Our domestic-firm data therefore captures the integration channel but undercounts the labor that goes into developing and producing the physical machines abroad.

[7]This assumption is more plausible for specialized suppliers whose workforce is dedicated to the same set of products or services, a good description of the machine integrators and other machine-complementary suppliers central to our findings. As Section 4.5 shows, these suppliers' workforces are highly specialized, with stable skill mixes invariant to customer composition.

Table 1: Firm Employment (Year of Investment Spike)

	Total (FTE)	Share of Total (%)			
		High STEM	High Non-STEM	Low STEM	Low Non-STEM
In-House Employment	39.7	5.0%	14.2%	25.5%	55.3%
External 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 in-house and external employment of spiking firms. *Sample*: Private sector firms in the year of their first machinery investment spike.

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

$$\mathbf{L}_{jt}^{O} = \sum_{k} \frac{X_{kjt}}{X_{kt}} \mathbf{L}_{kt}^{H}, \tag{5}$$

where X_{kjt} denotes the sales of firm k to firm j in year t, and $\mathbf{L}_{kt}^{H}$ is the in-house employment of firm k. In effect, $\mathbf{L}_{jt}^{O}$ captures the skill content embodied in firm j's purchases, a firm-level domestic analogue of the factor content of trade (e.g., Davis and Weinstein, 2001; Trefler, 1995). 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 employs 40 workers in-house and sources external labor equivalent to 23 full-time workers, including around 4 from machine supplier firms. Appendix B.2.1 illustrates this measurement for a typical robot-integration project, detailing how the external labor for installation and servicing maps into the annual firm-to-firm transactions we observe.

Notably, the share of high-STEM workers among external workers at machine suppliers (13.9%) is nearly three times higher than among in-house employees at spiking firms (5.0%). This pattern provides a first indication that machine suppliers are a source of skill bias from new machinery. Moreover, machine suppliers pay about 3.6% higher wages than investing firms do, holding skill composition fixed, consistent with the effi-

ciency gains from outsourcing we explore in Section 4.[8]

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 in-house and external employment. Section 3.1 describes our empirical strategy and considers threats to identification. Section 3.2 presents our main results.

3.1 Empirical Strategy

The ideal experiment to test our model's predictions would exogenously vary investment costs to induce variation in investment I and capital K, and trace the resulting effects on labor demand for integration and production tasks, both within and outside the investing firm. We approximate this with the "investment spikes" design pioneered by Bessen et al. (2025) and applied in Aghion et al. (2025), Hirvonen, Stenhammar and Tuhkuri (2025), and others. The idea is to exploit the lumpiness of capital investment, driven by non-convex adjustment costs (Cooper and Haltiwanger, 2006), to isolate episodes with sharp increases in I and K. We compare the labor adjustments of spiking firms (Section 2.2.1) to similar non-spiking firms in a stacked difference-in-differences framework.

We apply three sample restrictions. First, we focus on private sector firms with at least five workers (in-house plus external) in the year before the spike. Second, we use firms' first investment spike (65% of spiking firms experience only one). Third, we study a balanced sample for four years before and after each spike. This yields an analysis sample of 3,863 spiking firms (see Appendix Table C.1 for a sample reduction table). Section 5 shows our results are robust to varying these sample restrictions.

[8] Appendix Table D.6 reports this comparison. Regressing log firm wages on a machine-supplier indicator among machine suppliers and spiking firms in the year before the spike, machine suppliers pay about 3.6% higher wages after controlling for skill shares and year fixed effects (13.8% without the skill-share controls).

For each spiking firm, the comparison group is the average of firms in the same industry-year that meet the same sample criteria but have not yet experienced a spike as of the event year. Table 2 shows that the two groups have comparable total employment and skill composition two years before the spike, despite not being matched on these outcomes.[9] Section 5 shows our estimates are robust to how we select the comparison group.

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

$$Y_{sjt} = \beta_1 \text{Spike}_{je} + \sum_k \beta_{0k} \mathbf{1}_{\{t=e+k\}} + \sum_{k \neq -2} \beta_{1k} \text{Spike}_{je} \mathbf{1}_{\{t=e+k\}} + \varepsilon_{sjt}, \tag{6}$$

where Spike_{je} equals one if firm j undergoes an investment spike (Equation 4) in event year e and zero for its comparison firms, $\mathbf{1}_{\{t=e+k\}}$ 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 (6) by OLS separately for each skill group s, clustering the standard errors at the event (treated–control pair) level. Because our stacked difference-in-differences design compares each spiking firm only to not-yet-spiking firms in the same industry-year, it avoids the biases that can arise in two-way fixed-effects estimators when treatment is staggered and effects are heterogeneous (Callaway and Sant'Anna, 2021; Roth et al., 2023; Sun and Abraham, 2021).[10]

[9] We choose a two-year pre-spike comparison because investing firms may begin engaging machine integrators (especially for design and advisory services) prior to the physical investment; see Figure B.1 and the project timeline in Appendix B.2.1.

[10] Our estimator shares the imputation logic of Borusyak, Jaravel and Spiess (2024): each spiking firm's counterfactual is constructed from its own pre-spike outcome and the contemporaneous changes of firms in the same industry-year that had not yet spiked as of the event year. Unlike their estimator, which gains efficiency by leveraging all pre-treatment periods, we difference from a single pre-spike base year (as firms may engage integrators already in the year before the spike), use industry-year cells rather than estimated fixed effects, and place no restriction on comparison firms' investment after the event year.

Our identification strategy is consistent with a long tradition of dynamic production-function estimators that combine time-to-build with Markov dynamics of firm productivity (Doraszelski and Jaumandreu, 2013; Olley and Pakes, 1996). Under these assumptions, a firm's pre-spike factor choices encode its expected future technology, so firms matched on them share similar expected post-spike technologies; whether a matched firm spikes in the event year is then driven by idiosyncratic investment costs.[11] Neither group is restricted after the event year: treated firms may undertake follow-on spikes, and control firms may spike later in the window. Our estimates therefore identify the effect of investing at e relative to firms' counterfactual investment policies, rather than relative to never investing. Appendix E.2 shows our results are similar if we restrict the treatment group to "single-spiking" firms that do not spike in the post-event window.[12]

Our outcomes of interest, Y_{sjt}, are firms' total employment in each skill group s (high-STEM, high non-STEM, low STEM, and low non-STEM), measured in full-time equivalents and summing in-house and external labor. To obtain relative effects, we express these as percentages of pre-spike levels (averaged over years -3 to -1), and winsorize the resulting variables at the 5th and 95th percentiles to mitigate the influence of outliers. An advantage of studying total employment (i.e., in-house plus external) for each skill category is that it circumvents the challenge of studying relative effects for outcomes that often contain zeros (Chen and Roth, 2024): for example, 64% of spiking firms have zero in-house high-STEM employment prior to the spike, likely reflecting the fixed costs of hiring emphasized in Section 1.2, whereas all firms in our sample have positive total pre-spike employment in each skill group.

To understand the sources of the skill bias, we further decompose the skill-specific

[11] See Humlum (2022) for a formal argument.

[12] Following the dynamic production-function estimators that motivate our design (Olley and Pakes, 1996), restricting firms to never spike within the event window implicitly conditions on future productivity innovations, selecting firms with systematically unfavorable realized shocks. Consistent with this, our estimated employment effects are smaller if we restrict treatment firms to single-spikers (Appendix E.2).

Table 2: Firm Employment before Machinery Investment Spikes

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

Notes: This table reports in-house and external employment in the treatment (Columns 1-2) and control (Columns 3-4) groups 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% are 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.

employment outcomes by supplier source: separating in-house from external labor, and within external labor, distinguishing machine suppliers from other industries. We express each component as a share of the skill group's total pre-spike employment:

$$Y_{sjt}^{M} = \frac{L_{sjt}^{M}}{L_{sj\text{pre}}^{H} + L_{sj\text{pre}}^{O}}, \qquad M \in \{H, O\}, \tag{7}$$

where L^H and L^O denote in-house and external employment and the "pre" subscript averages over years -3 to -1. Because both components share this common denominator, they are measured on the same scale — directly comparable, and additive: $Y_{sjt}^{H} + Y_{sjt}^{O}$ recovers the skill group's total-employment response. It also avoids dividing by the in-house zeros noted above. The larger external responses we estimate below are therefore not an artifact of a smaller base. If anything, this common normalization works against our main findings on two fronts. First, because in-house employment is generally larger than external (Table 2), the common denominator makes external responses look smaller,

understating the role of external labor. Second, because machine supplier industries represent a minority of external employment (Table 1), the same logic understates their relative importance. Appendix C.2 decomposes the contribution of external employment to the total skill bias into (i) differential increases in in-house versus external employment and (ii) shifts in external employment across skill groups.

3.1.1 Identification Threats and Validity Checks

Investment spikes are endogenous firm decisions. The primary threat to identification is that a spike coincides with other changes in firm fundamentals — production (F), investment technology (G), or demand — that themselves induce skill bias. We assess this threat through five validity checks.

First, spiking and non-spiking firms are similar prior to the spike, even though comparison firms are selected only on industry and year. Table 2 shows balance in employment (in-house and external) and skill shares. The flat pre-trends in all event-study figures below confirm that the two groups' fundamentals evolve in parallel before the spike.[13]

Second, the investment-spikes design has been validated against quasi-experimental estimates in prior work: Hirvonen, Stenhammar and Tuhkuri (2025) and Aghion et al. (2025) show it yields similar estimates to designs based on technology subsidies and foreign machine-supply shocks, which exogenously shift investment costs.

Third, the spikes themselves are discontinuous jumps in investment and capital (Figure 1), arising naturally from non-convex adjustment costs (Cooper and Haltiwanger, 2006). Provided fundamentals evolve smoothly, the spikes can be interpreted as a regression-discontinuity design in time, lending greater credibility to short-run responses around the spike year than to longer-run adaptations.

[13]These balance and pre-trend checks are the empirical counterpart of the pre-spike matching assumption of the dynamic production-function estimators above: if a firm's pre-spike fundamentals encode its expected technology, spiking and not-yet-spiking firms should be balanced and move in parallel before the spike.

Fourth, in Appendix C.1.1, we directly consider the role of confounding demand or productivity shocks. In particular, sales evolve smoothly around the investment spikes, and controlling for their growth leaves our conclusions intact (Appendix Figure C.2). More generally, Lindner et al. (2024) shows that output demand shocks raise employment but do not affect the skill mix under homothetic production. For this reason, we focus on the differential changes across skill groups rather than the absolute employment growth around investment spikes.[14]

Fifth, our heterogeneity analyses across capital types (Section 4) help rule out confounders correlated with undertaking large investments. Such confounders would affect all capital types similarly; instead, building spikes generate weaker bias (Section 4.3), intangible spikes leave the skill mix essentially unchanged, and machinery from new suppliers generates the strongest bias of all (Section 4.4), consistent with capital-embodied technical change (Greenwood, Hercowitz and Krusell, 1997; Krusell et al., 2000).

3.2 Main Results

Figure 2 presents our first key result, plotting employment by skill category separately for in-house (Panel (a)) and external labor (Panel (b)). In both panels, we measure effects relative to each skill category's total pre-spike employment (Equation 7), so that Panels (a) and (b) sum to the total relative effects for each skill group.

Total employment (summing Panels (a) and (b)) shows a sharp rise in high-STEM demand, which jumps by 51% in the spike year and remains 34% above baseline four years later. The other skill categories, by contrast, grow by only 11–20% in the spike year and 19–26% four years later.

The key finding is that this shift is sourced entirely externally. Panel (a) shows that in-house employment grows evenly across skill categories, contributing only 2–4% to total

[14]Lashkari, Bauer and Boussard (2024) present a framework in which scale shocks induce IT investment; insofar as the resulting skill-biased effects operate through capital investment, they continue to identify the capital–skill complementarity of interest.

employment at the spike and 8–12% after four years. Panel (b) shows the high-STEM surge comes entirely from external suppliers.[15]

Which external suppliers drive this effect? Figure 3 decomposes external employment into machine suppliers (Panel (a)) and other industries (Panel (b)), revealing a two-stage pattern.

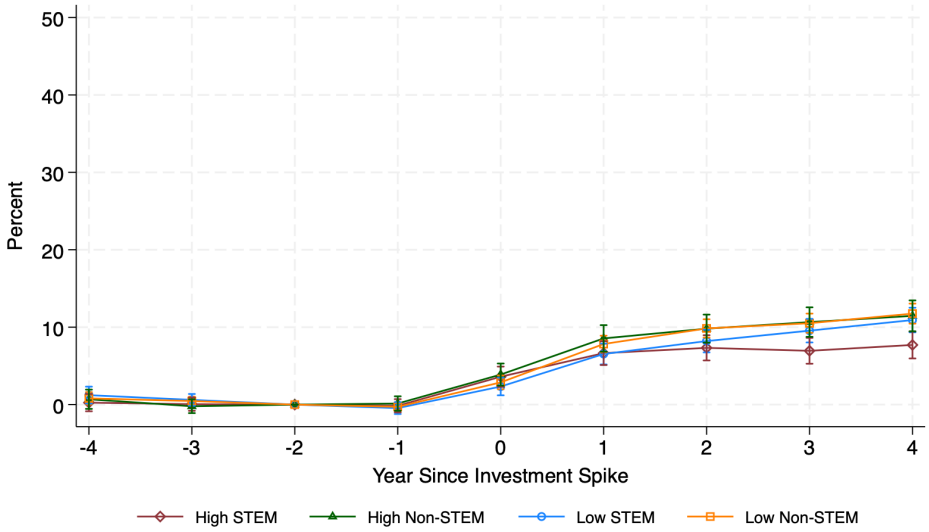
Machine suppliers are an important driver of the initial spike (Panel (a)), raising total high-STEM demand by 15% in the event year. Notably, however, the dependency on high-STEM machine suppliers never fully disappears, but instead converges to around 5% four years later, consistent with the recurring maintenance, support, and reprogramming services that follow an installation (Appendix B.2.1 provides an illustrative example of a robot-integration project). By contrast, employment of other skill categories through machine suppliers moves little in the investment year and fades entirely over time.

The longer-run employment gains predominantly come from other industries (Panel (b)), generating a 25% increase in total high-STEM demand at the spike and a persistent 17% four years later. While part of the initial spike may reflect misclassification of machine supplier industry codes (see Section 2.2.2), the pattern also shows that the external skill bias from new machinery extends well beyond pure machine supply and integration. Appendix C.2.1 shows that the rise of other services is pervasive across supplier sectors but most pronounced in computer programming and software, skilled services complementary to a more machine-intensive production process. These gains are not confined to technical skills: high non-STEM employment through other industries also rises and remains elevated, reaching the second-largest response by year 4 (Panel (b)). This pattern suggests that operating a more capital-intensive production also draws on complementary commercial and business services: wholesale distribution contributes

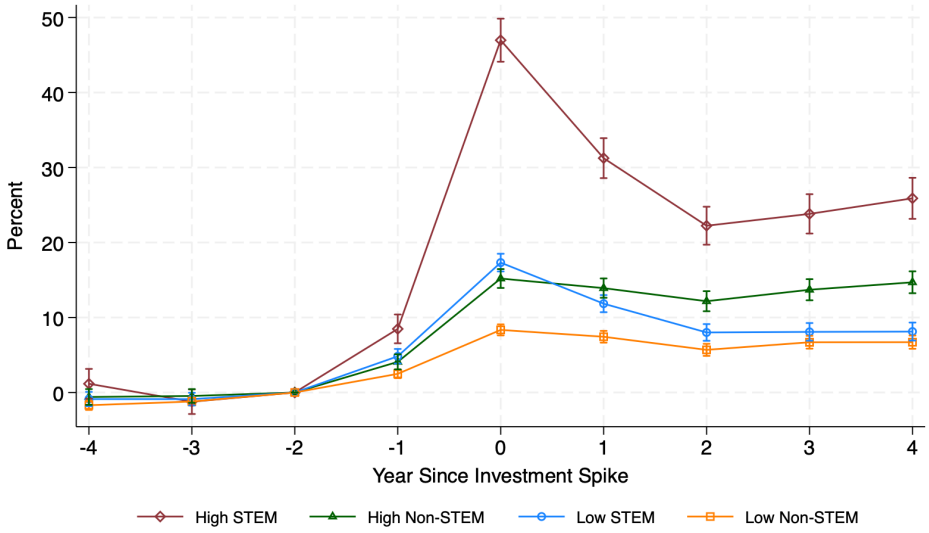
[15]Appendix Figure C.3 shows that the larger effects for external high-STEM labor reflect both that external employment increases more than in-house employment and that spiking firms shift their external employment toward high-STEM skills.

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

(a) In-House



(b) External

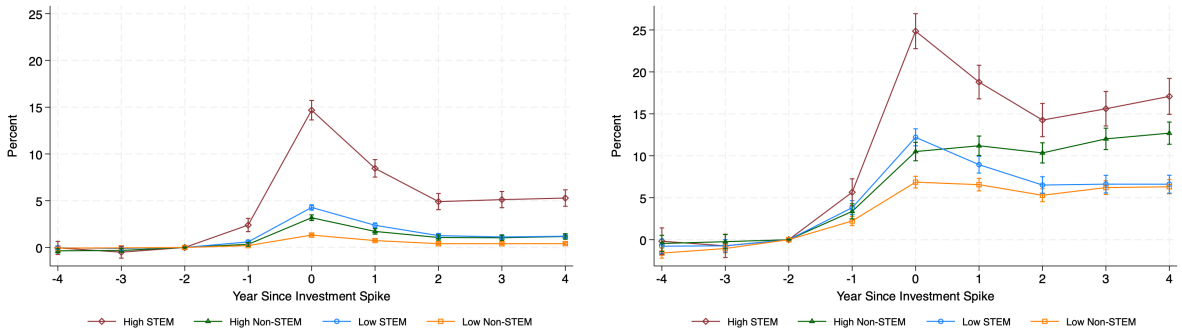


Notes: This figure shows the employment of high-skilled STEM, high-skilled non-STEM, low-skilled STEM, and low-skilled non-STEM in percent of total pre-spike employment by skill category (Equation 7). Panel (a) considers in-house employment, while Panel (b) considers external employment at supplier firms. Total pre-spike employment is the sum of in-house and external 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 (6), 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.

the largest high non-STEM gains, and the contributions of management consulting and legal services are tilted toward high non-STEM workers (Appendix Table C.2).

Figure 3: External Employment by Supplier Industry
(Diff-in-Diffs, In Percent of Pre-Spike Total Employment by Skill Group)

(a) Machine Suppliers (b) Other Industries



Notes: This figure shows the external 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 (Equation 7). Panel (a) considers external employment of machine suppliers, while Panel (b) considers external employment from all other industries. Total pre-spike employment is the sum of in-house and external 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 (6), 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 empirical support for Prediction 1 of Section 1.2. Consistent with the investment-skill complementarity of Goldin and Katz (1998) (Prediction 1(b)), integrating new machinery sharply raises demand for skilled workers around the spike year, especially from machine suppliers. Consistent with the capital-skill complementarity of Griliches (1969) (Prediction 1(a)), operating more machine-intensive production further raises the demand for skilled labor in complementary services such as software, with effects that persist well beyond the investment event. These dynamics mirror the investment profile: the temporary integration response coincides with the one-off investment flow (Appendix Figure E.1), whereas the persistent production response tracks the machinery

stock, which steps up and remains elevated (Figure 1).

The key surprise — and our main contribution — is that both 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 raise employment without raising the in-house skill share (Aghion et al., 2025; Curtis et al., 2023; Hirvonen, Stenhammar and Tuhkuri, 2025). Because these studies observe only in-house payrolls, they conclude that the evidence challenges the capital-skill complementarity hypothesis.[16]

Figure 2(b) resolves this apparent puzzle by showing that external suppliers are the missing channel linking capital accumulation to skill bias, a channel uniquely visible through our firm-to-firm transaction data.[17] The importance of external suppliers for machinery investments corroborates the anecdotal evidence on robot integrators that initially motivated our study. Importantly, our comprehensive buyer-supplier data reveals that the external high-STEM bias from new machinery is pervasive across supplier types. The finding that even the long-run increase in high-STEM labor, reflecting a more capital-intensive production, is also entirely outsourced is perhaps more surprising still. The fact that these are often tradable services such as software, most often sourced from outside the firm's local labor market (Section 6.1), helps rationalize why these too are not brought in-house.

Our estimated magnitudes also speak to the structural elasticities at the heart of the

[16]Curtis et al. (2023) conclude that *"our results are not compatible with the capital–skill complementarity hypothesis."* Motivated by the same framework, Hirvonen, Stenhammar and Tuhkuri (2022) 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. (2025) similarly note that their *"…results differ from the estimates of seminal structural models of capital–skill complementarity."* Relatedly, Berlingieri et al. (2026) 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).

[17]Bilgin, Faia and Ottaviano (2026) use similar firm-to-firm transaction data to study how robot adoption affects the *performance* of *downstream* customer firms; we instead identify the *skill bias* of a broader set of capital investments operating through investing firms' *upstream* supplier networks.

capital–skill complementarity literature. Krusell et al. (2000) propose that Equation (1) follows a nested-CES structure that combines capital with skilled labor and, in turn, that composite with less-skilled labor. Using that structure, Appendix A.3 shows that our reduced-form estimates identify the ratio of the outer-nest substitution elasticity (σ_{HU}) to the inner-nest elasticity (σ_{KS}):

$$\frac{\sigma_{HU}}{\sigma_{KS}} = 1 + \frac{1}{s_K^H} \cdot \frac{\Delta \ln L_S - \Delta \ln L_U}{\Delta \ln K - \Delta \ln L_S}, \tag{8}$$

where $\Delta \ln L_S$, $\Delta \ln L_U$, and $\Delta \ln K$ denote the four-year responses of high-STEM employment, low non-STEM employment, and the machinery stock, and s_K^H is machinery's cost share within the machinery–high-STEM nest. Evaluating this equation at our estimates from Figures 1 and 2 gives a ratio of about 1.6. This confirms capital–skill complementarity at the firm level (the ratio exceeds one), although less strongly than the aggregate ratio of about 2.5 implied by Krusell et al. (2000). However, this calibration does not include the investment–skill complementarity of the integration stage, which Figure 3 shows is another key source of skill bias. In Section 7, we aggregate our firm-level estimates, including both capital–skill and investment–skill complementarities, to quantify the overall economy-wide skill bias from new machinery.

Finally, our results reinforce a key conclusion from existing firm-level estimates (e.g., Aghion et al., 2025; Hirvonen, Stenhammar and Tuhkuri, 2025): machinery investments are associated with increased employment, and this effect is only strengthened once we take external employment into account.[18]

[18]This conclusion differs from the negative employment effects of industrial robots in local labor markets estimated by Acemoglu and Restrepo (2020). Several elements help explain the difference. First, because external labor complementary to new machinery is overwhelmingly sourced from suppliers outside the local labor market (see Section 6.1), this channel is not captured by a local-labor-market analysis. Second, local-labor-market analyses capture other spillovers not considered here, including competition in product markets (especially for non-tradables) and poaching in labor markets. Finally, as Benmelech and Zator (2025) show, industrial robots represent only a small fraction of the total firm-level machinery investments we study.

4 Why Firms Outsource Capital-Complementary Skills

When and why do firms outsource capital-complementary skills? Our model (Section 1.2) predicts where outsourcing should be most pronounced: among smaller firms, whose demand falls furthest below the scale of a full-time hire; for lumpier investments, where hiring and firing costs bite hardest; and for capital undergoing rapid technological change, where specialized skills matter most. Motivated by these predictions, we study heterogeneity across investing firm characteristics (Sections 4.1–4.2) and capital types (Sections 4.3–4.4). In Section 4.6, we discuss what the patterns reveal about why firms outsource their capital-complementary skills.

4.1 Firm Size

Figure 4 separates spiking firms into smaller and larger firms based on their pre-spike total employment, split at the median (13.1 FTE). Figure D.1 shows that both smaller and larger spiking firms experience a similar increase of roughly 50 thousand euros in machinery stock per worker, so that any differences in responses do not reflect differences in the magnitude of the capital investment shock.[19] Smaller firms rely much more heavily on external high-STEM workers to implement their investment spikes: external hires raise high-STEM employment by 58% in smaller firms versus 36% in larger firms at the spike year, persisting to 35% vs. 18% four years later.[20] By contrast, in-house employment expands more similarly across firm sizes, accounting for less than 5% of total employment at the spike and roughly 10% after four years, with little difference across skill groups.

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

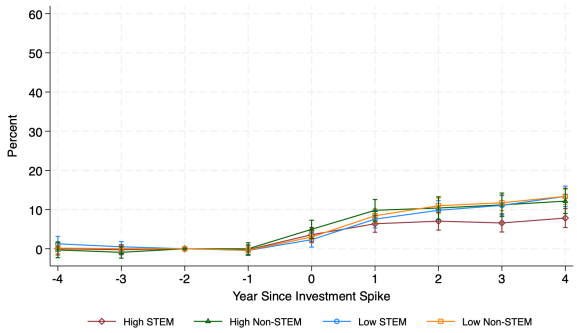
[19]Figure D.2 shows that their difference-in-difference estimates are similar, too.

[20]Consistent with smaller 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 larger firms.

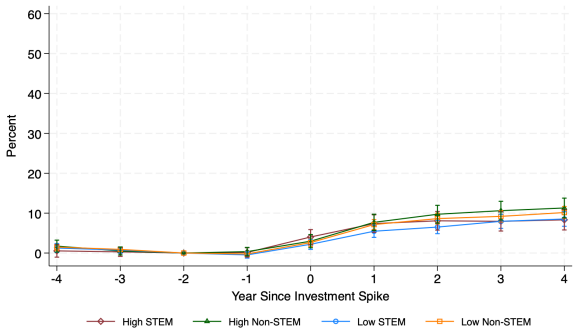
spikes (Appendix Tables D.1 vs. D.2). Hence, the differences between smaller and larger firms in Figure 4 partly reflect differences in initial outsourcing strategies rather than differences in the underlying skill bias of the machinery.

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

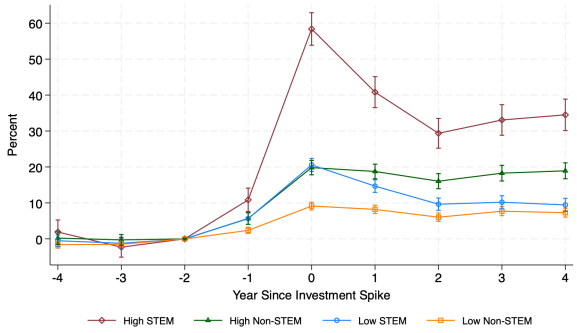
(a) In-House: Smaller Firms



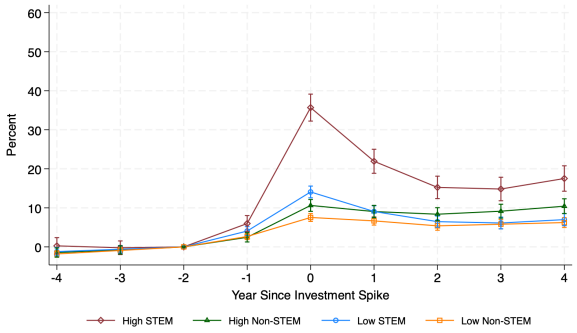
(b) In-House: Larger Firms



(c) External: Smaller Firms



(d) External: Larger Firms



Notes: This figure shows employment around machinery investment spikes, splitting by the size of the investing firm. Smaller firms have pre-spike total employment (year −1) below the median (13.1 FTE). Panels (a) and (b) consider in-house employment, while Panels (c) and (d) consider external employment at supplier firms. The figures show 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 (Equation 7). Total pre-spike employment is the sum of in-house and external 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 (6), 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.

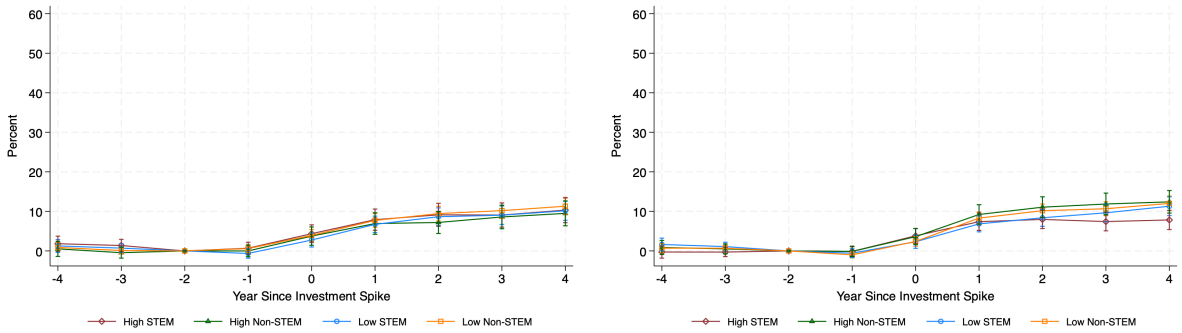
4.2 Application Sector

Figure 5 separates spiking firms by sector, with manufacturing firms shown in Panels (a) and (c) and services firms in Panels (b) and (d).[21]

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

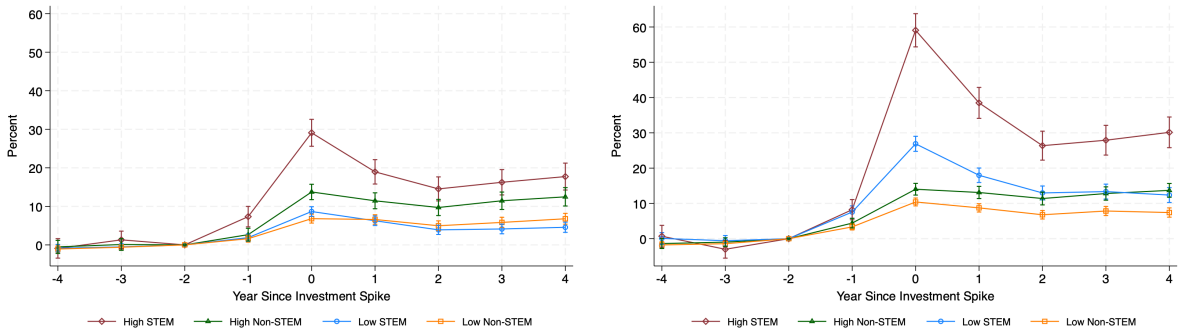
(a) Manufacturing: In-House

(b) Services: In-House



(c) Manufacturing: External

(d) Services: External



Notes: This figure shows employment around machinery investment spikes for manufacturing (Panels (a) and (c)) and services (Panels (b) and (d)). Panels (a) and (b) consider in-house employment, while Panels (c) and (d) consider external employment. The figures show 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 (Equation 7). Total pre-spike employment is the sum of in-house and external 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 (6), with whiskers representing 95% confidence intervals. *Sample*: Private sector firms around first investment spike. Balanced sample for four years before and after the spike.

Although machinery investments are more prevalent in manufacturing,[22] Panels (c)

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

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

and (d) show that the skill-biased effects are pervasive across sectors; if anything, the relative shift toward external high-STEM labor is larger in services. This mirrors the pattern for smaller firms in Section 4.1: services firms also employ fewer high-STEM workers to begin with (Appendix Tables D.3 vs. D.4). Thus, while industrial robots are a prominent example of skill-complementary capital, our comprehensive data show that the external skill bias of new machinery extends well beyond robotics and manufacturing. Panels (a) and (b) confirm that in-house employment expands more similarly across sectors, contributing less than 5% to total employment at the spike and roughly 10% after four years, with little difference across skill groups.

4.3 Capital Types

Figure 6 replicates the investment-spikes design for buildings (Panels (a) and (c)) and intangibles (Panels (b) and (d)), restricting to manufacturing firms to hold the type of investing firm fixed.

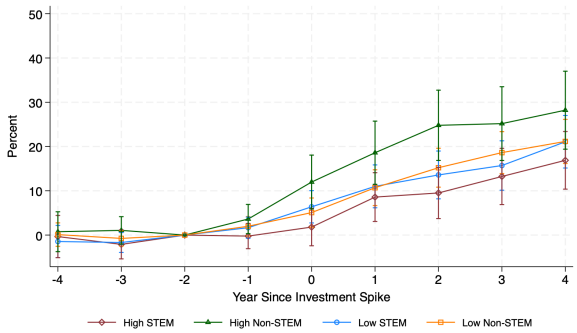
Building spikes generate weaker and less persistent skill bias. External high-STEM employment grows only two to three times as much as low-STEM and low-non-STEM (compared to three- and four-fold for machinery in Figure 5), and this differential largely dissipates by year two.[23]

Intangible spikes generate weaker skill bias still: the external employment responses are essentially flat across skill groups.

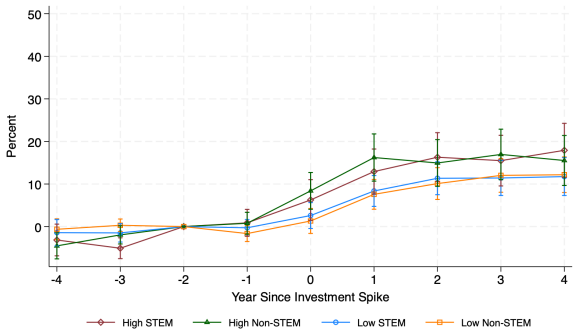
[23]Part of the skill bias from building spikes reflects simultaneous machinery installation (Appendix Figure D.6): isolating building spikes that do not coincide with machinery spikes further reduces the skill bias (Appendix Figure D.7), though it does not disappear entirely, likely reflecting the involvement of architects and building engineers.

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

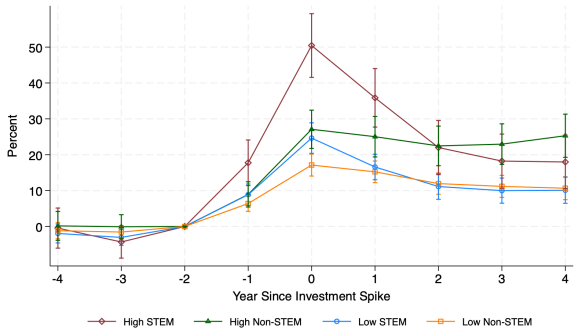
(a) Building Spikes: In-House



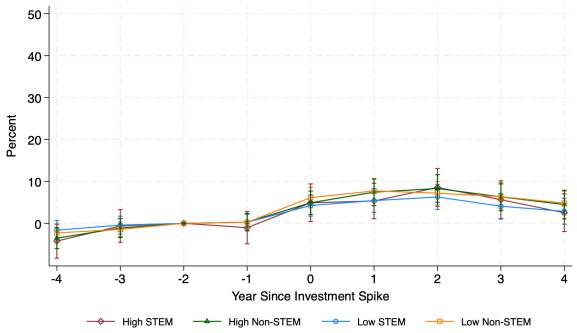
(b) Intangible Spikes: In-House



(c) Building Spikes: External



(d) Intangible Spikes: External



Notes: This figure shows in-house and external employment of manufacturing firms around investment spikes in buildings (Panels (a) and (c)) and intangibles (Panels (b) and (d)). Panels (a) and (b) consider in-house employment, while Panels (c) and (d) consider external. The figures show 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 (Equation 7). Total pre-spike employment is the sum of in-house and external 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 (6), with whiskers representing 95% confidence intervals. Figure 5, Panels (a) and (c) show the corresponding estimates for machinery spikes. Appendix Figure D.5 plots the capital stock per worker around each type of spike. *Sample*: Manufacturing firms around first investment spike. Balanced sample for four years before and after the spike.

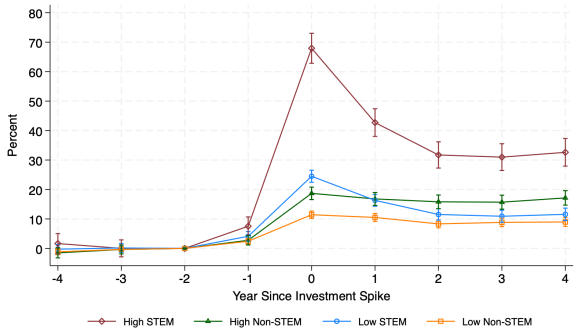
4.4 New versus Existing Machine Supply

A measure of whether machinery investments embody new technologies, rather than merely replacing or deepening existing capital, is whether they are sourced from suppliers new to the investing firm.

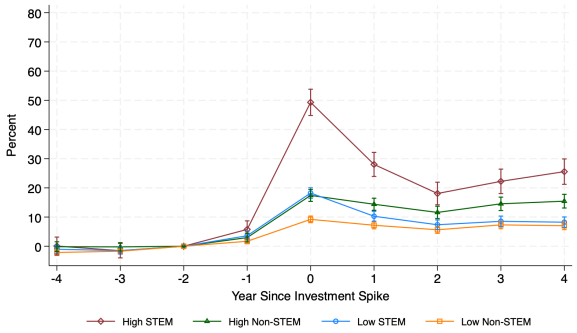
Figure 7 separates machinery spikes by whether the dominant machine supplier is new to the investing firm. External high-STEM skill bias is substantially stronger for new-supplier spikes (Panel (a)) than for existing-supplier spikes (Panel (b)), especially around the event year. Appendix Figure D.9 shows that in-house employment responds similarly across new- and existing-supplier spikes, and Appendix Figure D.10 confirms that the differential external high-STEM bias for new-supplier spikes shows up at both machine suppliers and other industries.

Figure 7: External Employment around Machinery Spikes: New versus Existing Suppliers (Diff-in-Diffs, In Percent of Pre-Spike Total Employment by Skill Group)

(a) Spikes Driven by New Suppliers



(b) Spikes Driven by Existing Suppliers



Notes: This figure shows external employment around machinery investment spikes, split by whether the dominant machine supplier is new to the investing firm (Panel (a)) or existing (Panel (b)). Spikes in which the increase in machine-supplier purchases comes predominantly from suppliers that are new to the firm (above the sample median of the new-supplier share) are classified as new-supplier spikes; the remainder are existing-supplier spikes (see Appendix D.4 for the exact definition). The figures show 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 (Equation 7). Total pre-spike employment is the sum of in-house and external 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 (6), 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.

4.5 Supply-Side Evidence

The previous figures considered the impacts of new machinery from the perspective of *investing* firms. To deepen our understanding of why investing firms outsource capital-complementary skills, we now complement this with evidence from the perspective of the machine *suppliers*. Three facts support the fixed-cost (Prediction 2) and adjustment-cost (Prediction 3) rationales for outsourcing.

First, machine suppliers' workforces are highly specialized in high-STEM workers. As shown in Table 1, 13.9% of machine-supplier employees are high-skilled STEM, roughly three times the in-house share at investing firms (5.0%). Appendix Table D.5 further shows that machine suppliers' skill mix is invariant to the share of revenue from spiking-firm clients, consistent with a structurally specialized workforce.

Second, each individual investing firm's demand for capital-complementary high-STEM labor is small in absolute terms. Even summing across all of its suppliers, the median spiking firm sources only 0.05 high-STEM full-time-equivalents in the spike year, and even the 90th percentile reaches just 0.77 (Appendix Figure D.11), both well below the single full-time worker that would represent the minimum efficient scale of a dedicated in-house integration role. This suggests that most investing firms' demand is not large enough to support even a full-time in-house integrator, let alone a team at minimum efficient scale.

Third, machine suppliers absorb the lumpy demand of individual investing firms by spreading their workforce across many uncorrelated clients. Appendix Figure D.12 shows, at the supplier-year level, that within-supplier high-STEM employment changes are roughly 15.4 times smaller than the sum of absolute changes across the supplier's individual client allocations: one client's expansion absorbs another's contraction at the supplier level. This is consistent with adjustment costs of hiring capital-complementary skills, absorbed at the supplier rather than at the investing firm.

4.6 Connecting Empirics to Theory

Each heterogeneity pattern maps to a specific prediction from our conceptual framework.

The stronger external skill bias among smaller firms (Section 4.1) and firms in services (Section 4.2) is consistent with fixed costs of hiring high-STEM workers (Prediction 2). By contrast, larger firms, especially those in manufacturing that rely more on high-STEM workers generally, can better amortize the in-house fixed cost, consistent with these firms hiring more high-STEM workers already before the spikes. Békés et al. (2025) show similarly that larger manufacturers are more likely to import robots directly, rather than rely on intermediation by domestic robot integrators, likely reflecting their greater internal know-how to identify and select appropriate robots.

The observation that intangible spikes rely far less on external skills and do not cause skill bias is consistent with adjustment costs in hiring capital-complementary skills (Prediction 3): because intangibles follow a much smoother investment profile, they entail lower adjustment costs for in-house hiring. Skills complementary to intangible capital may also be harder to outsource due to their tacit and firm-specific nature.[24]

The fact that new machinery, especially if sourced from new suppliers, generates stronger skill bias than building spikes is consistent with capital-embodied technical change (Prediction 4): while a modern office or factory looks broadly similar to one from 20 years ago, modern machinery embodies very different technologies than two decades ago, a distinction Krusell et al. (2000) build explicitly into their model.

The supply-side evidence in Section 4.5 provides direct support for these mechanisms. The finding that each investing firm's demand is too small to support an in-house integra-

[24]Lindner et al. (2024) find skill bias for in-house employment in response to innovation shocks (the introduction of new products, services, processes, or organizational methods) and R&D tax reforms. One reconciliation with our evidence is that innovation-related skills are harder to outsource than skills complementary to new physical capital, consistent with our finding of no external skill bias for intangible investments. More broadly, this reconciliation highlights the distinction between "innovation-skill" and "capital-skill" complementarities.

tor team supports the fixed-cost rationale (Prediction 2). Machine suppliers' workforce smoothing across many uncorrelated clients supports the adjustment-cost rationale (Prediction 3), with adjustment costs absorbed at the supplier rather than at the investing firm. The fact that machine suppliers' skill mix is invariant to which clients they serve supports both rationales: it reflects a structurally specialized workforce that absorbs client-level fluctuations without reshuffling skill composition.

The wage premium documented in Section 2.2.3 — machine suppliers pay about 3.6% higher wages than investing firms do, holding skill composition fixed (Appendix Table D.6) — reinforces the efficiency-gains interpretation of these specialization and smoothing patterns. By contrast, if wage-savings motives were the primary driver behind outsourcing, we should see the opposite pattern: lower wages at external suppliers (Abraham and Taylor, 1996, § II.A). Moreover, Appendix Figure D.13 shows that, if anything, lower-wage firms outsource their capital-complementary skills more. This is the opposite of what a wage-savings motive would predict, further weighing against wage savings as the primary driver.[25]

Taken together, our evidence strongly aligns with theories of capital-embodied, skill-biased technical change, once we recognize that the fixed and adjustment 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 robustness checks of our main results. Taken together, these checks confirm that our main result — that machinery investments increase the demand for

[25] Abraham and Taylor (1996) provide evidence that wage-savings motives are more important for the outsourcing of janitorial services and other lower-pay occupations than for higher-pay occupations like engineering and machine maintenance. Hence, while wage-savings motives are a first-order driver of outsourcing for lower-pay jobs (Goldschmidt and Schmieder, 2017), our evidence shows that other drivers are at play for the high-pay jobs complementary to capital.

high-STEM skills, and that this effect runs entirely through external suppliers — does not depend on the precise implementation of our empirical design.

Investment Spikes. Our baseline defines an investment spike at the 90th percentile of positive changes in machinery stock per worker; Appendix E.1 shows that our key patterns are highly similar at the 85th and 95th percentiles. Likewise, our findings are robust to restricting the treatment group to single-spiking firms (Appendix E.2).

Unbalanced Panel. Our main results focus on a balanced sample of firms observed 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 baseline comparison group averages firms in the same industry-year that meet our pre-sample criteria but have not yet experienced a spike as of the event year. Appendix E.4 shows that the results remain virtually unchanged if we instead use one-to-one random matching.

Higher-Order Links. Our main analysis focuses on first-order external employment, the labor that firms employ through their first-order suppliers. Appendix E.5 shows that our results are robust to including higher-order links (suppliers of suppliers); if anything, these additional layers only amplify the quantitative importance of external employment relative to in-house hires.

6 Accounting for External Employment

The importance of external employment for skill bias raises the question of whether alternative measurement approaches, which do not rely on firm-to-firm transactions data, can account for these effects. We evaluate two approaches commonly used in the lit-

erature: aggregating the analysis to local labor markets (as in Acemoglu and Restrepo (2020); Aghion et al. (2023); Dauth et al. (2021), among others), and applying fixed sectoral input-output matrices to firm-level changes in total input purchases (as in Humlum (2022), among others). Both approaches turn out to miss most of the skill bias from new machinery. This is because the effects primarily reflect a shift toward suppliers that are both more skill-intensive than the sector average and most often located outside the investing firm's local labor market.

6.1 Local Labor Markets

A local labor market analysis will capture the external 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.[26] In particular, we follow Persyn and Torfs (2011) and split Belgium into 11 functional labor markets, similar or larger in size 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).[27]

Figure 8 splits external employment by whether the suppliers are located inside or outside the local labor markets of investing firms. Most of the external 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 external employment of machine suppliers increases total high-STEM employment by around

[26] 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.

[27] 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.

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 shows, the increases in "other industries" often reflect tradable services, e.g., computer programming or software, where providers can 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 aligns with our findings.

6.2 Sectoral Input-Output

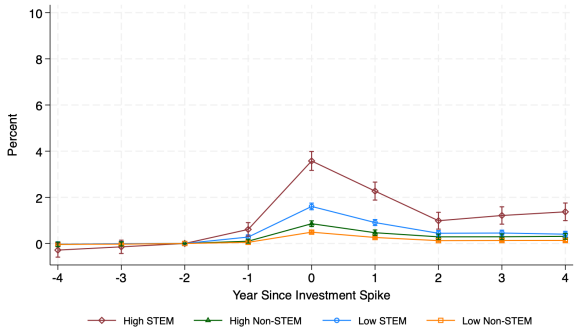
Another common strategy in the literature is to apply sectoral input–output matrices (e.g., from the National Accounts) to firm-level changes in total input purchases. This approach captures the external employment effects if these reflect a general shift toward the typical suppliers of the firm's industry. Both this method and our transaction-based measure are firm-level analogues of the factor content of trade; they differ only in whether the embodied skill content is imputed from sectoral averages or measured directly from each firm's purchases. Figure 9 evaluates this method by scaling firms' intermediate input purchases using sectoral input–output tables.[28]

While this approach captures some of the external employment effects of investment spikes, it still misses most of the high-STEM skill bias associated with new machinery. The shortfall arises because investing firms shift toward suppliers that are more high-STEM-intensive than the industry average.

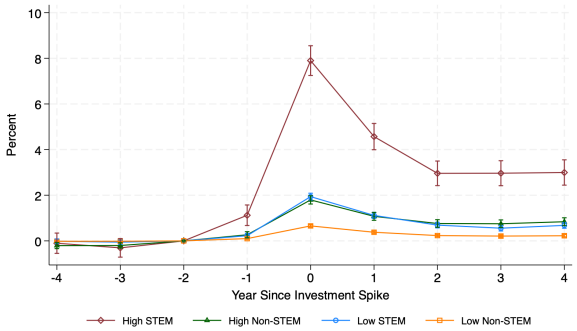
[28]To ensure consistency with our previous analysis, we construct the sectoral input–output tables directly from our firm-to-firm transaction data, ensuring that differences relative to the main analysis reflect only the level of aggregation of input–output relationships.

Figure 8: External Employment by Local Labor Markets (LLM)
(Diff-in-Diffs, In Percent of Pre-Spike Total Employment by Skill Group)

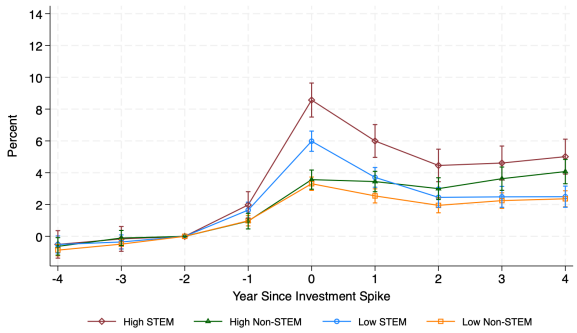
(a) Machine Suppliers: Inside LLM



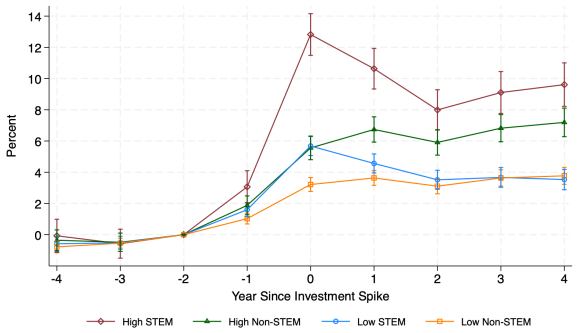
(b) Machine Suppliers: Outside LLM



(c) Other Industries: Inside LLM



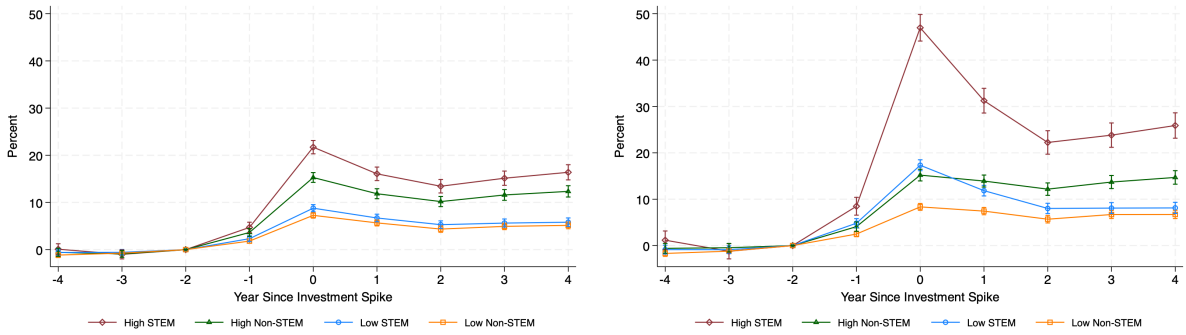
(d) Other Industries: Outside LLM



Notes: This figure splits external 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 external employment of machine suppliers, while Panels (c) and (d) consider the external employment from all other industries. The figures show 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 (Equation 7). Total pre-spike employment is the sum of in-house and external 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 (6), 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 9: External Employment by Measurement Method
(Diff-in-Diffs, In Percent of Pre-Spike Total Employment by Skill Group)

(a) Sectoral Input-Output (b) B2B Transactions (Figure 2(b))



Notes: This figure shows external 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 (Equation 7). Panel (a) uses sectoral input-output tables to calculate external 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 (6), 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 circle back to the macro-labor question of aggregate skill bias that motivated our analysis (Krusell et al., 2000): are the estimated effects large enough to matter for the aggregate demand for skills?

To evaluate this question, we follow a simple two-step sufficient-statistics approach outlined in Appendix F. First, assuming each firm takes the market wage as given, we calculate the *partial-equilibrium* aggregate demand shift by scaling our firm-level difference-in-difference estimates by the aggregate increase in machinery stocks and investments (Figure F.1). This is the proportional change in aggregate skill demand that would prevail if wages remained at their initial levels. As in Krusell et al. (2000), we assume the

underlying driving force is a decline in machinery prices. Whereas they feed in directly measured price declines, we calibrate the price shocks to drive the entire observed rise in aggregate machinery per worker. As in our conceptual framework in Section 1, we include both the skills needed to integrate new machinery (Prediction 1(b), reflected in the temporary effects during years 0–2) and to operate a more machine-intensive production (Prediction 1(a), reflected in the stable effect by year 4). To isolate skill bias, we focus on differential impacts relative to the low non-STEM group.[29] Second, we close the model in *general equilibrium*: the split between skill-premium growth and skilled-employment growth depends on the elasticities of labor supply and demand.[30]

Table 3 reports the partial-equilibrium aggregate demand shift broken down by mode (in-house vs. external) and stage (integration vs. production) (Columns 1–3), along with the general-equilibrium aggregate effects under our central calibration[31]: aggregate employment growth (Column 4) and skill-premium growth (Column 5). The table yields two main takeaways.

First, the aggregate impact of our estimated effects is substantial. Skill bias from the rise of machinery between 2003 and 2021 raised the partial-equilibrium demand for high-STEM workers by 20 percentage points (Column 3), which under our central calibration translates into approximately 10 percentage points of additional aggregate employment growth (Column 4) and 7 percentage points of additional skill-premium growth (Column 5) for high-STEM workers. This shift accounts for about a quarter of the observed

[29]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.

[30]The general-equilibrium step nests the approach of Autor, Dorn and Hanson (2013); Mian and Sufi (2014) as the polar case of perfectly elastic skill supply ($\varepsilon_s^S = \infty$), and the approach of Krusell et al. (2000) as the other polar case of perfectly inelastic supply ($\varepsilon_s^S = 0$). It addresses the "missing intercept" problem of Moll (2021) by embedding the partial-equilibrium shifts from the difference-in-difference effects into a general-equilibrium framework. See Appendix F.2 for details.

[31]We calibrate the absolute labor demand elasticity at $\varepsilon_s^D = 1.5$ from estimates of the elasticity of substitution between high- and low-skill labor in the macro-labor literature (Goldin and Katz, 2008; Katz and Murphy, 1992; Krusell et al., 2000). We set $\varepsilon_s^S = \varepsilon_s^D$ as a natural baseline and treat ε_s^S as the key parameter in the sensitivity analysis. See Appendix F.2 for details.

rise in high-STEM employment (Figure F.3).[32]

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

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

	Partial-Equilibrium Shift			General-Equilibrium Impacts	
	In-House	External	Total	Employment	Skill Premium
	(1)	(2)	(3)	(4)	(5)
High STEM	**-3.7**	**24.2**	**20.5**	**10.2**	**6.8**
– Integration	-0.3	8.0	7.7		
– Production	-3.4	16.2	12.8		
High Non-STEM	**-0.1**	**8.7**	**8.7**	**4.3**	**2.9**
– Integration	0.2	2.0	2.2		
– Production	-0.2	6.7	6.5		
Low STEM	**-1.1**	**2.8**	**1.7**	**0.9**	**0.6**
– Integration	-0.4	1.6	1.2		
– Production	-0.7	1.2	0.5		

Notes: This table reports the impact of new machinery on the aggregate demand for skills, expressed as differentials relative to the low non-STEM group. Columns 1–3 report the partial-equilibrium aggregate demand shift implied by our firm-level estimates—the firm-level investment-spike effects scaled by the aggregate change in machinery stocks (Appendix F.1)—broken down by in-house and external employment and across integration and production stages. The integration stage corresponds to the investment-skill complementarity (Prediction 1(b)); the production stage corresponds to the capital-skill complementarity (Prediction 1(a)). Columns 4–5 report the corresponding general-equilibrium aggregate effects under the central calibration $\varepsilon_s^S = \varepsilon_s^D = 1.5$ (Appendix F.2): the implied aggregate employment growth (Column 4) and the implied skill-premium growth (Column 5). Because the general-equilibrium adjustment operates at the aggregate skill-market level, Columns 4–5 are reported only at the bold skill-group totals.

These aggregate magnitudes reaffirm a core message of the macro-labor literature (Krusell et al., 2000): investment–skill and capital–skill complementarities are quantitatively important for understanding both rising skilled employment and rising skill premiums in the aggregate labor market. Our contribution is to clarify *where* these complemen-

[32]These firm-level magnitudes also admit a structural reading: embedded in a nested-CES production function, they imply a ratio of outer- to inner-nest substitution elasticities above one—capital–skill complementarity at the firm level—but more muted than the aggregate benchmark of Krusell et al. (2000). This is the elasticity-space counterpart of machinery accounting for only about a quarter of the aggregate rise (Appendix A.3).

tarities operate — at specialized external suppliers, beyond the boundaries of investing firms — thereby reconciling the macro-labor story with recent firm-level evidence of skill-neutral investment effects.

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 of investing firms. 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 incidence of technology diffusion.[33]

Finally, our findings raise a broader question about which other phenomena primarily operate beyond the boundaries of the firms directly involved. The key question is whether the affected labor is more cheaply provided by the market. While machine-

[33]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) and recent work documenting the role of robot integrators (Békés et al., 2025; Brynjolfsson et al., 2023).

complementary skills provide a clear example, investigating whether similar dynamics arise in other settings, such as exporting or AI, is a promising avenue for future research. AI is particularly intriguing because external suppliers may not only employ the complementary skills (e.g., AI consultants) but also the labor being potentially displaced (e.g., freelancers). We believe the data infrastructure and conceptual framework we develop here are well-suited to tackle these questions.

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Online Appendix

Integrators: The Firm Boundaries of Capital-Skill Complementarity

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A Conceptual Framework

This appendix specifies firms' full dynamic program from Section 1 and provides formal proofs for the model predictions.

Firms face in-house labor costs $C^H_{jt}(\mathbf{L}^H_{jt}|\mathbf{L}^H_{jt-1})$ (which may include fixed and adjustment components), external labor costs $C^O_{jt}(\mathbf{L}^O_{jt})$, and investment costs $c^I_{jt}(I_{jt})$ that may include non-convex components. The firm's dynamic problem is to choose labor demands (hired and outsourced) and capital investments to maximize the present-discounted sum of profits:

$$\begin{aligned} V_{jt}(K_{jt}, \mathbf{L}^H_{jt-1}) = \max_{\{\mathbf{L}^H_{jt}, \mathbf{L}^O_{jt}, I_{jt}\}} & \underbrace{P_{jt}F(K_{jt}, \mathbf{L}^P_{jt})}_{\text{Revenues}} - \underbrace{C^H_{jt}(\mathbf{L}^H_{jt}|\mathbf{L}^H_{jt-1})}_{\substack{\text{In-house} \\ \text{labor costs}}} - \underbrace{C^O_{jt}(\mathbf{L}^O_{jt})}_{\substack{\text{External} \\ \text{labor costs}}} \\ & - \underbrace{c^I_{jt}(I_{jt})}_{\substack{\text{Investment} \\ \text{costs}}} + \beta \mathbb{E}_t \underbrace{V_{jt+1}\left((1-\delta)K_{jt} + G(I_{jt}, \mathbf{L}^I_{jt}), \mathbf{L}^H_{jt}\right)}_{\text{Continuation Value}} \\ & \text{s.t.} \quad \mathbf{L}_{jt} = \mathbf{L}^H_{jt} + \mathbf{L}^O_{jt} \ \text{ for } \mathbf{L} \in \{U^P, S^P, U^I, S^I\}, \end{aligned} \tag{9}$$

where β is the discount factor, firms face output prices P_{jt}, and $\mathbf{L}^P_{jt} \equiv (S^P_{jt}, U^P_{jt})$ and $\mathbf{L}^I_{jt} \equiv (S^I_{jt}, U^I_{jt})$ stack the production- and integration-stage labor inputs.[34]

A.1 Capital Investment and the Demand for Skills

This section shows that, under the investment-skill and capital-skill complementarity hypotheses, profit-maximizing firms increase their relative demand for skilled workers in response to increases in investment I and capital K.

To distill our exposition, we make three simplifying assumptions. First, firms are price-takers with linear, static labor costs. Second, we abstract from the make-or-buy decision (Section A.2 considers it) by assuming identical labor costs across in-house and external supply. Third, production and integration functions exhibit neutrality between skilled and unskilled labor within each activity, $F_{S_P U_P} = G_{S_I U_I} = 0$, allowing us to

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

focus on complementarities with investment and capital.[35] Under these assumptions, the general program (equation 9) reduces to:

$$V(K) = \max_{\{I,L\}} PF(K, L_P) - w_S(S_P + S_I) - w_U(U_P + U_I) - c^I(I) + \beta \mathbb{E}V((1-\delta)K + G(I, L_I)), \tag{10}$$

where $L_k = (S_k, U_k)$, $k \in \{P, I\}$, with $S_k \equiv S_k^H + S_k^O$ and $U_k \equiv U_k^H + U_k^O$ collapsing the make-or-buy distinction. Throughout this appendix, we write the activity (P or I) as a subscript, freeing the superscript for the in-house/external mode and keeping the derivative notation below legible.

Prediction 1 (Capital investment and the demand for skills)**.** *Capital investment raises the relative demand for skills through two channels:*

Prediction 1(a) (Capital-skill complementarity in production)**.** *Capital raises skilled production employment if $F_{S_PK} > 0$, and raises the relative demand for skilled production workers if the elasticity of skilled-labor demand with respect to capital exceeds that of unskilled labor: $\varepsilon_{S_P,K} > \varepsilon_{U_P,K}$ (Griliches, 1969).*

Proof. The first-order conditions for production labor are $PF_{S_P}(K, S_P, U_P) = w_S$ and $PF_{U_P}(K, S_P, U_P) = w_U$. Differentiating with respect to K (holding P, w_S, w_U fixed) and using $F_{S_PU_P} = 0$ yields

$$\frac{dS_P}{dK} = -\frac{F_{S_PK}}{F_{S_PS_P}}, \qquad \frac{dU_P}{dK} = -\frac{F_{U_PK}}{F_{U_PU_P}},$$

with $F_{S_PS_P}, F_{U_PU_P} < 0$ by strict concavity. Hence $\text{sign}(dS_P/dK) = \text{sign}(F_{S_PK})$ and symmetrically for U_P. The factor-demand elasticities are $\varepsilon_{S_P,K} = -F_{S_PK}K/(F_{S_PS_P}S_P)$ and $\varepsilon_{U_P,K} = -F_{U_PK}K/(F_{U_PU_P}U_P)$, and the skill-bias condition $d\log(S_P/U_P)/d\log K = \varepsilon_{S_P,K} - \varepsilon_{U_P,K} > 0$ reduces to the stated inequality. □

[35] The neutrality assumption is expositional: it removes cross-effects between skilled and unskilled labor from the comparative statics below. For example, the conclusion that capital raises skilled production employment when $F_{S_PK} > 0$ extends to $F_{S_PU_P} > 0$ provided $F_{U_PK} \geq 0$.

Prediction 1(b) (Investment-skill complementarity in integration)**.** *Investment raises skilled integration employment if $G_{S_I I} > 0$, and raises the relative demand for skilled integration workers if $\varepsilon_{S_I,I} > \varepsilon_{U_I,I}$ (Goldin and Katz, 1998).*

Proof. Differentiating the Bellman equation (10) with respect to integration labor yields the first-order conditions $q\, G_{S_I} = w_S$ and $q\, G_{U_I} = w_U$, where the shadow value of installed capital $q \equiv \beta \partial \mathbb{E}V/\partial K$ plays the role of the output price. Assuming G is strictly concave in labor and treating q as parametric (exact when the continuation value is locally linear in capital), the argument for Prediction 1(a) applies with G, I in place of F, K: differentiating the first-order conditions with respect to I (holding w_S and w_U fixed) under $G_{S_I U_I} = 0$ gives $\text{sign}(dS_I/dI) = \text{sign}(G_{S_I I})$ and the skill-bias condition follows. Both conditions scale with q, so their ratio, $G_{S_I}/G_{U_I} = w_S/w_U$, holds independently of the shadow price. □

A.2 Outsourcing of Labor Services

We now study firms' make-or-buy decisions — the choice between $\mathbf{L}_{jt}^H$ and $\mathbf{L}_{jt}^O$ in the general program (equation 9) — and derive how specific features of the in-house cost function C^H shape outsourcing. We focus throughout on skilled integration labor; analogous arguments hold for production labor. Let total demand be $S_I = S_I^H + S_I^O$. Firms choose the in-house/external split to minimize total labor cost:

$$C_S^*(S_I) = \min_{\{S_I^H, S_I^O\}} \left\{ C_S^H(S_I^H) + C_S^O(S_I^O) : S_I^H + S_I^O = S_I \right\}. \tag{11}$$

We write w_S^H for the in-house marginal wage and w_S^O for the external supplier price, with $w_S^O > w_S^H$ reflecting a supplier markup.

Prediction 2 (Fixed costs and outsourcing)**.** *If C^H includes fixed costs of hiring capital-complementary workers, these labor services are more likely to be sourced from specialized external suppliers. Smaller firms and firms in less capital-intensive sectors (e.g., services)*

should rely more on outsourcing, as they cannot amortize the fixed costs across enough projects (Abraham and Taylor, 1996, § II.C).

Proof. Let $C_S^H(S_I^H) = w_S^H S_I^H + f_S^H \cdot \mathbf{1}\{S_I^H > 0\}$ with fixed hiring cost $f_S^H > 0$ paid only when the firm hires any in-house labor, and $C_S^O(S_I^O) = w_S^O S_I^O$. Because $w_S^H < w_S^O$, total cost is decreasing in S_I^H whenever $S_I^H > 0$, so the firm chooses between corners: hire all in-house (cost $w_S^H S_I + f_S^H$) or outsource all (cost $w_S^O S_I$). Comparing:

$$w_S^H S_I + f_S^H \leq w_S^O S_I \iff S_I \geq S_I^* \equiv \frac{f_S^H}{w_S^O - w_S^H}. \tag{12}$$

Firms with demand above the threshold S_I^* amortize the fixed cost across enough labor to make in-house hiring worthwhile; firms with lower demand — the smaller ones, or those in the service sector — outsource. □

Prediction 3 (Lumpy investments and outsourcing)**.** *If C^H includes adjustment costs of hiring, outsourcing should be more prevalent for lumpier investment categories (e.g., machinery versus intangibles) (Abraham and Taylor, 1996, § II.B).*

Proof. To highlight the comparative static, we make a series of simplifying assumptions. Suppose in-house costs include a prohibitive adjustment component, so that $C_S^H(S_{I,t}^H | S_{I,t-1}^H)$ penalizes deviations $S_{I,t}^H \neq S_{I,t-1}^H$ arbitrarily: in-house integration labor is effectively fixed over the investment cycle. Consider an investment profile that arrives in occasional spikes, $I_t = \bar{I}$ in spike years and zero otherwise, with average investment $\tilde{I}$ over the cycle and lumpiness ratio $\lambda \equiv \bar{I}/\tilde{I} \geq 1$. Suppose further that investments and skilled integrators are perfect complements ($G(I, S_I) = \min\{I, S_I\}$, as in Goldin and Katz (1998)).

To meet peak demand via in-house hiring, the firm hires $S_I^H = \bar{I}$ persistently, at annual wage cost $w_S^H \bar{I}$.[36] Full outsourcing scales with current demand at annual cost

[36]The firm would leave money on the table if $S_I^H \neq \bar{I}$, as it could then either decrease its peak investments (if $\bar{I} > S_I^H$) or lower its integration labor (if $\bar{I} < S_I^H$), without losing effective capital.

$w_S^O \tilde{I}$. The firm outsources iff

$$w_S^O \tilde{I} < w_S^H \bar{I} \iff \lambda > \frac{w_S^O}{w_S^H}. \tag{13}$$

For smooth profiles ($\lambda = 1$), outsourcing would be chosen only if external labor were cheaper per unit ($w_S^O < w_S^H$). For lumpy profiles ($\lambda > 1$), outsourcing can dominate despite being more expensive on a per-unit basis. □

These simplifying assumptions are not essential to the comparative static. With a positive base load of investment, the firm covers the constant base with in-house labor (cheaper per unit and requiring no adjustment) and applies the same threshold to the transitory spike component, so lumpier profiles still tilt toward outsourcing. Likewise, finite adjustment costs preserve the prediction: lumpier investments favor outsourcing.

Prediction 4 (Advanced capital and outsourcing)**.** *If outsourcing reflects the specialization of capital-complementary skills, the outsourcing rationales should be exacerbated for capital types undergoing rapid technological change (e.g., machinery versus buildings, or machinery from new suppliers) (Greenwood, Hercowitz and Krusell, 1997).*

Proof. The outsourcing effects in Predictions 2 and 3 strengthen with the in-house cost parameters: the threshold for in-house hiring in Equation (12) rises with the fixed cost f_S^H, so more firms outsource, and larger adjustment costs in C_S^H make tracking lumpy investment demand in-house costlier, widening the range of profiles for which outsourcing dominates (Equation (13) is the limiting case of prohibitive adjustment costs). These cost parameters are larger when the relevant skills are scarcer or more specialized, as typical for newer or more rapidly changing capital. □

A.3 Substitution Elasticities and the Magnitude of Skill Bias

In this appendix, we show how our estimated responses map into the structural elasticities at the heart of the capital–skill complementarity literature. We derive Equation (8) of

the main text, reproduced in Equation (20) below, and detail its calibration.

Following Krusell et al. (2000), we posit that production F follows a nested CES function that combines machinery K with high-STEM labor L_S in the inner nest, and that composite H with low non-STEM labor L_U in the outer nest:

$$H = [\alpha K^{\rho} + (1-\alpha) L_S^{\rho}]^{1/\rho}, \qquad \sigma_{KS} = \tfrac{1}{1-\rho}, \tag{14}$$

$$Y = [(1-\mu) H^{\eta} + \mu L_U^{\eta}]^{1/\eta}, \qquad \sigma_{HU} = \tfrac{1}{1-\eta}. \tag{15}$$

Here σ_{KS} is the elasticity of substitution between machinery and high-STEM labor, and σ_{HU} the elasticity between the machinery–high-STEM composite and less-skilled labor. Capital–skill complementarity in the sense of Griliches (1969) and Krusell et al. (2000) corresponds to $\sigma_{HU} > \sigma_{KS}$: capital substitutes less readily for skilled than for less-skilled labor.

Derivation. Treat the investment spike as a firm-specific decline in the capital user cost r, holding wages fixed within the event window (the same wage-taking assumption as in Section F.2). Log-differentiating the cost-minimizing factor demands implied by (14)–(15) yields four relations, in which all changes are treated-minus-control responses:

$$\text{(i) inner first-order condition:} \quad \Delta \ln K - \Delta \ln L_S = -\,\sigma_{KS}\, \Delta \ln r, \tag{16}$$

$$\text{(ii) inner price index:} \quad \Delta \ln P_H = s_K^H\, \Delta \ln r, \tag{17}$$

$$\text{(iii) outer first-order condition:} \quad \Delta \ln L_U - \Delta \ln H = \sigma_{HU}\, s_K^H\, \Delta \ln r, \tag{18}$$

$$\text{(iv) composite quantity index:} \quad \Delta \ln H = s_K^H\, \Delta \ln K + (1 - s_K^H)\, \Delta \ln L_S. \tag{19}$$

Relation (16) is the inner-nest relative factor demand; (17) applies Shephard's lemma to the inner-nest unit cost P_H, so the elasticity of P_H with respect to r equals capital's inner-nest cost share s_K^H; (18) is the outer-nest relative demand; and (19) is the CES

quantity index. Substituting (16) and (19) into (18) eliminates the latent shock $\Delta \ln r$, which cancels, leaving

$$\frac{\sigma_{HU}}{\sigma_{KS}} = 1 + \frac{1}{s_K^H} \cdot \frac{\Delta \ln L_S - \Delta \ln L_U}{\Delta \ln K - \Delta \ln L_S}. \tag{20}$$

The ratio exceeds one (capital–skill complementarity) if and only if high-STEM employment rises more than less-skilled employment ($\Delta \ln L_S > \Delta \ln L_U$), given that capital deepens faster than skilled employment ($\Delta \ln K > \Delta \ln L_S$). As in the main text's identification argument, the mapping requires only that no factor-*biased* productivity shock coincide with the spike: Hicks-neutral and pure scale shocks wash out of the *relative* responses in (20).

Calibration and Benchmarking. We calibrate the capital–skill complementarity of production from the stable year-four effects in Figures 1 and 2, when the temporary integration response has largely faded (Figure 3).

Total (in-house plus external) high-STEM employment rises by about 34% ($\Delta \ln L_S = 0.29$) and low non-STEM employment by about 18% ($\Delta \ln L_U = 0.17$), against a machinery-stock deepening of $\Delta \ln K \approx 0.9$ at year four (from about €16,000 pre-spike to about €40,000; Figure 1). We approximate the machinery response by the treated-firm path in Figure 1, as not-yet-spiking firms' machinery moves little over the event window. The remaining object is capital's cost share within the inner nest, $s_K^H \equiv rK/(rK + w_S L_S)$,

where r is the capital user cost. With $s_K^H \approx 1/3$,[37] Equation (20) gives

$$\frac{\sigma_{HU}}{\sigma_{KS}} = 1 + \frac{1}{s_K^H} \cdot \frac{\Delta \ln L_S - \Delta \ln L_U}{\Delta \ln K - \Delta \ln L_S} \approx 1 + 3 \cdot \frac{0.29 - 0.17}{0.9 - 0.29} \approx 1.6.$$

By comparison, Krusell et al. (2000) estimate at the aggregate level an inner elasticity of 0.67 and an outer elasticity of 1.67, implying a ratio of roughly 2.5. However, the calibration does not include the investment–skill complementarity of the integration stage, another key source of skill bias in our estimates (Section 3.2); our aggregation in Section 7 incorporates both margins.

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.

[37] We build s_K^H from two annual flows, both at the pre-spike baseline (Table 2). The machinery service flow is rK, with user cost $r \approx 0.17$ (a $\approx 5\%$ required return plus the machinery depreciation rate $\delta = 0.12$) applied to pre-spike machinery of $\approx$ €16,000 per worker (Figure 1) across the average spiking firm's 38.8 in-house workers, giving $K \approx$ €620,000 and $rK \approx$ €105,000. The high-STEM wage bill is $w_S L_S$, where baseline in-house ($38.8 \times 4.9\%$) plus external ($19.4 \times 5.8\%$) high-STEM labor gives $L_S \approx 3.0$ FTE. We use a fully loaded annual cost of $w_S \approx$ €75,000 per high-STEM full-time equivalent, in line with official statistics for Belgian manufacturing over our 2003–2021 period (Eurostat, 2026*a*,*b*). Then $w_S L_S \approx$ €225,000 and $s_K^H \approx 105/(105 + 225) \approx 1/3$.

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 refers to total investment and is not disaggregated by type (machinery, buildings, etc.).

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.[38]

Tables B.1 and B.2 list the education categories by level and field.[39] 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.

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

[39] 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 the cross of these two dimensions:

- **High STEM**: tertiary education or higher in STEM fields.
- **High Non-STEM**: tertiary education or higher in non-STEM fields (including "not specified").
- **Low STEM**: less than tertiary education in STEM fields.
- **Low Non-STEM**: 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, the midpoint of our sample period.

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, the midpoint of our sample period.

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.[40] 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.

[40]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).

Linking Annual Accounts and B2B Transactions. We link the annual accounts (complemented with KSZ employment data) to the B2B transactions using the same 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.[41] Since we use the B2B transaction data mainly to calculate first-order external employment, dropping transactions with suppliers without employment has no bearing on our estimates.

B.2 Measurement

B.2.1 A Robot-Integration Example

To fix ideas about the external skills required to integrate and operate new machinery, and how they enter our data, Box B.1 traces a typical robot-integration project through the buyer–supplier transactions we observe. The structure of the project — its phases, the split between hardware and integration labor, the milestone-based billing, and the recurring service relationship — follows standard industry practice and contract terms.[42] While robot integration is a leading example of the machine-complementary services we measure, it is just one instance of the broader skill bias of new machinery.

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

[42] We thank Søren Peters (HowToRobot), Maarten Daemen (KUKA), Peter Kiekens (Industrial Cobotics), Benjamin Parent (Stäubli), Alain Wayenberg (Agoria), Søren Peter Johansen (Danish Technological Institute, Robot Technology), Bo Hanfgarn Eriksen (Region Syddanmark), Per Rasmussen (BILA Robotics), and Martin Jespersen (Odense Robotics) for conversations that greatly helped us understand the structure of the robot-integrator industry.

Box B.1: A Robot-Integration Project in the Transaction Data

A manufacturer decides to automate a production step and orders a robot cell from a specialized *integrator*. The installed system costs roughly €250,000 (Anandan, 2015), of which about one-third is the robot hardware and two-thirds is integration: engineering and cell design, safety guarding, programming, installation, commissioning, and operator training (Anandan, 2015; IFR, 2022). The project moves from design and engineering through build and factory testing to on-site installation, commissioning, and training (Elkins, 2025), typically over a few months. This integration work is performed by the integrator's high-STEM engineers and technicians, not by the manufacturer's own staff.

The project (spike year). Billing follows the work. The European engineering industries' standard contract conditions (Orgalime S 2012) stipulate one third of the price at the order, one third when the system is ready for delivery, and the remainder at delivery (Orgalime, 2012, Clause 19); bespoke contracts often tie further milestones to the project's sign-off gates, such as design approval and acceptance testing (Elkins, 2025). Because the project is short, essentially the entire €250,000 is recorded as the manufacturer's purchases from the integrator within a single year, the investment-spike year, and the payments coincide in time with the integration labor they compensate. Under our proportionality assumption (Section 2.2.3), if the manufacturer accounts for a share s of the integrator's sales that year, we attribute the share s of the integrator's workforce to the manufacturer. The transaction thus reveals the integration labor embodied in the investment, even though none of these workers appear on the manufacturer's payroll.

After commissioning (later years). The relationship need not end at handover. The manufacturer may keep purchasing from the integrator: preventive maintenance and spare parts, technical support, and reprogramming and re-tooling if the manufacturer changes its product mix (Anandan, 2015). Industry estimates put such running costs on the order of 10–12% of the initial system cost per year (HowToRobot, 2024), with maintenance requirements rising as components wear. These smaller, recurring transactions sustain the buyer–supplier link, attributing a now-smaller share of the integrator's engineers to the manufacturer for years after the installation.

The example clarifies the time profile of our estimates: external high-STEM demand at machine suppliers (Figure 3, Panel (a)) rises sharply in the spike year (the integration burst) and then declines without returning to baseline, reflecting the persistent servicing relationship.[43]

[43]The contractual architecture also clarifies that outsourcing integration is not legally mandated. Robot manufacturers' warranties typically condition coverage on installation in accordance with the manufacturer's instructions, not on installation by a certified external firm, and end users may integrate

B.2.2 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, international suppliers, the downstream stages of the value chain are primarily domestic and 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

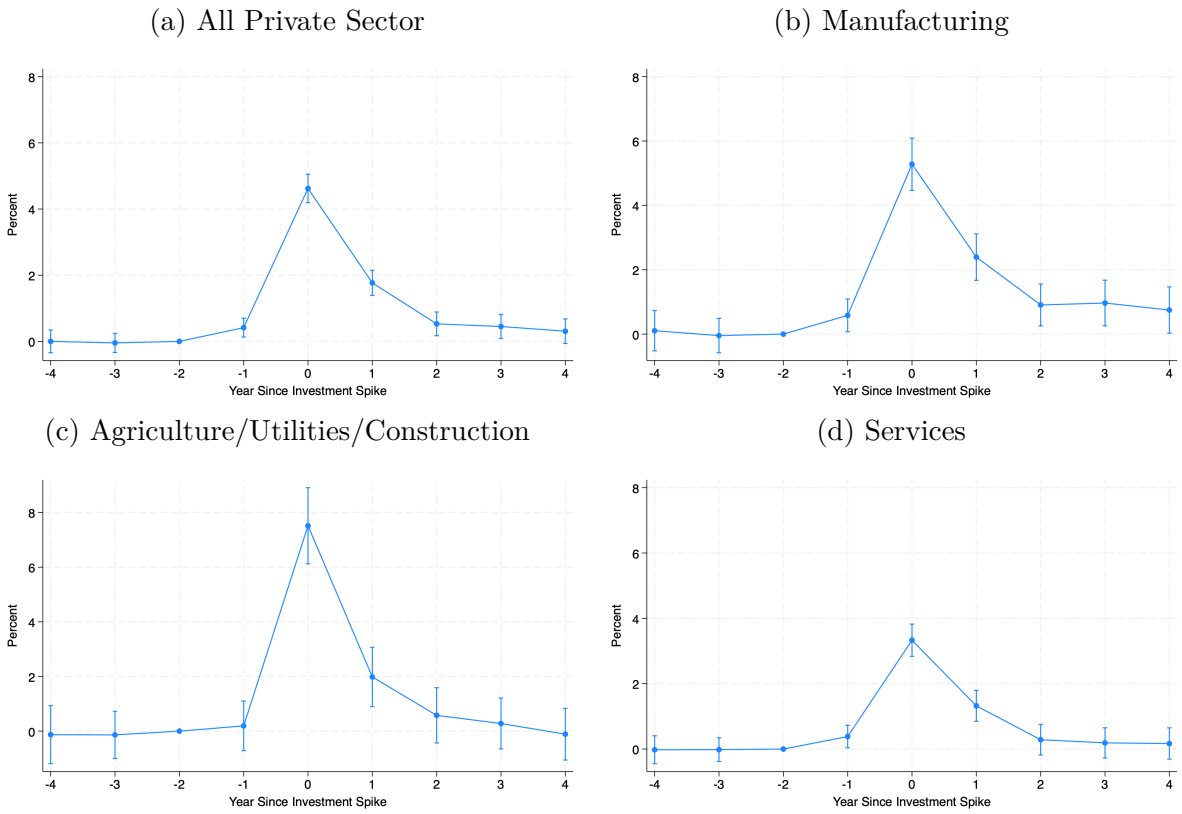
Type	NACE
Builders	2562, 28
Installers	33, 4321
Distributors	4614, 466
Advisors	71, 7022

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.

robots themselves: under the EU Machinery Directive, an industrial robot is normally "partly completed machinery," and whoever constitutes the final robot cell (an external integrator or the user itself) becomes the legal manufacturer of the cell, responsible for its risk assessment and conformity (CE) marking (European Commission, 2024; International Organization for Standardization, 2025). Self-integration is thus permitted but internalizes these regulatory obligations: a fixed cost of integration capability that specialized integrators spread across clients (Prediction 2).

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 use a market report on robot suppliers and integrators in Belgium (compiled by `www.HowToRobot.com`, a digital platform that connects manufacturing firms to machine suppliers).[44] 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.

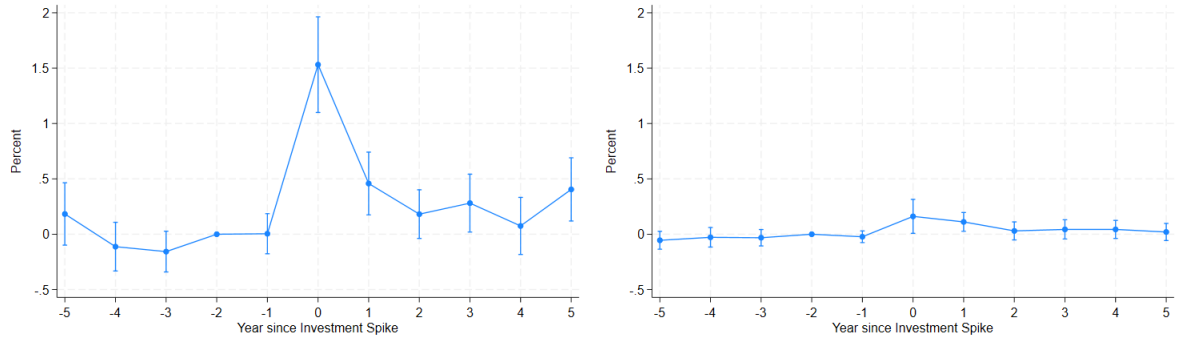
Figure B.2 decomposes purchases from firms on the external lists by whether they fall in our machine-supplier industry codes. As the figure shows, our industry classification

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

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

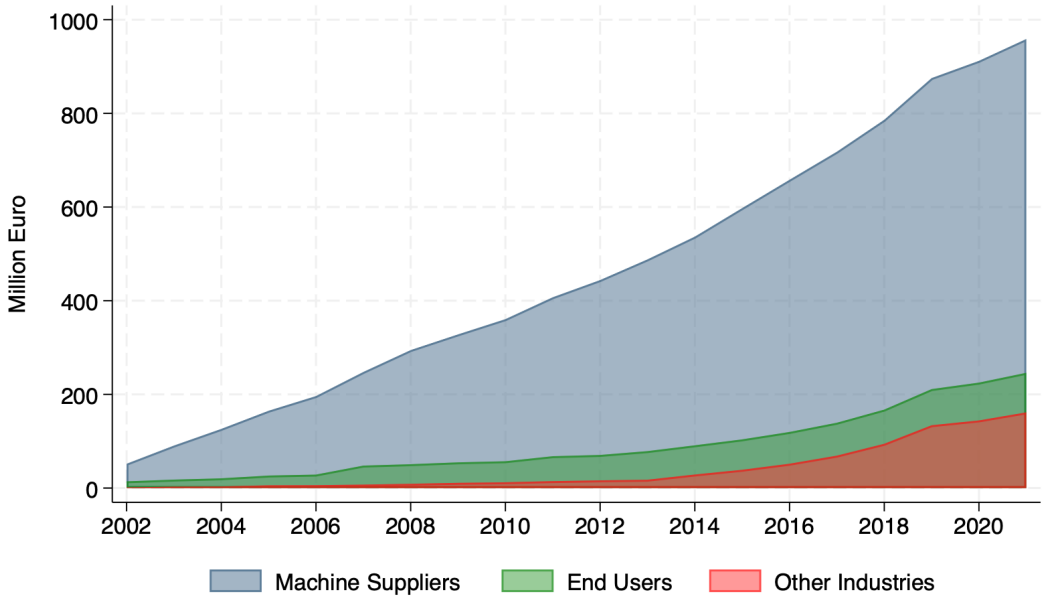


Notes: This figure splits the purchases of spiking firms from the robot supplier firms (in percent of total purchases) according to whether the suppliers are in our classified machine supplier industry codes. The estimates are differences-in-differences in outcomes (measured relative to year −2) between 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.

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.

C New Machinery and the Demand for Skills

C.1 Empirical Strategy

Table C.1 shows how our analysis sample shrinks with the sample restrictions described in Section 3.1.

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

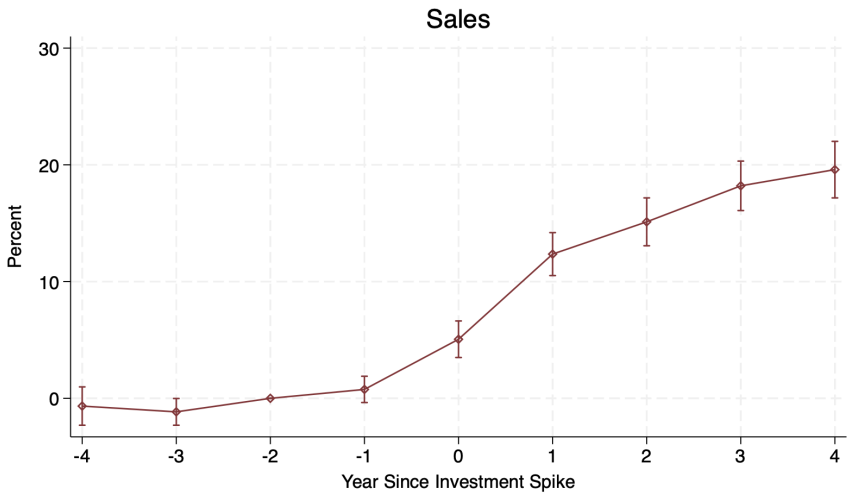
Notes: This table shows how our analysis sample shrinks with the sample criteria listed in Section 3.1. Column (1) shows the number of eligible firms, and Column (2) shows their number of machinery investment spikes.

C.1.1 Proxy Controls

This appendix examines the role of confounding demand or productivity shocks by controlling for the growth in firm sales around the investment spikes.

Figure C.1 shows the difference-in-differences estimate for log sales around machinery investment spikes, using the same specification as in Figure 2. Sales evolve smoothly around the spike, with no discernible pre-trend, and grow to about 20% (0.2 log points) four years after the spike, a relative increase similar to that for total employment. This smooth, gradual path is inconsistent with a discrete confounding demand or productivity shock coinciding with the investment spike. Consistent with the homothetic-production argument of Lindner et al. (2024), such proportional scale shocks raise employment across skill groups but do not by themselves generate the differential high-STEM bias we document.

Figure C.1: Sales around Machinery Investment Spikes



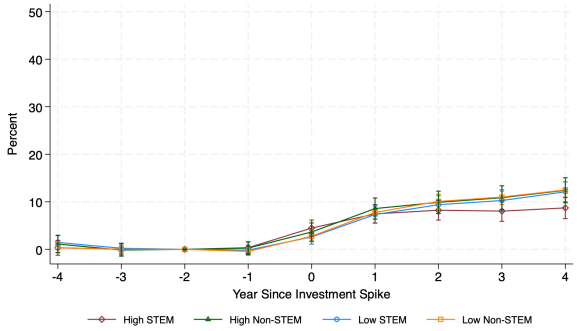
Notes: This figure shows the difference-in-differences estimate for log sales (in %) around machinery investment spikes, using the same specification as in Figure 2 (Equation (6)). The estimates are differences-in-differences in log sales (measured relative to year −2) between the "spiking" and "non-spiking firms" from Table 2, 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 C.2 adds controls for this sales growth directly to our employment specification.[45] Panels (a) and (b) reproduce the in-house and external employment effects from Figure 2; Panels (c) and (d) re-estimate them controlling for the firm's growth in sales from year −2 to the event year. The controls lower absolute employment growth somewhat (most visibly for in-house employment in the spike year, where the year-0 effect falls by 1–2 percentage points off a 2–4% base), but the external high-STEM skill bias, our central finding, remains intact.

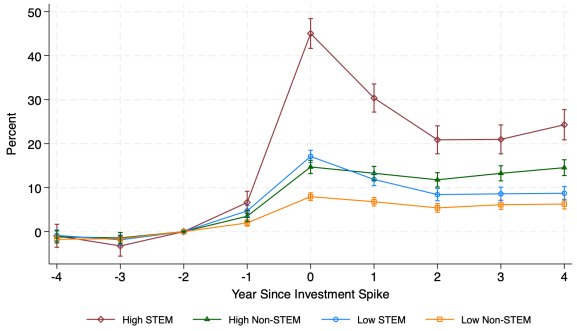
[45]This control is consistent with the conceptual framework in Section 1: because capital takes a year to install (Equation (2)) and integration labor does not enter production (Equation (1)), year-0 sales reflect output produced with the firm's existing, pre-spike capital stock, so controlling for them is not a "bad control". We thank John Van Reenen for this suggestion.

Figure C.2: Employment around Machinery Spikes: Controlling for Sales Growth
(Diff-in-Diffs, In Percent of Pre-Spike Total Employment by Skill Group)

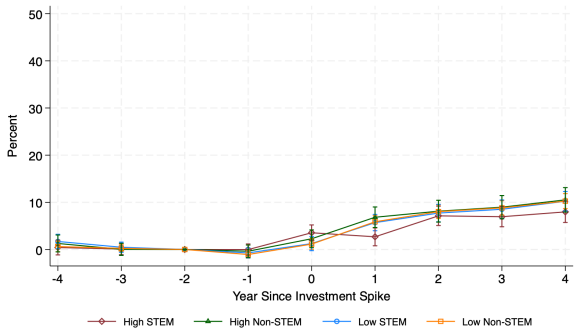
(a) In-House: Main Specification



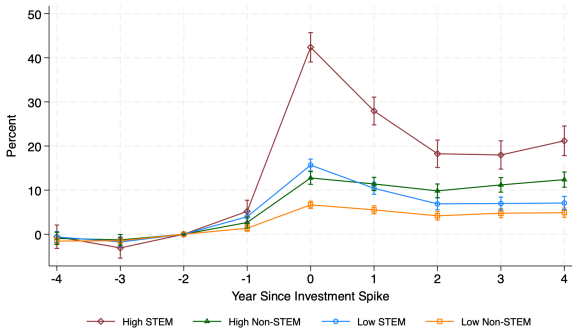
(b) External: Main Specification



(c) In-House: Controlling for Sales Growth



(d) External: Controlling for Sales Growth



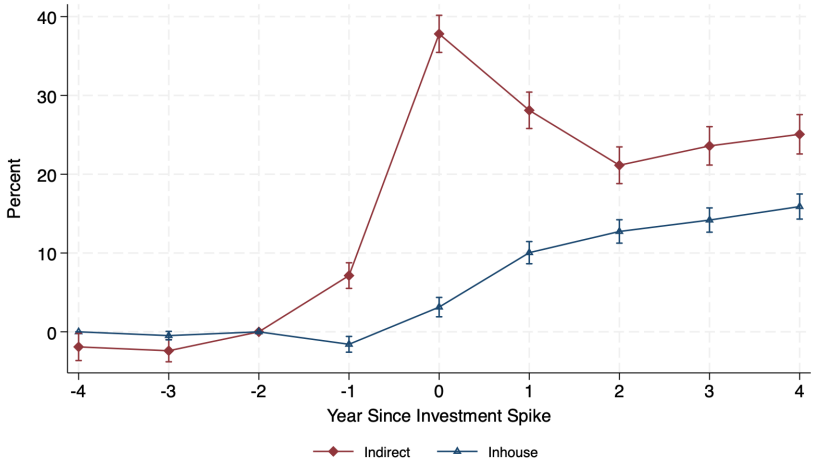
Notes: This figure reproduces the in-house and external employment effects from Figure 2 with and without controls for the investing firm's sales growth. Panels (a) and (b) show the main specification (no controls); Panels (c) and (d) add controls for the firm's growth in log sales from year -2 to the event year (year 0). The figures show 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 (Equation 7). The estimates are differences-in-differences in outcomes (measured relative to year -2) between the "spiking" and "non-spiking firms" from Table 2, based on the specification in Equation (6), 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.

C.2 Main Results

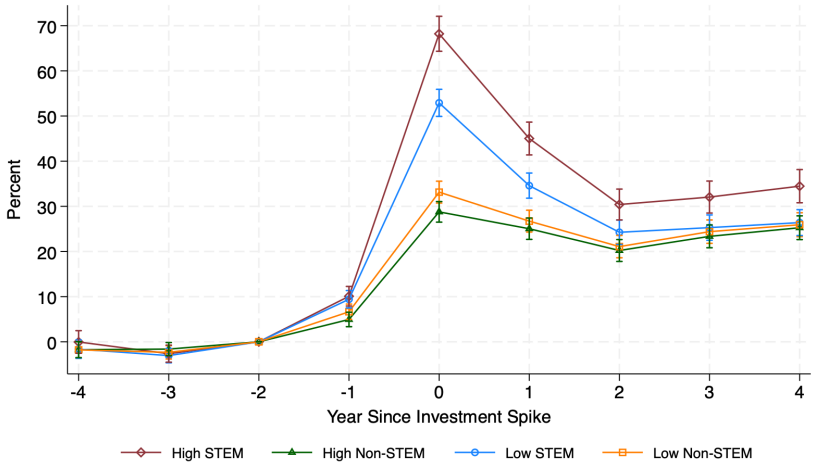
Figure C.3 decomposes the external high-STEM bias from Figure 2 into two channels. Panel (a) shows that external employment grows faster than in-house employment around machinery investment spikes, while Panel (b) shows that the skill composition of external employment shifts toward high-STEM workers. Both channels reinforce each other in generating the patterns observed in Figure 2: more outsourcing of an increasingly high-STEM–intensive supplier mix.

Figure C.3: Drivers of External Skill Bias around Machinery Investment Spikes

(a) In-House and External Employment Growth



(b) External Employment of Skills
(Diff-in-Diffs, In Percent of Pre-Spike External Employment by Skill Group)



Notes: Panel (a) shows the in-house and external employment growth around machinery investment spikes. The figure shows in-house employment in percent of pre-spike in-house employment and external employment in percent of pre-spike external 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 external employment of private sector firms around investment spikes in machinery. The figures show the external employment of high-skilled STEM, high-skilled non-STEM, low-skilled STEM, and low-skilled non-STEM workers in percent of pre-spike external employment by skill category. External pre-spike employment is the average external 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 external 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 External Employment through Other Industries

	Pre-Spike Share	Effect on External 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 external employment (as in Figure 3) across two-digit subindustries. Column (1) shows the percent share of the industry in external 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 external employment before the spike. *Sample*: Private sector firms around first machinery investment spikes. Balanced sample for four years before and after the spike.

D Why Firms Outsource Capital-Complementary Skills

This appendix collects supplementary results for the analysis of why firms outsource capital-complementary skills in Section 4. Appendix D.1 reports balance and machinery-stock dynamics for the smaller- and larger-firm subsamples, Appendix D.2 does so for the manufacturing and services subsamples, Appendix D.3 reports additional results for building and intangible spikes, and Appendix D.4 provides supplementary results on new versus existing machine supply.

D.1 Firm Size

Tables D.1 and D.2 report pre-spike employment for the smaller- and larger-firm subsamples, where smaller firms have pre-spike total employment (year -1) below the sample median (13.1 FTE). Spiking and non-spiking firms are well balanced on total employment and skill shares within each subsample, validating the difference-in-differences design for both groups.

Comparing across subsamples, larger firms employ substantially more high-STEM workers in-house already before the spike: their in-house high-STEM share is roughly twice that of smaller firms (6.5% versus 3.3%). This pre-existing in-house capacity helps explain why larger firms rely less on external skills to integrate and operate more capital-intensive production: the fixed cost of in-house high-STEM hires has already been absorbed.

Figures D.1 and D.2 show that the underlying investment shock is similar for smaller and larger firms: both subsamples experience an increase of roughly 50,000 euros in machinery stock per worker, and the difference-in-differences estimate of machinery per worker is statistically indistinguishable across firm size. Hence, the differences in in-house and external employment responses across smaller and larger firms in Figure 4 reflect heterogeneous responses to a common shock, not differences in the magnitude of

the shock itself.

Figure D.3 shows that smaller firms rely more on purchases from external machine suppliers when upgrading their machinery: their share of machine suppliers in total purchases rises by six percentage points in the year of the spike, versus four percentage points for larger firms.

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

	Spiking		Non-Spiking		Std. Difference	
	In-House	External	In-House	External	In-House	External
	(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			

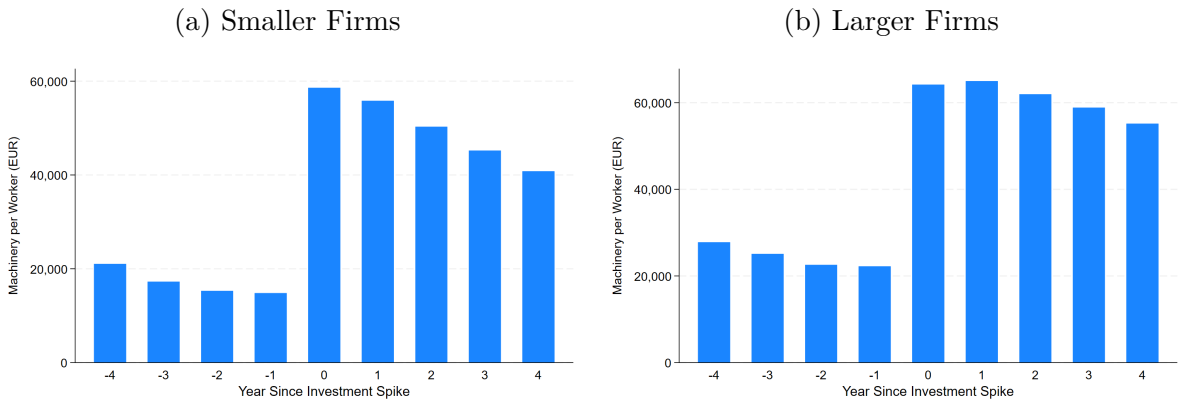
Notes: This table reports in-house and external employment in the treatment (Columns 1-2) and control (Columns 3-4) groups in year $t-2$. The table reports total employment in full-time equivalents and the employment share of different skill groups. Columns 5-6 show the standardized difference between the treatment and control group means, calculated in standard deviations of the treatment group, where absolute values above 25% are a standard threshold for assessing imbalance (Stuart and Rubin, 2008). *Sample*: Smaller firms (pre-spike total employment below the sample median of 13.1 FTE) around first machinery investment spike. Balanced sample for four years before and after the spike.

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

	Spiking		Non-Spiking		Std. Difference	
	In-House	External	In-House	External	In-House	External
	(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			

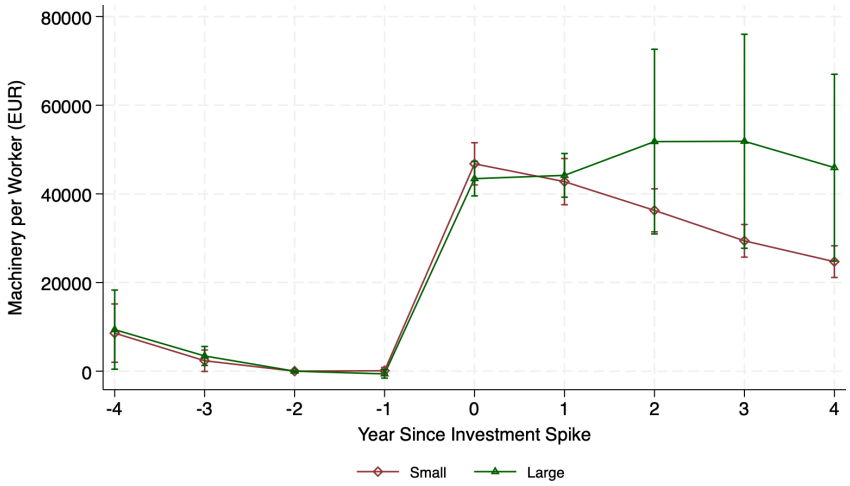
Notes: This table reports in-house and external employment in the treatment (Columns 1-2) and control (Columns 3-4) groups in year $t-2$. The table reports total employment in full-time equivalents and the employment share of different skill groups. Columns 5-6 show the standardized difference between the treatment and control group means, calculated in standard deviations of the treatment group, where absolute values above 25% are a standard threshold for assessing imbalance (Stuart and Rubin, 2008). *Sample*: Larger firms (pre-spike total employment at or above the sample median of 13.1 FTE) around first machinery investment spike. Balanced sample for four years before and after the spike.

Figure D.1: Machinery Stock per Worker around Spike



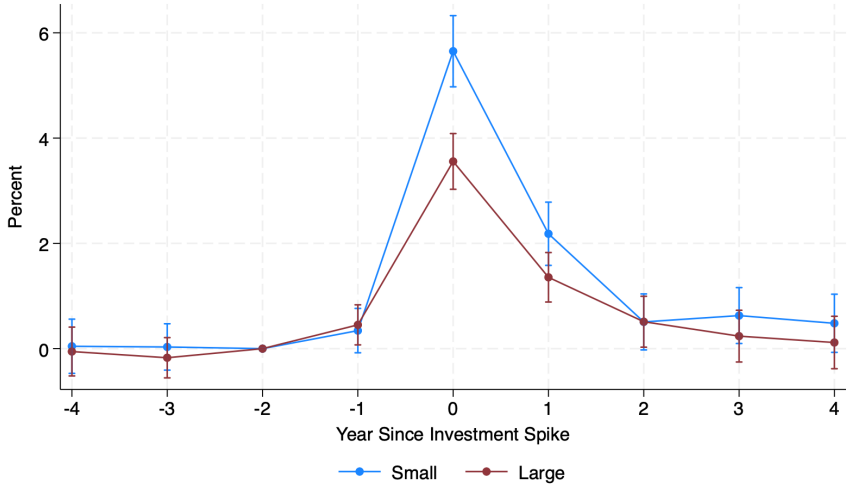
Notes: This figure shows the machinery capital stock per worker around years of machinery investment spikes. Panel (a) focuses on smaller firms, and Panel (b) on larger firms. Smaller firms have pre-spike total employment (year -1) below the median (13.1 FTE). *Sample*: Private sector firms around first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

Figure D.2: Machinery per Worker: Larger versus Smaller Firms



Notes: This figure shows the machinery per worker around investment spikes. Smaller firms have pre-spike total employment (year −1) below the median (13.1 FTE). 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 spikes. Balanced sample for four years before and after the spike.

Figure D.3: Share of Machine Suppliers in Total Purchases: Smaller versus Larger Firms



Notes: This figure shows the share of machine suppliers in total purchases around the first machinery investment spike, separately for smaller and larger firms. Smaller firms have pre-spike total 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.

D.2 Application Sector

Tables D.3 and D.4 report pre-spike employment for the manufacturing and services subsamples. Spiking and non-spiking firms are well balanced on total employment and skill shares within each subsample, validating the difference-in-differences design for both groups.

Comparing across subsamples, manufacturing firms are both larger (63.5 FTE in-house, versus 26.1 FTE in services) and employ a higher share of high-STEM workers in-house already before the spike (6.1% versus 4.3% in services). While both sectors display external high-STEM bias (Figure 5), the relative magnitudes are larger for services firms, consistent with manufacturing firms already having absorbed part of the fixed cost of in-house high-STEM hires before the investment spike. This pattern parallels the firm-size comparison (Appendix D.1).

Figure D.4 extends the analysis to the remaining private-sector industries (agriculture, utilities, and construction) and shows that the skill-biased external pattern from the main text holds in these sectors as well.

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

	Spiking		Non-Spiking		Std. Difference	
	In-House	External	In-House	External	In-House	External
	(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 in-house and external employment in the treatment (Columns 1-2) and control (Columns 3-4) groups 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% are 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.

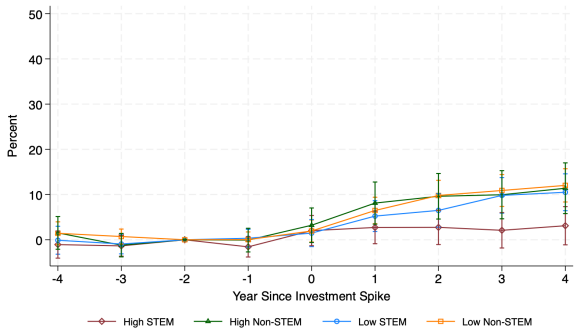
Table D.4: Services: Firm Employment before Machinery Investment Spikes

	Spiking		Non-Spiking		Std. Difference	
	In-House	External	In-House	External	In-House	External
	(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			

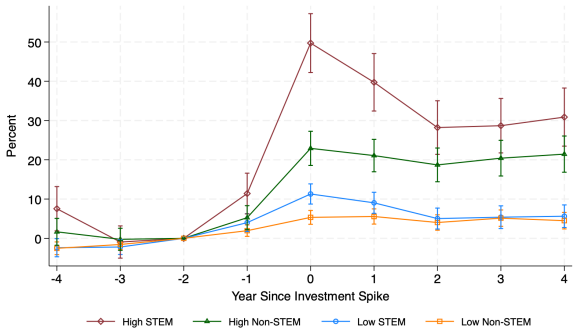
Notes: This table reports in-house and external employment in the treatment (Columns 1-2) and control (Columns 3-4) groups in year $t-2$. The table reports total employment in full-time equivalents and the employment share of different skill groups. Columns 5-6 show the standardized difference between the treatment and control group means, calculated in standard deviations of the treatment group, where absolute values above 25% are 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) In-House Employment



(b) External Employment



Notes: This figure shows the in-house and external employment around machinery investment spikes for firms in agriculture, utilities, and construction. 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 group (Equation 7). Total pre-spike employment is the sum of in-house and external 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. *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

D.3 Capital Types

Figure D.5 plots the capital stock per worker around each type of spike, mirroring Figure 1 for machinery. Each spike captures a discrete jump in the corresponding capital stock. The figure uses the 85th-percentile cutoff for defining spikes.

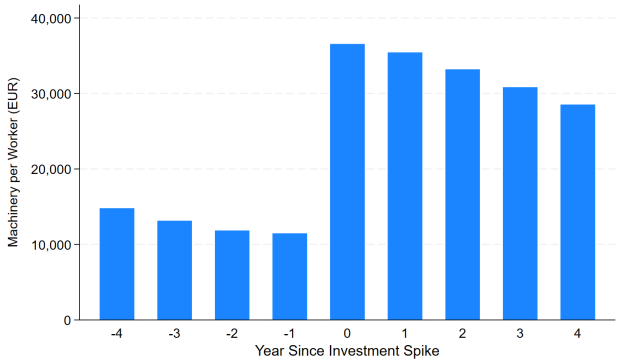
Figures D.6 and D.7 address the concern that building spikes coincide with machinery installation. Figure D.6 confirms that the machinery stock per worker rises around building spikes, suggesting that part of the external skill bias from buildings in Figure 6 reflects simultaneous machinery investment. Figure D.7, which excludes building spikes that coincide with the top 25% of machinery-per-worker increases, shows that the external skill bias narrows further but does not vanish entirely when buildings do not coincide with large machinery investment. This likely reflects the involvement of architects and building engineers.

Figure D.8 extends the building analysis to the full private sector at the 85th-percentile

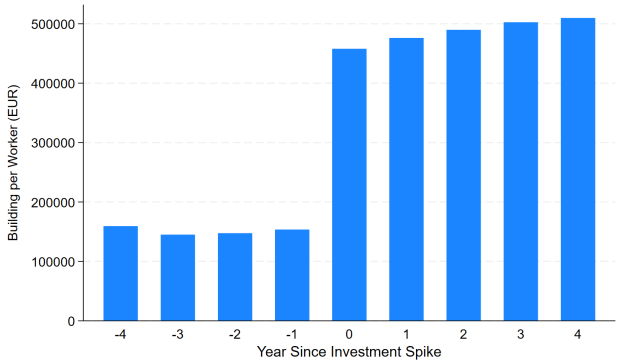
cutoff (€137,000), made feasible by the lower cutoff. The qualitative pattern from Figure 6 carries through: building spikes generate a modest, transient external skill bias and a limited in-house response, well below the magnitudes for machinery spikes.

Figure D.5: Capital Stocks per Worker around Investment Spikes

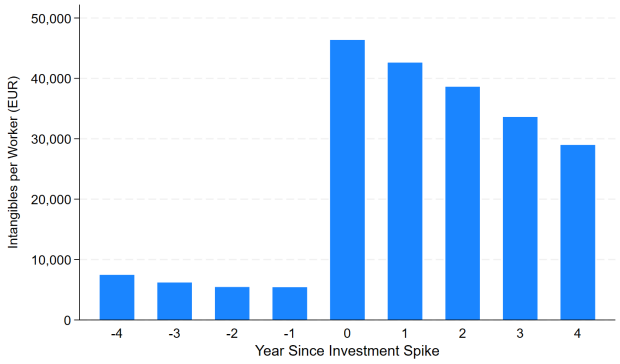
(a) Machine Spikes



(b) Building Spikes

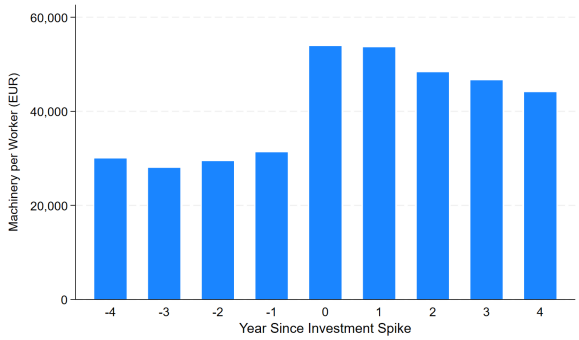


(c) Intangibles Spikes



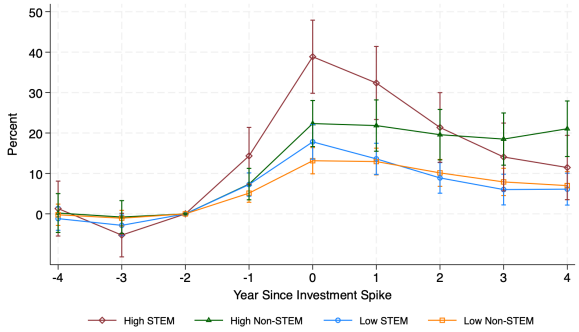
Notes: Panels (a)–(c) plot the capital stock per worker around, respectively, machinery, building, and intangible investment spikes, mirroring Figure 1 for machinery. Machinery spikes are defined as years in which the firm's change in machinery stock per worker exceeds the 85th percentile of positive 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 Stock per Worker around Building Investment Spikes



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.

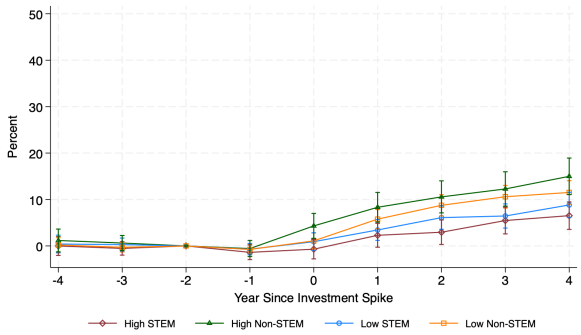
Figure D.7: External Employment around Building Spikes (Excluding Machine Spikes)



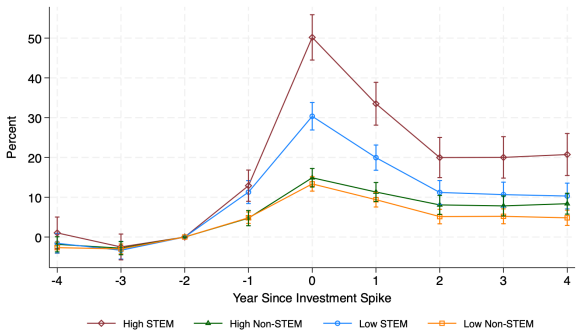
Notes: This figure shows the external employment of manufacturing sector firms around investment spikes in buildings, excluding building spikes that coincide with the top 25% of machinery-per-worker increases. Building spikes are defined at the 90th percentile of positive changes in the building stock per worker. The figure shows 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 group (Equation 7). Total pre-spike employment is the sum of in-house and external 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". *Sample*: Manufacturing sector firms around first building investment spike. Balanced sample for four years before and after the spike.

Figure D.8: Building Spikes: 85th-Percentile Cutoff

(a) In-House Employment



(b) External Employment



Notes: This figure shows the in-house and external employment of private-sector firms around investment spikes in buildings, defined at the 85th percentile of positive changes in the building stock per worker (€137,000). The figure shows 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 group (Equation 7). Total pre-spike employment is the sum of in-house and external 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". *Sample*: Private sector firms around first building investment spike. Balanced sample for four years before and after the spike.

D.4 New versus Existing Machine Supply

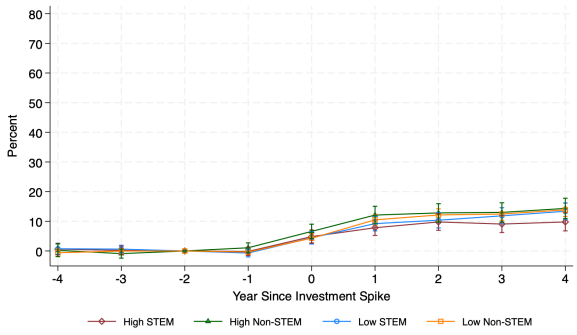
This appendix presents supplementary results for the new- versus existing-supplier analysis in Section 4.4.

Figure D.9 shows the in-house employment estimates that correspond to Figure 7 from the main text. The in-house response is similar across spikes driven by new versus existing suppliers, in line with the limited in-house effects of machinery spikes overall (Section 3.2).

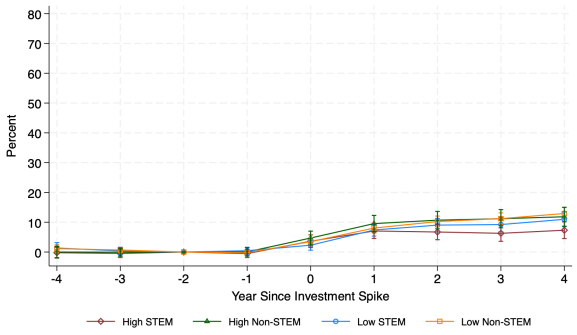
Figure D.10 decomposes the external employment response by supplier industry. The differential high-STEM bias for new-supplier spikes shows up both at machine suppliers (Panel (i)) and at firms in other industries (Panel (ii)), consistent with new machinery embodying new technologies that demand specialized skills throughout the supply chain.

Figure D.9: In-House Employment around Machinery Spikes: New versus Existing Machine Supply

(a) Spikes Driven by New Suppliers



(b) Spikes Driven by Existing Suppliers

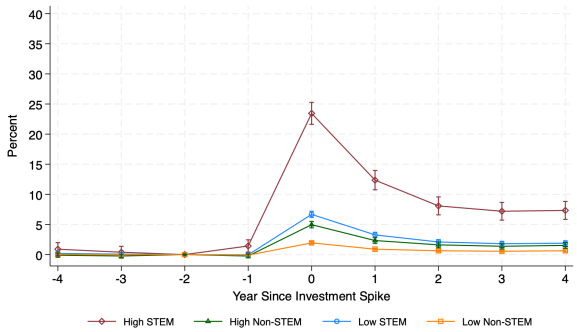


Notes: This figure shows in-house employment around machinery investment spikes, in percent of total pre-spike employment by skill group (Equation 7). Panel (a) focuses on spikes driven by new suppliers; Panel (b) focuses on spikes driven by existing suppliers. The classification is based on the ratio 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 firms with non-positive 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.

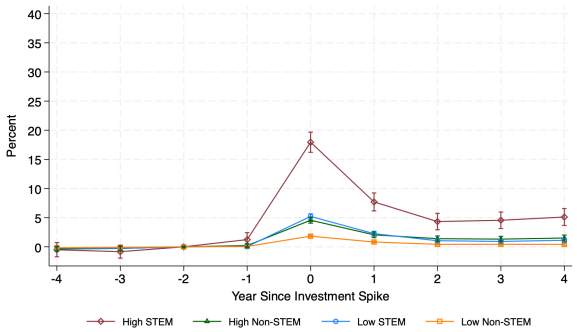
Figure D.10: External Employment around Machinery Spikes: By Supplier Industry

(i) Machine Suppliers

(a) Spikes Driven by New Suppliers

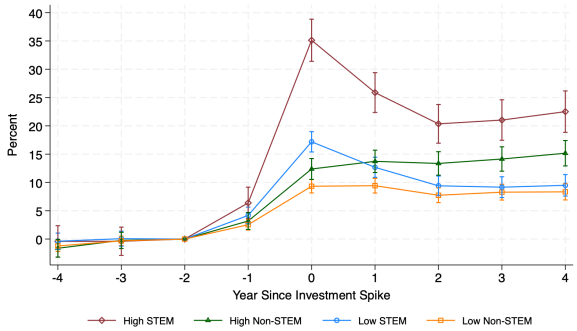


(b) Spikes Driven by Existing Suppliers

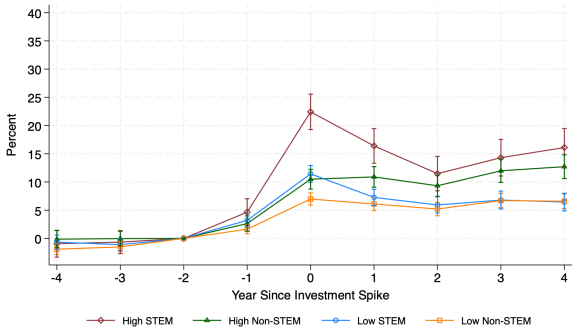


(ii) Other Industries

(a) Spikes Driven by New Suppliers



(b) Spikes Driven by Existing Suppliers



Notes: This figure decomposes the external employment response from Figure 7 (main text) by supplier industry: machine suppliers (Panel (i)) and other industries (Panel (ii)). Subpanels (a) focus on spikes driven by new suppliers; Subpanels (b) focus on spikes driven by existing 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.

D.5 Supply-Side Evidence

This appendix provides supporting material for the supply-side evidence in Section 4.5.

Figure D.11 documents that each investing firm's demand for capital-complementary high-STEM labor is small in absolute terms, supporting the fixed-cost rationale for outsourcing. Even summing across all of its suppliers, the median spiking firm sources only 0.05 high-STEM full-time equivalents (FTEs) in the year of the investment spike, far be-

low a single FTE (arguably the minimum feasible employment quantity for an in-house integration role). Even at the 90th percentile of the distribution, external high-STEM demand reaches only 0.77 FTEs, still well below one full-time worker. This suggests that no single investing firm's demand is large enough to justify dedicated in-house integration capacity at minimum efficient scale.

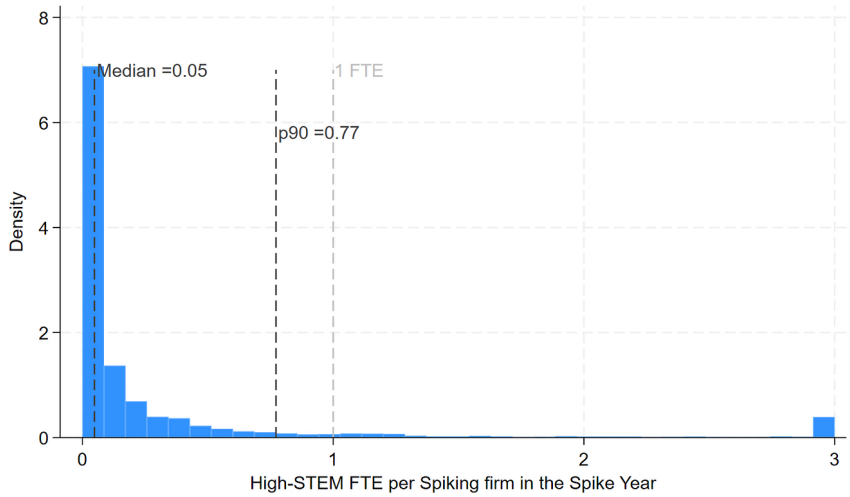
Figure D.12 documents that machine suppliers absorb the lumpy demand of individual investing firms by spreading their workforce across many uncorrelated clients, supporting the adjustment-cost rationale. The figure plots machine suppliers' absolute year-over-year changes in own high-STEM employment against the sum of their client-level absolute changes in the same quantity. Both quantities are scaled by the midpoint of the supplier's own high-STEM employment in the two adjacent years,[46] such that the x-axis runs between 0 and 2 by construction. If machine suppliers' workforce volatility were a one-for-one reflection of their clients' demand changes, the binned means would lie on the 45-degree line. Instead, the relationship is roughly 15.4 times steeper: every 15.4 units of gross client-level volatility translate into only one unit of supplier-side volatility, with the difference absorbed by offsetting demand changes across the supplier's portfolio: one client's expansion absorbs another's contraction at the supplier level. To assess whether this workforce smoothing is especially pronounced at machine integrators, the figure also shows the corresponding pattern for non-machine suppliers serving spiking firms as a benchmark.

Table D.5 reports estimates of the relationship between machine suppliers' skill mix and the share of their revenue accruing from spiking-firm clients. Across all four skill groups, the estimated coefficients are economically and statistically close to zero: machine suppliers do not differentiate their workforce based on customer composition, consistent with a structurally specialized workforce. Machine suppliers also rely more on spiking-

[46] Davis and Haltiwanger (1992) use a similar midpoint normalization in measuring job creation and destruction.

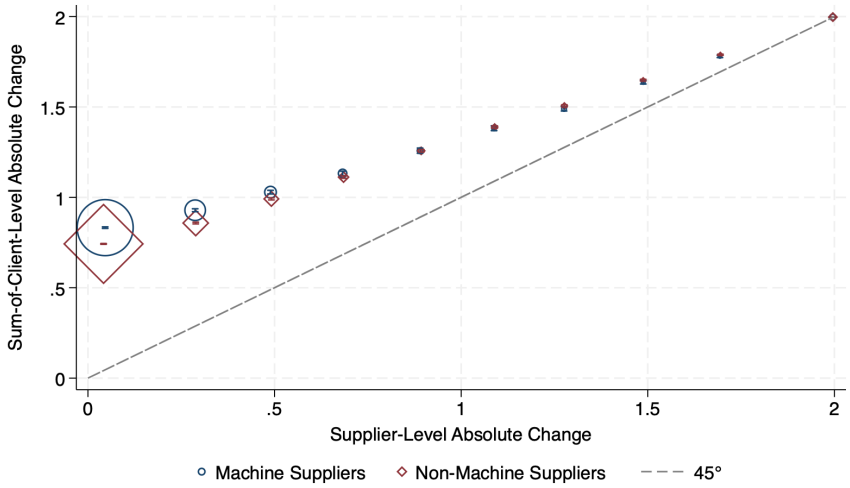
firm clients: they derive 1.76% of their revenue from these firms, more than double the 0.69% at non-machine suppliers.

Figure D.11: External High-STEM Labor per Spiking Firm



Notes: This figure shows the distribution of external (indirect) high-STEM employment at spiking firms in the spike year, summed across all of the firm's suppliers (not only its machine suppliers). The vertical reference line marks one full-time equivalent (FTE), an arguable minimum efficient scale for an in-house integration role. The median is 0.05 FTEs and the 90th percentile is 0.77 FTEs, both well below one FTE. *Sample*: Spiking firms; year of investment spike.

Figure D.12: Workforce Smoothing at Machine Suppliers



Notes: This binned scatter plots, at the supplier-year level, the supplier's absolute change in high-STEM employment from year $t-1$ to year t (x-axis, normalized by the midpoint of the two years) against the sum across the supplier's clients of absolute year-on-year changes in their high-STEM labor allocations (y-axis, with the same supplier-midpoint denominator). Bins have fixed width, and marker size is proportional to total high-STEM machine-supplier employment ($\bar{S}$) in the bin. The 45-degree reference line corresponds to perfectly correlated client demand changes; points above 45 degrees indicate smoothing. The weighted-average ratio of the y- to x-axis quantities (weighting bins by $\bar{S}$) is 15.4 for machine suppliers. Non-machine suppliers serving spiking firms are shown as a benchmark. *Sample*: Belgian machine and non-machine suppliers, 2003–2021.

Table D.5: Skill Mix Stability across Customer Mixes (Machine Suppliers)

	High STEM	High Non-STEM	Low STEM	Low Non-STEM
	(1)	(2)	(3)	(4)
Spiking-Client Revenue Share (%)	.0018	−.0012	−.0012	.0006
	(.0042)	(.0067)	(.0048)	(.0063)
Mean of dep. var. (%)	13.3	22.8	23.0	40.9
Supplier FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	257,332	257,332	257,332	257,332

Notes: This table reports estimates from supplier-year-level regressions of machine suppliers' skill-group employment shares on the share of their revenue accruing from spiking-firm clients. The spiking sample includes all spikes for which total employment was larger than 5 FTEs before the first spike. Each column corresponds to a separate regression with a different dependent variable (employment share in the indicated skill group, in percent). The regressor of interest is the share of the supplier's revenue coming from spiking-firm clients in that year. All specifications include supplier and year fixed effects. Standard errors clustered at the supplier level are shown in parentheses. On average, machine suppliers derive 1.76% of their revenue from spiking-firm clients, compared to 0.69% at non-machine suppliers. *Sample*: Belgian machine supplier firms, 2003–2021.

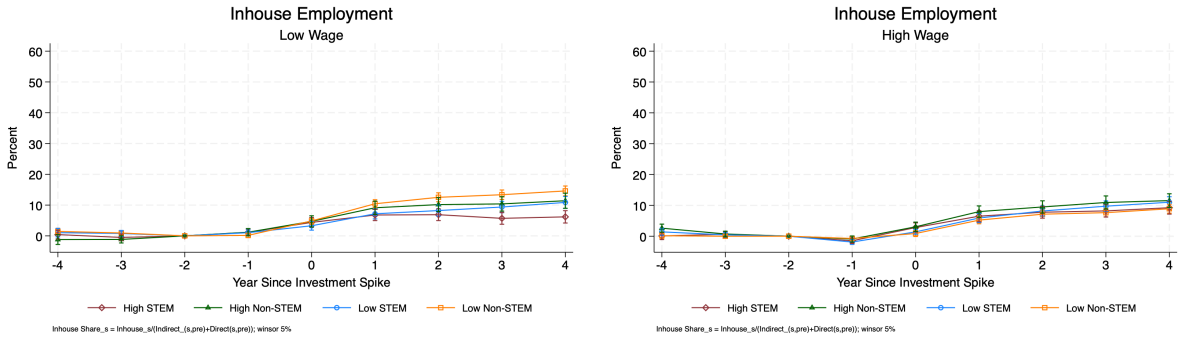
D.6 Wage-Savings Motive

Figure D.13 shows in-house and external employment by skill group around machinery investment spikes, split by whether the investing firm's residualized pre-spike wages are above or below the sample median. A wage-savings motive would predict that higher-wage firms outsource more, as they have more to save by sourcing capital-complementary labor externally. We find the opposite: lower-wage firms display, if anything, a *larger* external high-STEM skill bias. This pattern partly reflects that lower-wage firms are also smaller, which Section 4.1 documents are more likely to outsource their capital-complementary skills. Either way, the evidence weighs against wage savings as the primary driver of the outsourcing we document.

Figure D.13: Employment by Pre-Spike Investing-Firm Wage
(Diff-in-Diffs, In Percent of Pre-Spike Total Employment by Skill Group)

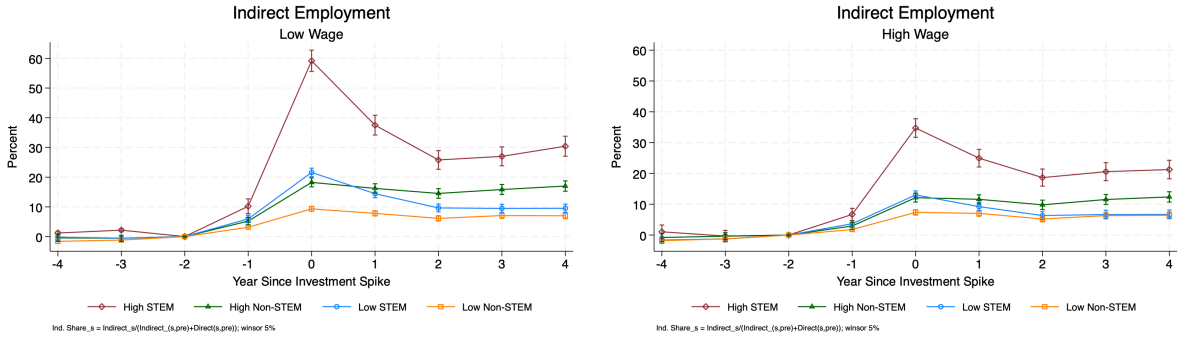
(a) In-House: Below-Median Wage

(b) In-House: Above-Median Wage



(c) External: Below-Median Wage

(d) External: Above-Median Wage



Notes: This figure shows in-house and external employment by skill group around machinery investment spikes, split by whether the investing firm has residualized pre-spike wages above or below the sample median. Firms are split by residualized pre-spike wages: firm-level log wages are residualized on skill shares and year fixed effects (estimated on the unbalanced sample of spiking firms); the residual in the year before the spike is then compared to the median residualized wage in the balanced sample. The figures show 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 (Equation 7). *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

Table D.6 turns to the second part of the wage-savings analysis: a direct comparison of the wages paid by machine suppliers and by investing firms in the year before the spike. We regress log average firm wages on a machine-supplier indicator. Column (1) controls only for year fixed effects: machine suppliers pay 13.8% higher wages than investing firms. Column (2) adds controls for the firm's skill shares, isolating the wage gap for a comparable workforce composition: machine suppliers still pay about 3.6% higher wages.

This premium is the opposite of what a wage-savings motive would predict, and instead points to the efficiency gains from outsourcing to specialized suppliers (Section 4.6).

Table D.6: Wage Premia of Machine Suppliers vs. Investing Firms

	Dependent variable: log average wage	
	(1)	(2)
Machine supplier	.138***	.036***
	(.008)	(.007)
Year fixed effects	✓	✓
Skill share controls		✓
Observations	86,196	86,196

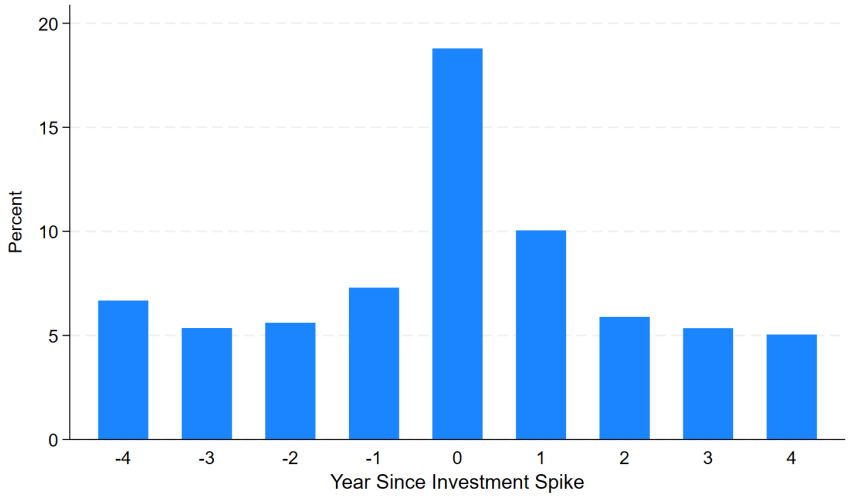
Notes: Sample consists of machine suppliers and firms that experience an investment spike, observed in the year preceding the spike. The sample is restricted to firms with more than five employees. Standard errors clustered at the firm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

E Robustness

E.1 Investment Spikes

Figure E.1 shows that the investment flow around a machinery spike is a one-off event: total fixed investment peaks at nearly 20% of sales in the spike year and returns to baseline within a few years, even as the machinery stock it produces remains elevated (Figure 1).

Figure E.1: Investment as a Share of Sales around Machinery Spikes



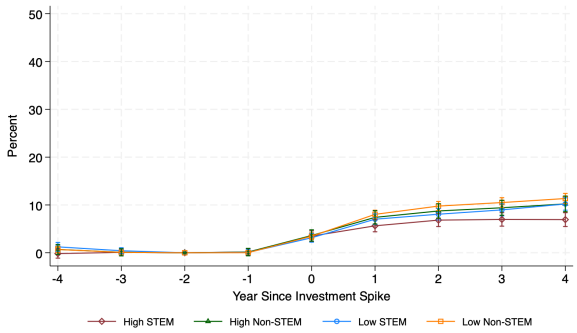
Notes: This figure plots total fixed investment as a share of total sales around machinery investment spikes (the VAT records do not split investment by asset type). Investment peaks in the spike year and returns to baseline within a few years, so the investment *flow* is a one-off event even as the machinery *stock* (Figure 1) remains elevated. *Sample*: Private sector firms around their first machinery investment spike. Balanced sample for four years before and after the spike.

Figures E.2 and E.3 show that our main findings are robust to varying the percentile cutoff for defining investment spikes. The 85th-percentile cutoff is €10,611 per worker and yields 5,539 spikes in the balanced panel; the 95th-percentile cutoff is €35,079 per worker and yields 1,826 spikes.

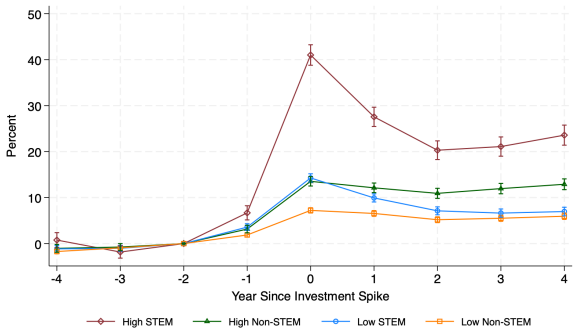
At both cutoffs, the qualitative pattern from Figures 2 and 3 carries through: machinery investment spikes raise the demand for high-STEM skills primarily through external suppliers, with the initial response driven by machine suppliers and the longer-run response by other industries.

Figure E.2: Employment around Machinery Spikes: 85th-Percentile Cutoff

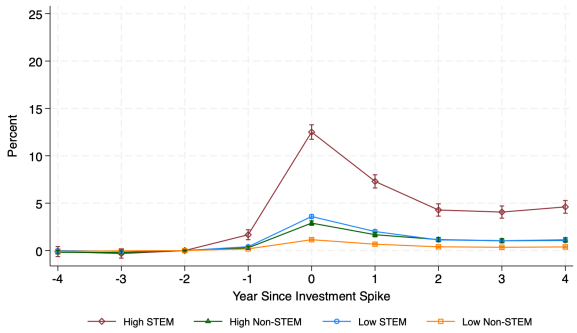
(a) In-House Employment



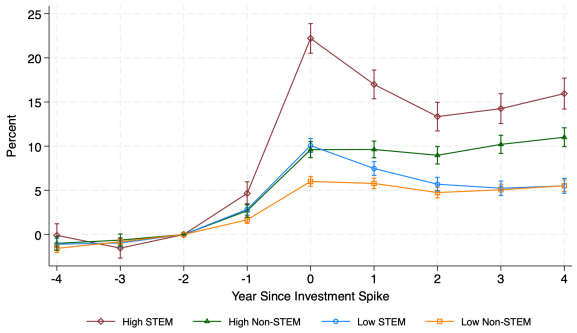
(b) External Employment



(c) Machine Suppliers



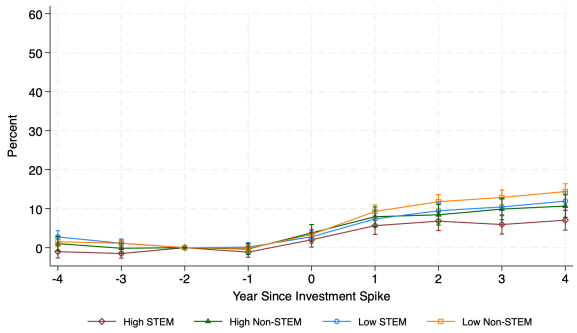
(d) Other Industries



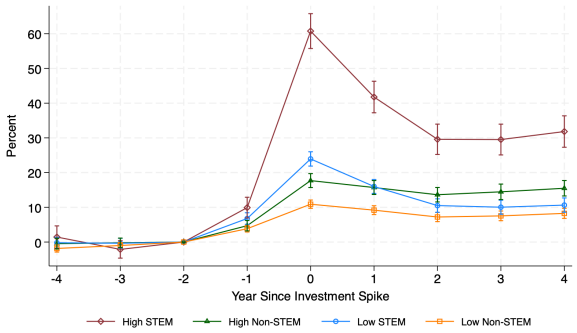
Notes: This figure reproduces the employment effects of machinery investment spikes using the 85th-percentile cutoff (€10,611 per worker). Panels (a) and (b) consider in-house and external employment, respectively; Panels (c) and (d) decompose external employment into machine suppliers and other industries. The figure shows 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 group (Equation 7). Total pre-spike employment is the sum of in-house and external 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. *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

Figure E.3: Employment around Machinery Spikes: 95th-Percentile Cutoff

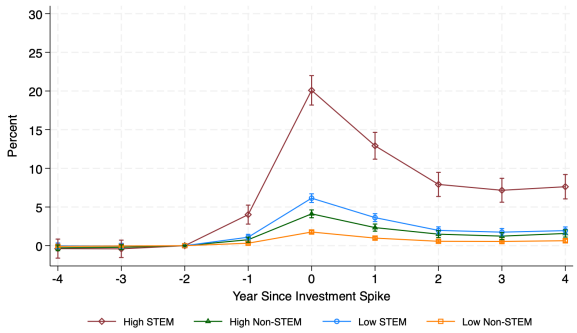
(a) In-House Employment



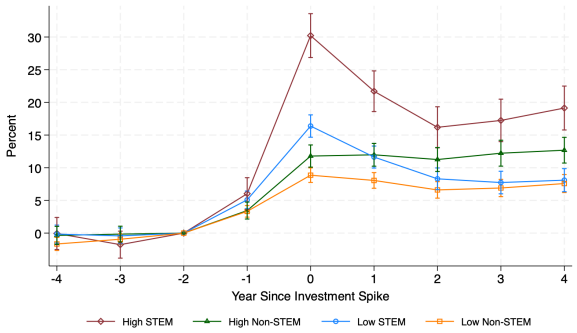
(b) External Employment



(c) Machine Suppliers



(d) Other Industries



Notes: This figure reproduces the employment effects of machinery investment spikes using the 95th-percentile cutoff (€35,079 per worker). Panels (a) and (b) consider in-house and external employment, respectively; Panels (c) and (d) decompose external employment into machine suppliers and other industries. The figure shows 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 group (Equation 7). Total pre-spike employment is the sum of in-house and external 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. *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

E.2 Single-Spiking Firms

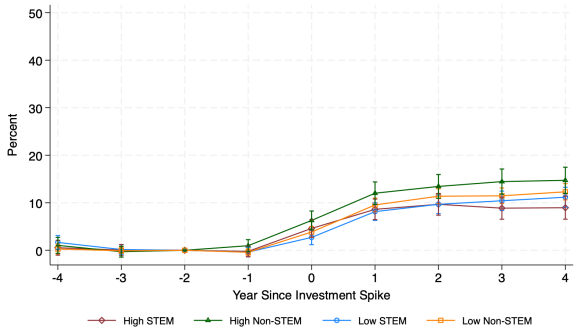
Figure E.4 reproduces the main employment effects of machinery investment spikes (Figures 2 and 3) restricting the sample to the 61% of firms that experience only one investment spike in the analysis window. The qualitative pattern is unchanged: in-house employment expands evenly across skill groups (Panel (a)), while external employment exhibits a sharp high-STEM bias (Panel (b)), driven by machine suppliers initially (Panel (c)) and by other industries over the longer run (Panel (d)). The quantitative estimates

are naturally closer to zero because we require the treatment group not to spike in the post-event window, while we place no such restriction on the matched control group.

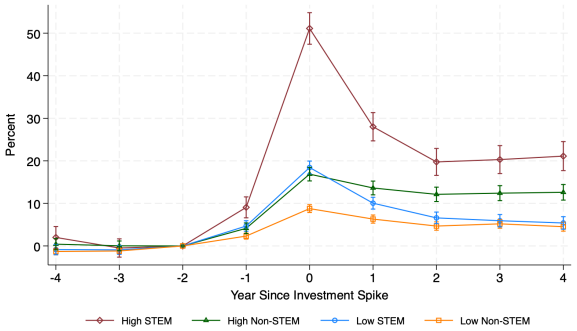
Figure E.5 shows that the external employment effects are quantitatively smaller for single-spiking firms than in the full sample, consistent with some growing firms in the full sample undertaking follow-on investments during the post-spike window.

Figure E.4: Single-Spiking Firms: Employment around Machinery Spikes

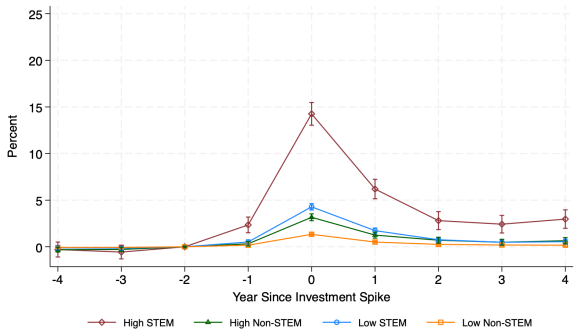
(a) In-House Employment



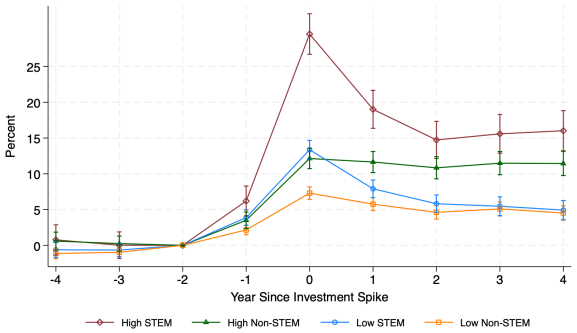
(b) External Employment



(c) Machine Suppliers

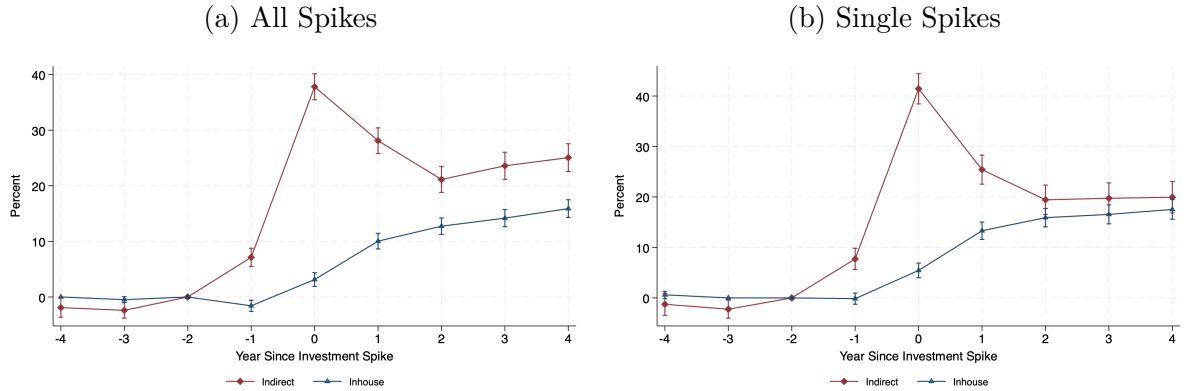


(d) Other Industries



Notes: This figure reproduces the employment effects of machinery investment spikes, restricting the sample to the 61% of firms that experience only one investment spike in the analysis window. Panels (a) and (b) consider in-house and external employment, respectively; Panels (c) and (d) decompose external employment into machine suppliers and other industries. The figure shows 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 group (Equation 7). Total pre-spike employment is the sum of in-house and external 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. *Sample*: Private sector firms around their only machinery investment spike. Balanced sample for four years before and after the spike.

Figure E.5: In-House and External Employment around Machinery Spikes: All Spikes versus Single Spikes

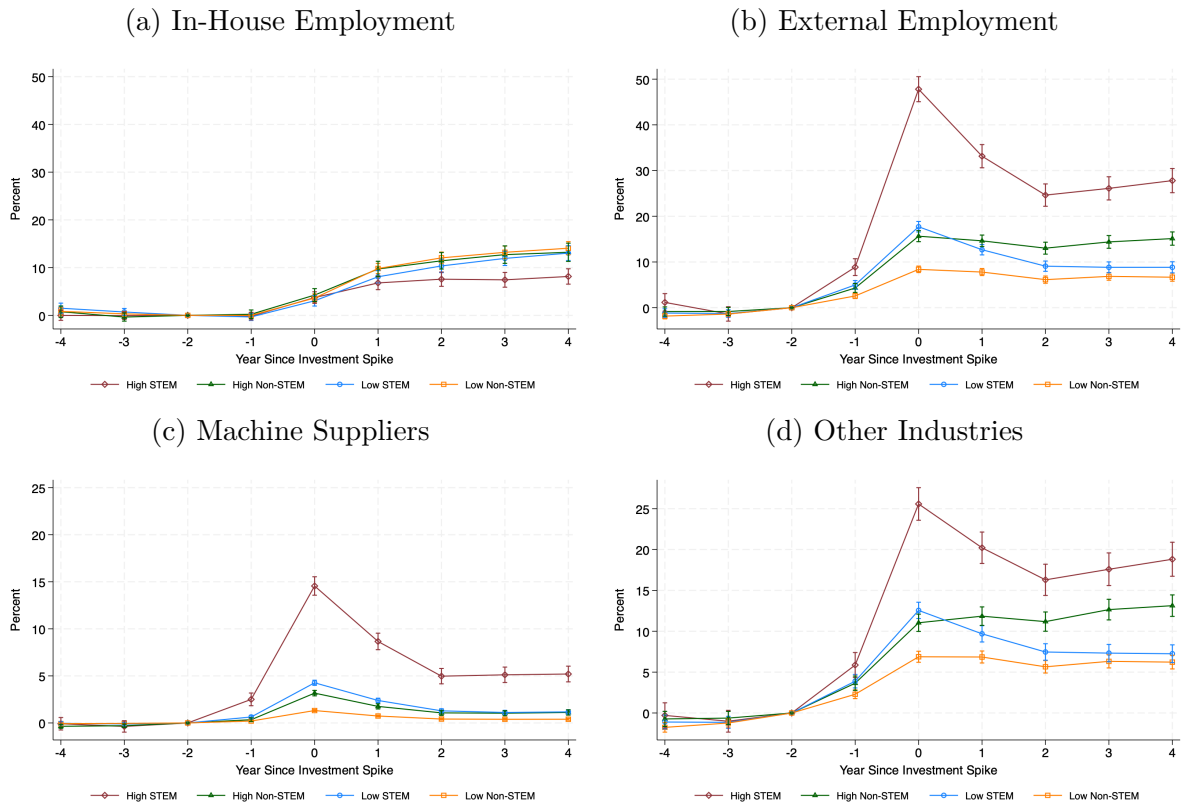


Notes: This figure shows in-house and external employment growth of private sector firms around machinery investment spikes. Panel (a) shows results for all spiking firms; Panel (b) restricts the sample to single-spiking firms. In-house employment is expressed in percent of pre-spike in-house employment; external employment is expressed in percent of pre-spike external employment. Pre-spike values are 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". *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.6 reproduces the main employment effects of machinery investment spikes (Figures 2 and 3), including firm exits as zero in-house and external employment. The qualitative pattern is unchanged: in-house employment expands evenly across skill groups (Panel (a)), while external employment exhibits a sharp high-STEM bias (Panel (b)), driven by machine suppliers initially (Panel (c)) and by other industries over the longer run (Panel (d)). The balanced-panel restriction in our main analysis is therefore not driving the result.

Figure E.6: Including Exiting Firms: Employment around Machinery Spikes



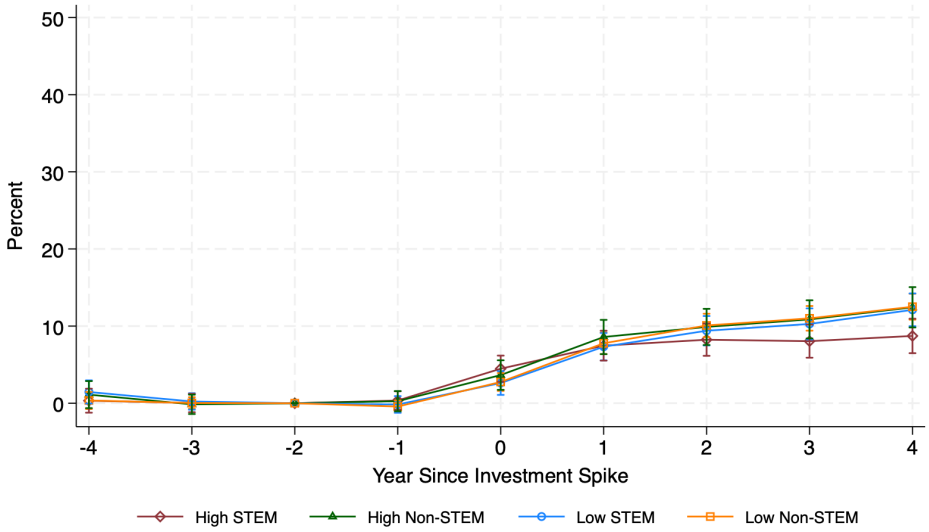
Notes: This figure reproduces the employment effects of machinery investment spikes, assigning zero employment to firm exits. Panels (a) and (b) consider in-house and external employment, respectively; Panels (c) and (d) decompose external employment into machine suppliers and other industries. The figure shows 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 group (Equation 7). Total pre-spike employment is the sum of in-house and external 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. *Sample*: Private sector firms around first machinery investment spike, active for four years before the spike.

E.4 Control Group

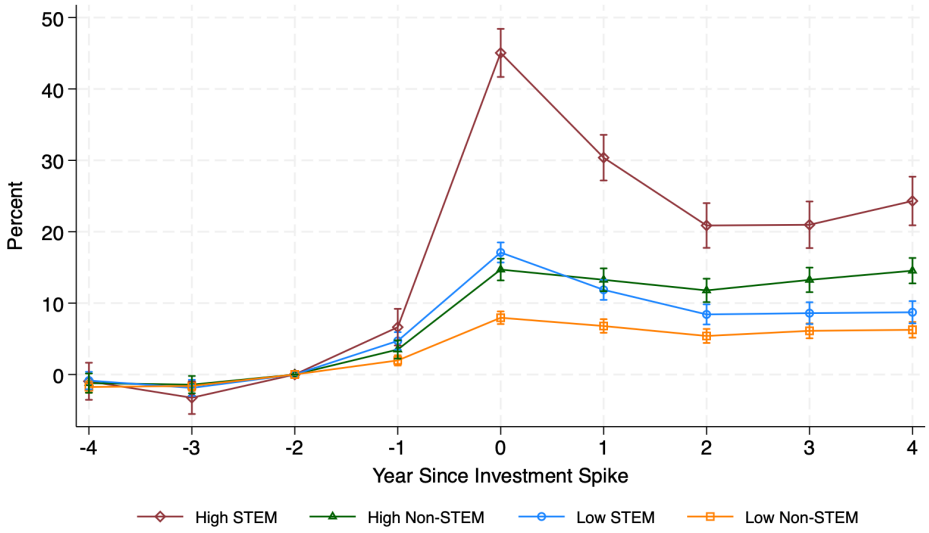
Figure E.7 reproduces the main employment effects of machinery investment spikes (Figure 2) using random one-to-one matching as the comparison group, in place of the average non-spiking firm in the same industry-year cell. For each spiking firm in year t, we randomly select one control firm from the same NACE 3-digit industry that has at least five employees in $t-1$, has not spiked before t, and is observed for the full event-study window. The results are highly similar to the baseline, with slightly larger standard errors.

Figure E.7: Employment of Skill Groups around Machinery Investment Spikes (Random One-to-One Matching)

(a) In-House



(b) External



Notes: This figure shows 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 group (Equation 7). Panel (a) considers in-house employment; Panel (b) considers external employment at supplier firms. Total pre-spike employment is the sum of in-house and external 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". The "non-spiking firms" are random one-to-one matches within the same industry-year cell. The estimates are based on the specification in Equation (6), 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.

E.5 Higher-Order Links

Our main analysis measures external employment through firms' direct (first-order) suppliers. This appendix extends the analysis to third-order links (the suppliers of suppliers of suppliers) to assess whether the broader network amplifies or attenuates our results. We compute third-order external employment as

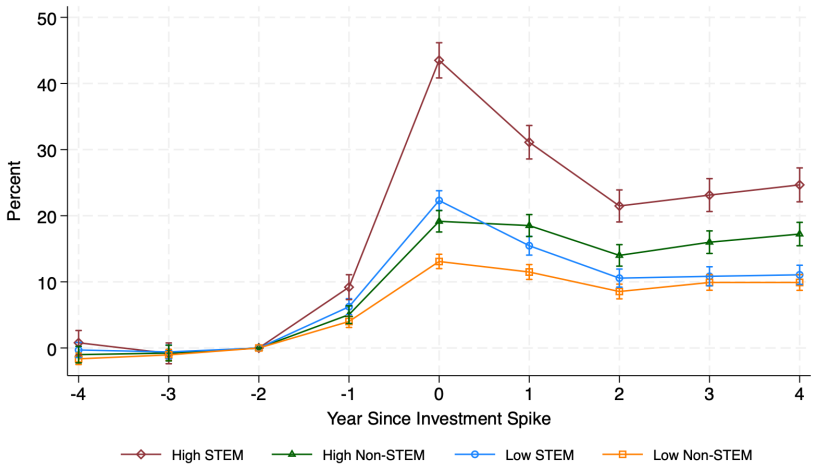
$$\mathbf{L}_{jt}^{O,3} = \sum_{k} \frac{X_{kjt}}{X_{kt}} \left(\mathbf{L}_{kt}^{H} + \sum_{r} \frac{X_{rkt}}{X_{rt}} \left(\mathbf{L}_{rt}^{H} + \sum_{s} \frac{X_{srt}}{X_{st}} \mathbf{L}_{st}^{H} \right) \right), \tag{21}$$

which iterates the first-order pass-through of in-house employment along the supply chain.

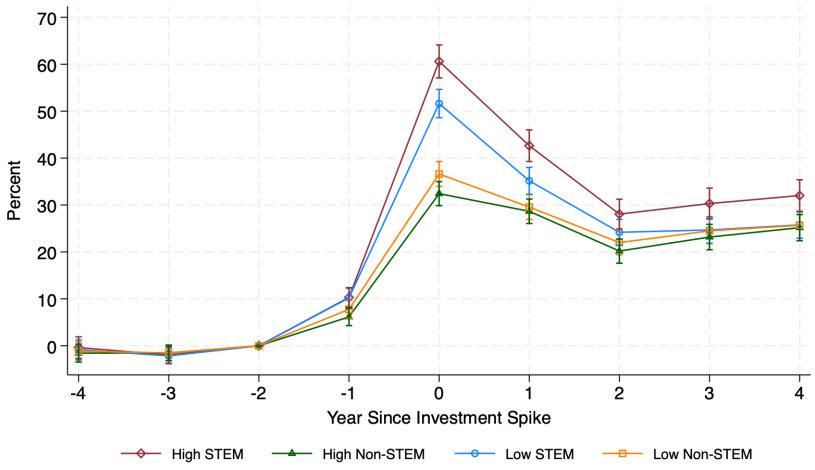
Figure E.8 shows that our main findings are robust to including these higher-order links. Panel (a) reproduces the main external employment effects (Figure 2) and Panel (b) reproduces the share-shift decomposition (Figure C.3), each measured using the third-order definition. If anything, incorporating higher-order links amplifies the quantitative importance of external employment relative to in-house hires.

Figure E.8: Including Higher-Order Supplier Links (Third-Order Definition)

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



(b) External Employment in Percent of Pre-Spike *External* Employment by Skill Group (Higher-Order Version of Figure C.3)



Notes: This figure shows third-order external employment growth around machinery investment spikes. Panel (a) shows external employment in percent of pre-spike total employment by skill group. Panel (b) shows external employment in percent of pre-spike external employment by skill group. Pre-spike values are 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". *Sample*: Private sector firms around first machinery investment spike. Balanced sample for four years before and after the spike.

F Aggregate Implications

This section describes our approach to aggregating the firm-level estimates to economy-wide implications for the private sector labor market, matching the scope of our investment-spike event studies. We follow a simple two-step sufficient-statistics approach. As in Krusell et al. (2000), we assume the underlying driving force is a decline in machinery prices. Whereas they feed in directly measured price declines, we calibrate the price shocks to drive the entire observed rise in aggregate machinery per worker. First, we scale our firm-level difference-in-difference estimates by the aggregate change in machinery stocks and investments to obtain the *partial-equilibrium aggregate demand shift*: the proportional change in aggregate skill-s labor demand that would prevail if wages remained at their initial levels (Section F.1). Second, we close the model in general equilibrium by allowing the wage of skill-s labor to adjust, splitting the partial-equilibrium shift between aggregate employment growth and skill-premium growth (Section F.2).

We assume each firm takes the market wage for each skill group as given: the wage is set by the broader market, not by the firm's own hiring. When firms invest, skill-s employment rises in two places: at investing firms, which take on more workers, and at their external suppliers, which take on workers to deliver the new services. Because these are different employers, summing the two effects gives the total partial-equilibrium shift in Equation (24) without double-counting. Section F.1 carries out this aggregation by scaling up our firm-level estimates.

By embedding our firm-level estimates in a general-equilibrium framework, our approach addresses the "missing intercept" problem of Moll (2021). The approach of Autor, Dorn and Hanson (2013) and Mian and Sufi (2014) corresponds to the polar case of perfectly elastic skill supply ($\varepsilon_s^S = \infty$), in which the entire partial-equilibrium shift translates into aggregate employment; the approach of Krusell et al. (2000) corresponds to the other

polar case of perfectly inelastic supply ($\varepsilon_s^S = 0$), in which it manifests entirely as wage growth.[47]

F.1 Partial-Equilibrium Aggregate Shift

Building on our conceptual framework in Section 1, we distinguish between *integration* and *production* labor. Integration labor is employed to install new machinery, while production labor captures changes associated with the expanded stock of machinery capital. 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_{ms}^u denote the estimates for employment of skill group s (low non-STEM, low STEM, high non-STEM, high STEM) in stage $u \in \{P, I\}$ (production, integration) through mode $m \in \{H, O\}$ (in-house, external). 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 partial-equilibrium impact on aggregate demand for *production* workers of skill

[47] Berlingieri et al. (2026); Oberfield and Raval (2021) develop structural approaches to the aggregation problem by recovering the underlying firm-level substitution elasticities and aggregating them across heterogeneous firms. We instead begin from our reduced-form firm-level labor demand responses, scale them up to obtain partial-equilibrium aggregate shifts, and derive equilibrium implications for wages and employment by closing the labor market for each skill group. Both approaches capture the employment effects within the investing firm. Outside the firm, they capture complementary margins: we measure the labor sourced from external suppliers, while the structural aggregation adds the reallocation of activity across firms of differing capital intensity.

group s sourced through mode m is:

$$\mathcal{B}^{P}_{ms} = \beta^{P}_{ms} \times \frac{\Delta M}{\beta_M}. \tag{22}$$

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

$$\mathcal{B}^{I}_{ms} = \beta^{I}_{ms} \times \delta \times \frac{\Delta M}{\beta_M}. \tag{23}$$

The factor δ reflects that integration labor is associated with the ongoing investment flow $\Delta I = \delta\,\Delta M$ needed to sustain the higher steady-state stock, rather than with the stock itself.

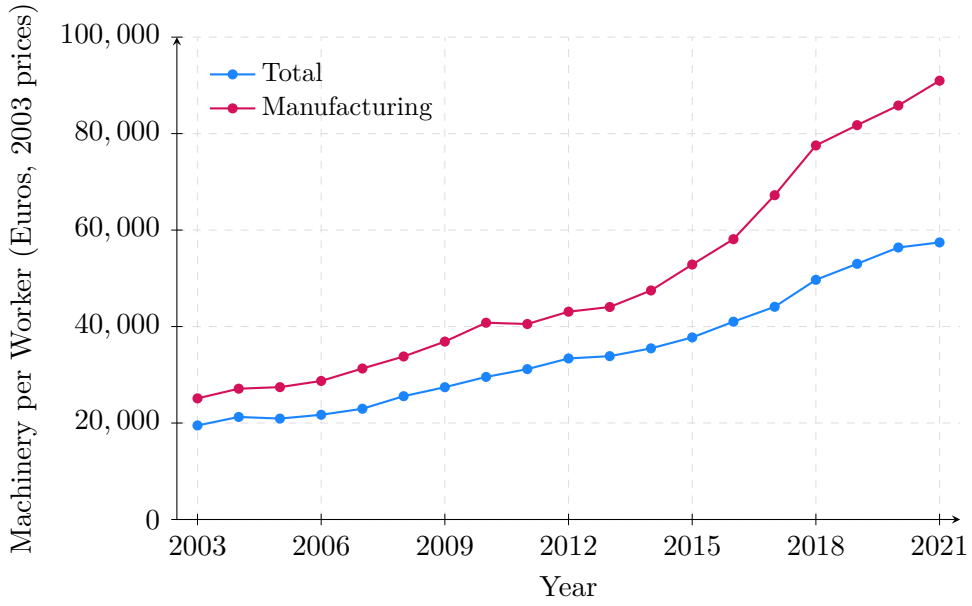
The total partial-equilibrium demand shift (the change in aggregate skill-s demand at the initial wage), summed across modes and stages, is:

$$\Delta \ln L^{\mathrm{PE}}_{s} = \mathcal{B}^{P}_{Hs} + \mathcal{B}^{P}_{Os} + \mathcal{B}^{I}_{Hs} + \mathcal{B}^{I}_{Os}. \tag{24}$$

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 of €45,000, the year-0 difference-in-differences estimate for machinery per worker (€45,100 pooled across spiking firms; Figure D.2 shows the estimates by firm size)
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).

Figure F.1: Aggregate Machinery Per Worker



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

Table 3, Columns (1)–(3) report the resulting partial-equilibrium shifts for each skill group expressed relative to low non-STEM workers, i.e., $\mathcal{B}^u_{ms} - \mathcal{B}^u_{m\text{Low-Non}}$. The total partial-equilibrium skill bias for high-STEM workers, relative to low non-STEM, is 20.5 percentage points. We focus on differentials relative to low non-STEM throughout. By the linearity of the partial-equilibrium scaling and the general-equilibrium formulas, applying these equations to the differentials yields the corresponding differentials in employment and wages directly. The aggregate-employment and wage responses derived in Section F.2 therefore represent skill bias and skill-premium growth, respectively.

F.2 General-Equilibrium Implications

We now let the skill-s wage adjust to clear the aggregate market for skill-s labor, which encompasses both in-house and external employment; external suppliers ultimately hire from the same skill pool as in-house employers, so their expansion competes for the same

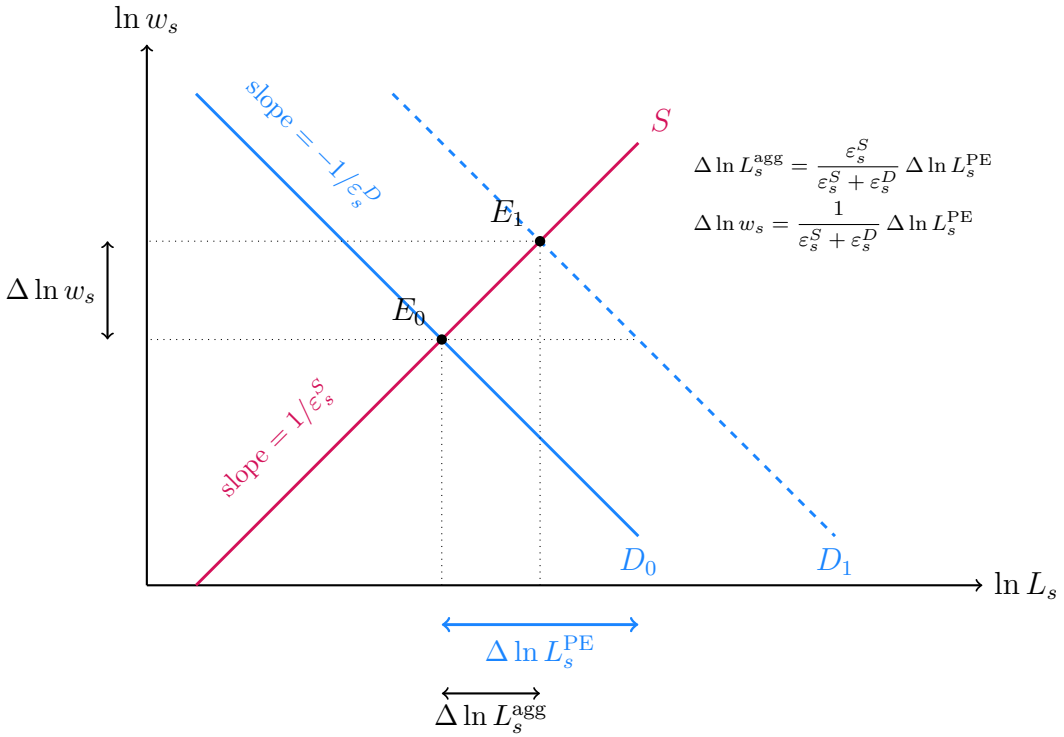
workers. Let ε_s^S denote the elasticity of aggregate skill-s labor supply, and let ε_s^D denote the (absolute) elasticity of skill-s labor demand with respect to its wage. Equating supply and demand gives:

$$\Delta \ln L_s^{\text{agg}} = \frac{\varepsilon_s^S}{\varepsilon_s^S + \varepsilon_s^D} \times \Delta \ln L_s^{\text{PE}}, \tag{25}$$

$$\Delta \ln w_s = \frac{1}{\varepsilon_s^S + \varepsilon_s^D} \times \Delta \ln L_s^{\text{PE}}. \tag{26}$$

The partial-equilibrium demand shift thus splits between aggregate employment expansion—a share $\varepsilon_s^S/(\varepsilon_s^S + \varepsilon_s^D)$ of the partial-equilibrium total—and skill-premium growth. Mechanically, the wage rise reduces non-spiking firms' demand for skill-s labor, so the wage response also captures the share of the spiking firms' apparent gains that comes via reallocation across firms (poaching workers from competitors and reorienting external suppliers' capacity away from non-spiking firms). Figure F.2 illustrates this adjustment graphically.

Figure F.2: General-Equilibrium Adjustment in the Skill Labor Market



Notes: Illustration of the general-equilibrium adjustment in the aggregate market for skill-s labor. The partial-equilibrium aggregate demand shift $\Delta \ln L_s^{\text{PE}}$ shifts the demand curve rightward from D_0 to D_1. The new equilibrium E_1 implies an aggregate employment response $\Delta \ln L_s^{\text{agg}}$ smaller than the partial-equilibrium shift, with the residual absorbed by skill-premium growth $\Delta \ln w_s$. The figure is drawn for the central calibration $\varepsilon_s^S = \varepsilon_s^D$, in which the two responses are equal in size.

Polar cases. The polar case of perfectly elastic skill supply ($\varepsilon_s^S \to \infty$) implies that the partial-equilibrium shift translates fully into aggregate employment and wages do not respond. This recovers the approach of Autor, Dorn and Hanson (2013) and Mian and Sufi (2014), commonly used to aggregate firm-level estimates in the literature on local labor market shocks. The opposite polar case of perfectly inelastic supply ($\varepsilon_s^S = 0$) implies that aggregate employment is unchanged and the entire impact materializes through wages, recovering the approach of Krusell et al. (2000) in which capital–skill complementarity manifests as rising relative wages of skilled workers rather than rising relative employment.

Time horizon and calibration. Our aggregation considers the rise in machinery stocks over a two-decade horizon (Figure F.1), so the relevant supply elasticity is a medium- to long-run object—the horizon over which students choose STEM majors in response to wage premiums, immigration adjusts, and training programs scale up.[48] The elasticity of substitution between high- and low-skill labor (which determines ε_s^D) is typically estimated at $\varepsilon_s^D \approx 1.5$ in the macro-labor literature (Goldin and Katz, 2008; Katz and Murphy, 1992; Krusell et al., 2000).[49] The skill labor supply elasticity ε_s^S is less precisely pinned down in the literature, which typically takes observed supply paths as exogenous when decomposing skill-premium dynamics (Goldin and Katz, 2008; Katz and Murphy, 1992). We set $\varepsilon_s^S = \varepsilon_s^D = 1.5$ as a natural baseline and treat ε_s^S as the key parameter in the sensitivity analysis. Under this central calibration, half of the partial-equilibrium demand shift translates into aggregate employment growth, with the remainder absorbed by skill-premium growth. Table F.1 reports the high-STEM aggregate skill bias and the corresponding skill-premium response across a grid of ε_s^S values, holding $\varepsilon_s^D = 1.5$ fixed and applying the formulas to the partial-equilibrium total of 20.5 percentage points from Table 3.

[48]The partial-equilibrium shift identified by our firm-level difference-in-differences, by contrast, is robust to short-run general-equilibrium adjustment in skill labor markets: any wage response within the four-year estimation window affects spiking and non-spiking firms symmetrically and differences out of the estimand.

[49]This anchor also converts the elasticity *ratio* of Appendix A.3 into levels: with $\sigma_{HU} \approx 1.5$ and $\sigma_{HU}/\sigma_{KS} \approx 1.6$, the implied inner elasticity is $\sigma_{KS} \approx 0.9$, so that machinery and high-STEM labor combine in a roughly Cobb–Douglas fashion at the firm level.

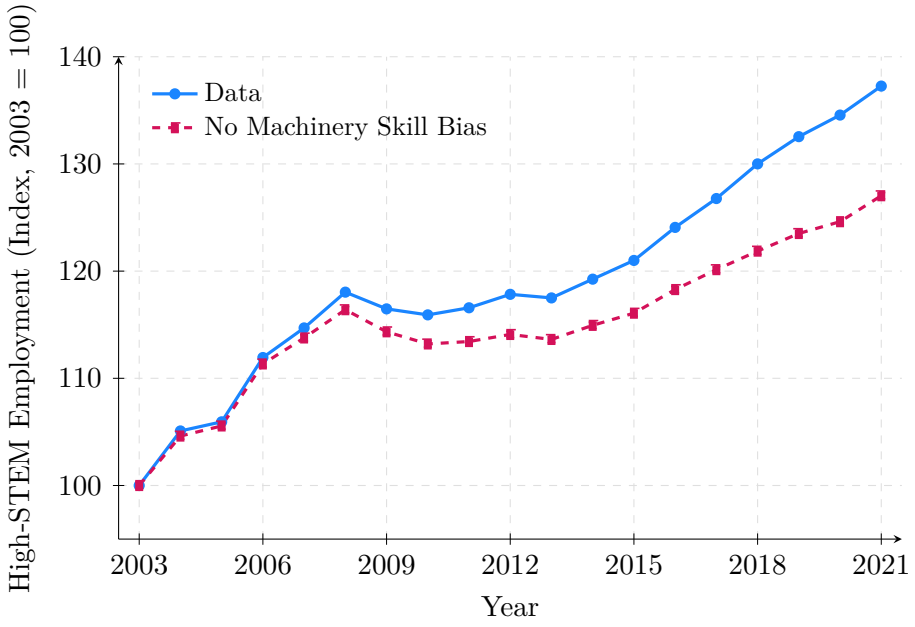
Table F.1: General-Equilibrium-Adjusted Aggregate Skill Bias for High-STEM Workers

ε_s^S	Employment Bias (pp)	Skill Premium (pp)
∞	20.5	0.0
4.50	15.3	3.4
1.50	10.2	6.8
0.50	5.1	10.2
0	0.0	13.6

Notes: This table reports the general-equilibrium-adjusted aggregate skill bias from new machinery for high-STEM workers, expressed relative to low non-STEM workers, across a grid of skill labor supply elasticity values ε_s^S. We hold the absolute labor demand elasticity fixed at $\varepsilon_s^D = 1.5$ throughout (Katz and Murphy, 1992; Krusell et al., 2000). The polar case $\varepsilon_s^S \to \infty$ recovers the approach of Autor, Dorn and Hanson (2013) and Mian and Sufi (2014) (the partial-equilibrium total from Table 3); the polar case $\varepsilon_s^S = 0$ recovers the approach of Krusell et al. (2000). See Equations (25)–(26).

Counterfactual. To put these magnitudes in perspective, Figure F.3 plots the counterfactual evolution of high-STEM employment in the absence of skill bias from machinery, under our central calibration ($\varepsilon_s^S = \varepsilon_s^D = 1.5$). This exercise indicates that machinery skill bias accounts for approximately 10 of the 37 percentage point rise in high-STEM employment since 2003, with the remainder of the demand impact showing up as growth in skill premiums.

Figure F.3: 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—setting the partial-equilibrium skill bias of high-STEM workers (relative to low non-STEM) to zero, applied under our central calibration of skill labor supply and demand elasticities ($\varepsilon_s^S = \varepsilon_s^D = 1.5$; see Table F.1).