Schooled by Trade?
Retraining and Import Competition *

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Abstract

Retraining is often hailed as a key policy tool for aiding displaced workers and smoothing the impact of sectoral shocks. We study the interaction of retraining and international trade in Germany, a highly open economy with extensive government-subsidized retraining programs. Using rich administrative data, we show that retraining is tightly linked to transitions across sectors and that workers retrain in response to rising import competition from China. We introduce retraining into a dynamic model of labor mobility across sectors embedded within a quantitative trade framework. Calibrated to match our empirical results, the model reveals that retraining lowers the cost of switching sectors costs by 28% and thus magnifies short-run rellocation. In the long run, however, retraining reduces the dispersion of welfare changes and thus the sectoral reallocation caused by the China shock.

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Introduction

International trade creates winners and losers, and a substantial literature points to a worker's sector of employment — and its exposure to import competition — as a key fault line (Dix-Carneiro 2014). But despite enormous interest from policymakers, relatively little is known about policies which might aid workers in declining sectors and ultimately blunt the uneven effects of trade. And with new sectoral shocks — from trade wars, supply chain disruptions, and the rollout of artificial intelligence — on the horizon, the need for policies that help workers and economies flexibly adjust will only grow.

We fill this gap by studying government-subsidized retraining in Germany, an open economy that has been at the front lines of the integration of China into the global economy. Using rich administrative data, we provide new evidence that retraining goes hand-in-hand with transitions across sectors and that workers use retraining to adjust to rising import competition from China. We then build a quantitative general equilibrium model of labor supply and international trade in which retraining eases worker transitions across sectors. As a result, retraining speeds up labor market adjustment in the short run. In the long run, however, retraining compresses worker option values, dampens aggregate sectoral shifts, and evens out the distributional effects of trade. Retraining thus offers an attractive proposition to policymakers concerned by the sluggish sectoral shifts the rising inequality that often accompany trade shocks.

German government-subsidized retraining operates via vouchers cashed in with private providers, whose courses provide both sector-specific skills and job-finding assistance. In the Sample of Integrated Labor Market Biographies (SIAB), we observe that retraining is common but brief: roughly a quarter of workers retrain over the course of their careers, and the median retraining spell lasts just under six weeks. Retraining is tightly linked to workers' most natural margin of adjustment to trade, namely switching sectors: even after controlling for a rich set of worker characteristics, workers who retrain are 36.7 percentage points more likely to switch sectors over the following decade than those who do not.

We next investigate how German workers use retraining to adjust to trade shocks by studying the sharp post-2000 increase in import competition from China. We find that manufacturing workers exposed to this "China shock" suffered relative declines in employment and earnings and, crucially, responded by switching to new sectors and by retraining. A one standard deviation increase in a sector's exposure to the China shock raises the probability that workers in that sector retrain by an economically-meaningful 8%. Together with the strong correlation between retraining and sector switching, we take this as suggestive evidence that retraining facilitates transitions across sectors.

The fact that the decisions to retrain and to switch sectors are made jointly, however, complicates the interpretation of this intuitive empirical link. We confront this identification challenge with a new theory that embeds the Gentzkow (2007) model of complementary choices in the dynamic sectoral choice framework of Artuç, Chaudhuri, and McLaren (2010). Workers face deterministic switching costs to enter a new sector and idiosyncratic shocks to their preferences for different

sectors. Our key innovation is that workers simultaneously decide whether or not to retrain, and the payoff to retraining depends on whether a worker enters a new sector. Our model is agnostic as to whether retraining yields greater or smaller gains for sector-switchers — instead, we allow the data to speak to the extent of complementarity versus substitutability.

In our analysis, we focus on the natural case in which retraining and switching are complements, and show that increases in the availability of retraining are in fact isomorphic to reductions in switching costs. Our model then highlights two key ways in which retraining helps economies cope with trade shocks.

First, just as in Artuç, Chaudhuri, and McLaren (2010), workers initially in adversely affected sectors nonetheless benefit from the option value of later switching to growing sectors. Retraining decreases the costs of such transitions, magnifies these option values, and thereby compresses the distribution of welfare effects across workers. In the aggregate, however, these shifts net out and leave the total gains or losses from the shock unchanged. Second, we show that retraining alters the pattern of employment reallocation caused by such a shock. Because it compresses the distribution of welfare changes across sectors, it also weakens workers' incentives to move and so dampens long-run employment changes. At the same time, because it lowers the costs of moving, it speeds up the transition towards the new steady state employment distribution. The net result is that in an economy with widespread retraining, trade shocks cause smaller employment shifts across sectors, and these shifts are completed more quickly.

To quantify the usefulness of retraining, we enrich our model with worker heterogeneity by age and skill, and then embed this description of the labor market within the quantitative trade framework of Caliendo and Parro (2015). Doing so allows us to connect our theory to our empirical evidence on the effects of the China shock and thus calibrate the model. We find – as expected – that retraining and sector-switching are complements. A worker who retrains faces switching costs that are 28% lower than one who does not, and as a result is roughly twice as likely to move to a new sector. We use our calibrated model to study the China shock under a range of retraining scenarios, from an economy with no retraining to one in which the aggregate retraining rate is three times its level in the data. Going from one extreme to the other compresses the standard deviation of welfare changes across workers by 17% and speeds up the post-shock transition, with the share of long-run employment reallocation completed within five years rising from 67% to 73%. The aggregate welfare gains from the China shock, on the other hand, are essentially unchanged. These effects are fairly modest, and those on employment reallocation in particular are strongly attenuated by general equilibrium forces: changes in real wages partly offset the direct effect of lower switching costs on labor mobility.

Expanding retraining is thus an attractive tool for policymakers concerned about the distributional consequences of international trade. Retraining compresses the distribution of changes in welfare and speeds up labor market adjustment, all without diminishing the aggregate gains from trade. At the same time, the magnitudes implied by our quantitative model are moderate: even with widely available retraining, some workers will inevitably lose from sectoral shocks. Retraining

is a useful complement to other adjustment policies, not a substitute for them.

Related Literature

An ever-growing set of papers, starting with Autor, Dorn, and Hanson (2013) in the US and W. Dauth, Findeisen, and Suedekum (2014) in Germany, studies inequality in the effects of trade shocks. The welfare effects of trade vary widely across sectors (W. Dauth, Findeisen, and Suedekum 2021), skill levels (Lee 2020; Traiberman 2019), space (Galle, Rodriguez-Clare, and Yi 2021), and even firms (Schott, Pierce, and Tello-Trillo 2020), in large part due to often-substantial barriers to worker mobility, e.g. the specificity of human capital (Dix-Carneiro 2014; Traiberman 2019; Caliendo, Dvorkin, and Parro 2019). In a similar vein, trade opening often increases the skill premium (Antràs, Gortari, and Itskhoki 2017; Lee 2020; Galle, Rodriguez-Clare, and Yi 2021). Our empirical results highlight a new margin of adjustment — retraining — and our quantitative model allows us to evaluate its usefulness in moderating the unequal effects of trade this literature has documented.

Simultaneously, a large empirical literature in labour economics evaluates the micro-level effects of worker training programs (McCall, Smith, and Wunsch 2016). While randomized experiments in developing countries find large causal effects on re-employment and firm switching (Alfonsi, Bandiera, et al. 2020; Alfonsi, Bassi, et al. 2024), meta analyses byKluve (2010) and Card, Kluve, and Weber (2010) find generally more modest effects. Studies in the German context have typically employed matching estimators (Fitzenberger and Speckesser 2007; Lechner and Wunsch 2009; Lechner, Miquel, and Wunsch 2011; Fitzenberger, Orlanski, et al. 2013) or estimated models of dynamic selection into retraining (Osikominu 2013; Biewen et al. 2014; Fitzenberger, Osikominu, and Paul 2023), again with mixed results. More recently, Humlum, Munch, and Rasmussen (2025) have used a judge-IV design to show that training programs in Denmark are effective in moving workers into employment, particularly in new occupations.

Finally, a growing strand of the literature studies the role of training as a margin of adjustment to labor market shocks. Empirically, Hyman (2018) exploits quasi-random caseworker assignment to identify the earnings effects of Trade Adjustment Assistance (TAA) subsidies in the US, Schulze (2024) studies community college enrollment during the Great Recession, and Humlum, Munch, and Rasmussen (2025) show that training is particularly beneficial for Danish workers in sectors exposed to offshoring. Smeets, Tian, and Traiberman (2025) and Adachi and Skipper (2025) both embed educational choices — by college students entering the labor market for the first time, and by adults entering long vocational training programs, respectively — in dynamic discrete choice models and explore how they shape the effects of labor market shocks. In contrast, we contribute a general equilibrium framework centered around the simultaneous decision to retrain and switch sectors. As a result, we can quantify how retraining alters the welfare effects of trade or other sectoral shocks, taking into account changes in prices and wages.

Outline

The remainder of the paper proceeds as follows. Section 1 describes the data and the institutional context of retraining in Germany. Section 2 presents our main empirical results on the interaction of import competition and retraining. Section 3 develops a theory of retraining, labor mobility, and trade. Section 4 calibrates the model's key parameters, and Section 5 uses the model to perform counterfactual experiments. Finally Section 6 concludes.

1 Retraining in Germany

German workers benefit from comprehensive government-sponsored retraining programs. In this section, we introduce the administrative labor market data with which we measure retraining and then discuss the institutional details of retraining in Germany.

1.1 Data

We observe workers' labor market outcomes and characteristics in the weakly anonymous version of the German Sample of Integrated Labour Market Biographies (SIAB) 1975-2021 (Graf et al. 2023).[1] The SIAB draws a 2% sample from Germany's primary administrative employment records, known as the Integrated Employment Biographies (IEB). The resulting worker-level panel records, for each worker and month between 1975 and 2021, all active employment spells, unemployment benefits, and participation in "active labor market policies" such as retraining (Schmucker, Seth, and Berge 2023).

To compute workers' trade exposure, we combine this labor market data with trade flows from the UN's Comtrade Database.[2] Following Autor, Dorn, and Hanson (2013) and W. Dauth, Findeisen, and Suedekum (2021), we focus on trade flows between China and Germany and, for identification, additionally draw on trade flows between a number of other high-income countries and China. Appendices A.1-A.2 further discuss the details of each data source as well as our cleaning and preparation procedures.

1.2 Institutional Context

The German Federal Employment Agency (BA) manages a variety of active labor market policies to support workers' employment prospects. These policies target workers across all career stages and regardless of their current employment status (C. Dauth 2020; Fitzenberger, Osikominu, and Paul 2023).

We focus on three categories of programs which we collectively define as *retraining* and which comprise two-thirds of active labor market policy episodes during our sample period. First,

[1] Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently via remote data access.

[2] https://comtradeplus.un.org.

Table 1: Retraining Curriculum Examples

Topic	*High-voltage fundamentals for electric vehicles*	*Career change: vehicle technology*
Provider	TÜV Rheinland Academy	TÜV Rheinland Academy
Length	1–4 weeks	3–6 months
Prerequisites	Interest in electric mobility	Interest in vehicle technology, ideally with initial experience
Degree Obtained	Completion certificate	Completion certificate
Cost with Subsidy	0	0
Contents	• Lithium-ion battery systems • Power converter applications • Hybrid and electric drivetrains • Charging technologies • Electrical hazards and safety • Relevant laws and regulations • Practical component	• Local job, training opportunities • Vehicle maintenance and repair • Safety inspections • Defect identification • Custom features and accessories • Driver assistance systems • Connected vehicle systems • Applied mathematics • Technical German vocabulary

Notes: Table reproduces summary curricula for two courses for which workers could use government-provided retraining vouchers. Both example courses are drawn from among the offerings of TÜV Rheinland Akademie GmbH, a nationwide private provider of worker training courses. Sources: Grundlagen Hochvolttechnik and Berufseinstieg Fahrzeugtechnik.

activation and vocational integration measures match workers with jobs and provide necessary skills, from job application training to foreign language classes, to re-enter the labor market. Second, *career choice and vocational training* programs offer career advising and tutoring as well as government-sponsored internships (Bundesagentur für Arbeit 2021a; Roesler et al. 2021). Third, *vocational retraining and further education* programs range from short job search or computer skills courses to year-long training in more general occupational skills, e.g. marketing (Osikominu 2013; Biewen et al. 2014).[3]

After a series of market-based reforms in the 1990s, German retraining programs typically operate via "Bildungsgutschein" vouchers. Workers receive vouchers through registration with the Employment Agency, whose caseworkers conduct an initial interview and assessment (Fitzenberger, Osikominu, and Paul 2023). Both employed and unemployed workers can qualify, as caseworkers apply broad eligibility criteria which require only a risk of unemployment, missing qualifications, or poor chances of re-employment (Kruppe 2008). In some cases, caseworkers may require unemployed workers to participate in retraining as a condition of receiving unemployment benefits. In

[3]These three program types correspond to the *erwstat* codes 10001 (activation and vocational integration), 10002 (career choice and vocational training), and 10003 (vocational retraining and further education) in the Participants-In-Measures History File (MTH/XMTH) portion of the SIAB. Note that the SIAB includes only retraining episodes starting in 2000 or later, so we restrict our worker panel to the post-2000 period.

practice, participation is often largely voluntary, as the Employment Agency frequently tolerates dropouts (Fitzenberger, Osikominu, and Paul 2023).[4] Subject to typically-mild caseworker-imposed restrictions on training content and sector, recipients can choose any certified private training provider (C. Dauth 2020; Fitzenberger, Osikominu, and Paul 2023). The voucher then covers the direct costs of training as well as ancillary expenses such as transportation, and workers receive unemployment benefits for the duration of the program (Bundesagentur für Arbeit 2021b).

Table 1 summarizes the curricula of two such courses, both offered by TÜV Rheinland Akademie, a regional private training provider. The first, a short course on high-voltage fundamentals for electric vehicles, targets workers already employed in the automotive sector and covers the geography of job opportunities, the fundamentals of EV batteries and charging, and safety practices over the course of one to four weeks. The second, a multi-month vehicle technology career entry program, serves workers retraining into the automotive sector from other industries. The three-to-six-month curriculum spans vehicle maintenance, diagnostics, new features at the frontier of automotive technology, and technical German vocabulary. Note that, like most German retraining courses, these examples encompass a mix of basic job search support and substantive, job-specific technical skills, and the aforementioned retraining vouchers would cover the full cost of either.

1.3 Four Retraining Facts

We now lay out four key facts to contextualize the role of retraining in the German labor market, and explain how they inform the model that will follow in Section 3. Appendices A.1 and A.3 detail the underlying data.

Retraining is widespread. On average, 3.3% of German workers in our sample retrain each year, and, over a lifetime, a full 23% will have completed a retraining course at some point. Roughly 13% of workers in our sample retrain more than once. Importantly, 74.9% of retraining spells coincide with non-employment: our model will allow employed and non-employed workers to face distinct retraining costs and thus generate different retraining rates by employment status.

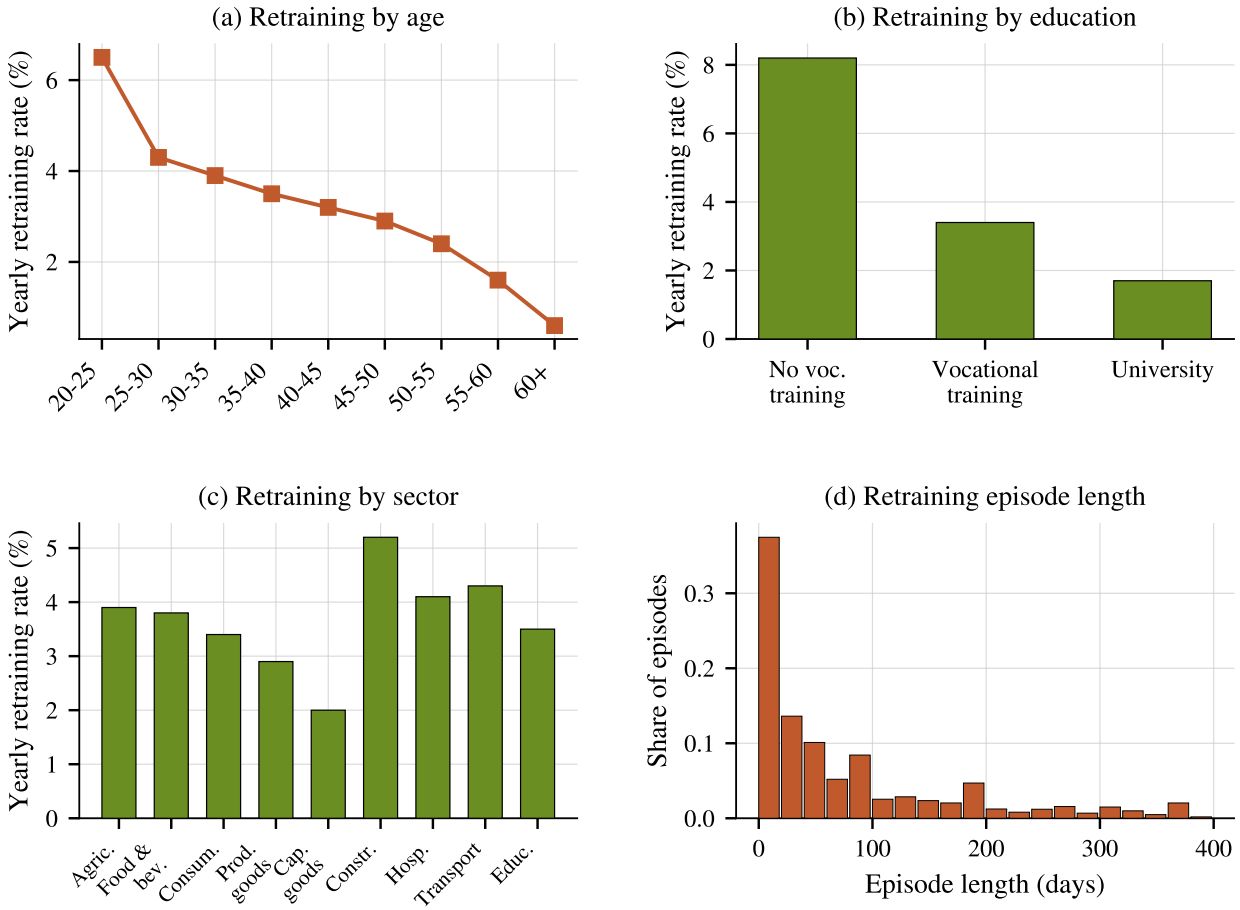
Retraining uptake is heterogeneous. A broad swath of the German labor force makes use of retraining, but with notable differences in uptake across workers. Panel (a) of Figure 1 shows that retraining rates decline monotonically with age, and Panel (b) shows that retraining is especially frequent among workers without vocational training or a degree. Panel (c) documents heterogeneity across broad sector groups. Informed by these patterns, our model will feature rich heterogeneity across ages and skill levels, and retraining rates will vary across sectors due to both differences in worker composition and endogenous differences in incentives to retrain.

[4] Employment Agency statistics indicate that 2.4% of *Sperrzeit* sanctions in 2010 were imposed due to refusal or dropout from career integration programs, which include retraining (Bundesagentur für Arbeit 2011).

Retraining courses are short on average, but vary widely in duration. Panel (d) of Figure 1 plots the distribution of retraining episode lengths, in days. The median retraining episode is relatively short at 41 days, with substantial variation around this average. While around a third of retraining episodes last less than 20 days, the distribution in Panel (d) features a long right tail: a full 29% of episodes exceed 100 days. Given the short duration of most retraining episodes, it seems unlikely that they would have permanent effects on human capital. Our model therefore focuses on relatively short-run effects of retraining, in particular its role in worker transitions across sectors.

Retraining is highly correlated with sector switching. The career-change course presented in Table 1 already hints at one potential use of retraining: switching sectors. We now explore more formally whether retrained workers tend to subsequently enter a new sector. Table 2 presents

Figure 1: Descriptive Statistics on Retraining



Notes: Figure displays yearly retraining rates by age (Panel a), education (Panel b), and broad sector groups (Panel c), along with the distribution of retraining episode lengths in days (Panel d), for workers in the SIAB (2000–2019). Episode lengths in Panel (d) are truncated at 400 days. Appendices A.3.1 and A.1.4 detail the associated calculations.

Table 2: Retraining and Sector Switching

	Pr(Switch Sector)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Young			Old		
Sample:	Full	Low-Skill	Med.-Skill	High-Skill	Low-Skill	Med.-Skill	High-Skill
Retraining dummy	0.367***	0.384***	0.375***	0.227***	0.329***	0.362***	0.366***
	(0.005)	(0.014)	(0.006)	(0.025)	(0.024)	(0.011)	(0.032)
Demographic Controls	✓	✓	✓	✓	✓	✓	✓
Initial Job Controls	✓	✓	✓	✓	✓	✓	✓
Observations	83,545	6,921	44,156	5,796	4,157	19,388	2,681

Notes: Robust standard errors in parentheses; *** indicates p<0.01, ** p<0.05, and * p<0.1. OLS estimates of a regression of a dummy for switching out of the worker's initial 2000 sector during 2001–2010 on a dummy for participation in subsidized retraining during the same period, for workers initially employed in manufacturing. Column (1) uses the full sample; Columns (2)–(7) split the sample by worker type, defined by the intersection of age (young: 24–44 in 2000; old: 45–65) and skill (low: no vocational training; medium: vocational training; high: university degree). Demographic controls include gender and foreign nationality. Initial, year-2000 job controls include tenure and firm size bins, manufacturing sector group indicators, an East Germany dummy, and log earnings summed across all jobs.

estimates from a regression of an indicator for sector switching on a dummy for participation in subsidized retraining over the course of a decade, controlling for demographics and initial job characteristics. In our full sample of manufacturing workers in Column (1), retrained workers indeed turn out to switch sectors at a rate 36.7 percentage points above their non-retrained counterparts. Columns (2)-(7) report the same specification separately for each of six worker types, defined by the intersection of two age groups, young (24-44) and old (45-65), and three skill levels: no vocational training, vocational training, and university-educated. The positive correlation between retraining and sector switching holds across all six types but declines to 23 percentage points for young, high-skill workers.

In Table 3, we investigate the sectors in which workers who retrain during unemployment find jobs, as compared to the unemployed who fail to retrain. Retrained workers flow disproportionately into transport and storage, which absorbs 37.9% of the retrained non-employed, as compared to 27.3% of the non-retrained. In contrast, retrained workers enter capital goods manufacturing and construction at noticeably lower rates.

2 Retraining, Import Competition, and the China Shock

We now show empirically that German workers use retraining to adjust to trade shocks: in our case, the post-2000 rise in imports from China to Germany. Following Autor, Dorn, and Hanson (2013), we refer to this as the China shock. We begin by documenting the adverse labor market consequences of exposure to the China shock and then explore the role of retraining as a margin of adjustment for workers.

Table 3: Post-Unemployment Sectors by Retraining Status

	Non-retrained	Retrained
Agriculture, forestry and fishing	0.046	0.030
Food and beverages	0.022	0.021
Consumables	0.017	0.014
Production goods	0.056	0.047
Capital and consumer goods	0.049	0.035
Construction	0.106	0.078
Hospitality	0.227	0.222
Transport and storage	0.273	0.379
Education	0.204	0.173

Notes: Table displays the share of non-employment spells which end with employment in each destination sector, separately for workers who participated in subsidized retraining during their spell of unemployment and for those who did not, over the years 2001–2010. Sectors correspond to the nine aggregate sectors delineated by W. Dauth and Eppelsheimer (2020).

2.1 Measuring the China Shock

We measure a worker's exposure to the China shock using their initial sector of employment. Specifically, we limit the sample to workers initially in manufacturing. Then, following W. Dauth, Findeisen, and Suedekum (2021), we define the import exposure of a worker ω employed in the base year in sector s as

$$\text{import exposure}_s \equiv \frac{\Delta\text{net imports}_s}{\text{wage bill}_s},$$

where $\Delta \textit{net imports}_s$ equals the 2001–2010 change in net imports from China to Germany. We focus not on a sector's imports in isolation but on its net imports, i.e. imports minus exports, to capture the full impact of the China shock on labor demand, and we normalize net imports by the total base-year sectoral wage bill.[5]

With our exposure measure in hand, we estimate specifications for a series of labor market outcomes $y_{\omega s}$ for workers ω employed in manufacturing in sector s in the year 2000 as a function of sectoral import exposure,

$$y_{\omega s} = \beta \times \text{import exposure}_s + X_{\omega s}\gamma + \varepsilon_{\omega s}. \tag{1}$$

Controls in $X_{\omega s}$ include demographic characteristics measured in 2000—age bins, gender, education, and foreign nationality—as well as characteristics of their primary base-year job: log earnings summed across all jobs, tenure and firm size bins, broad manufacturing sector group indicators, and an East Germany dummy. We relegate further details regarding the construction of our outcomes, import exposure measure, and controls to Appendix A.3.

The threat to identification of the coefficient of interest, β, in (1) is domestic supply and demand

[5] Our sectors are of a slightly aggregated version of 2-digit ISIC Rev. 4 sectors, as detailed in Appendix A.1.

Table 4: Labor Market Effects of Chinese Import Exposure

IV (2SLS)	(1) Share days employed	(2) Share days in manufacturing	(3) Earnings growth	(4) Sector switching
Sectoral import exposure	-2.340***	-4.880***	-2.748***	4.230*
	(0.701)	(1.610)	(0.930)	(2.380)
Demographic controls	✓	✓	✓	✓
Initial job controls	✓	✓	✓	✓
Observations	83,099	83,099	83,099	83,099
Mean of dependent variable	76.1	64.9	80.965	21.8
First-stage *F*-statistic	237.63	237.63	237.63	237.63

Notes: Robust standard errors in parentheses, clustered at the sector level; *** indicates p<0.01, ** p<0.05, and * p<0.1. We measure the share of days employed and share of days employed in manufacturing (unconditional on employment) in 2010, earnings growth as 100 times total 2010 earnings divided by those in 2000, and sector switching as employment in 2010 outside of a worker's initial sector. Shares and probabilities are multiplied by 100; these outcomes can be interpreted as percentage points.

shocks correlated with changes in sectoral import exposure. We therefore follow Autor, Dorn, and Hanson (2013) and instrument for *import exposure*$_s$ with an analogous measure which instead uses net imports from China to other high-income countries.[6]

2.2 Labor Market Effects of the China Shock

Table 4 presents 2SLS estimates of the labor market effects of Chinese import exposure between 2000 and 2010. We measure four outcomes at the end of the decade: the share of days employed (Column 1), the share of days employed in manufacturing, unconditional on employment (Column 2), cumulative earnings growth, defined as 100 times end-of-decade divided by base-year earnings (Column 3), and a dummy for switching out of the worker's initial sector (Column 4).

A one-standard-deviation increase in sectoral import exposure reduces total employment by 1.6 percentage points, or 2.1% of the mean (Column 1), and manufacturing employment by 3.3 percentage points, or 5.1% of the mean (Column 2). These employment declines translate directly into lower earnings growth: the same shock reduces cumulative earnings growth by 1.9 percentage points (Column 3). Taken together, these results confirm the adverse effects of trade exposure on the German labor market established by W. Dauth, Findeisen, and Suedekum (2021). To begin to understand how trade-exposed workers adjust, we look for evidence of sectoral reallocation. The same shock raises the probability of switching sectors by 2.8 percentage points, or 12.8% of the mean (Column 4). In Appendix A.4, Table A1, we show that these results are robust to measuring import exposure and sector switching at the finer 3-digit sector level.

[6] As in W. Dauth, Findeisen, and Suedekum (2021), these are the UK, Sweden, Norway, Canada, Australia, New Zealand, Japan, and Singapore.

2.3 The China Shock and Retraining

We now provide direct evidence of a new margin of adjustment to trade shocks: retraining. In Column (1) of Table 5, we estimate equation (1) with a dummy variable $y_{\omega s}$ equal to one for workers who retrain at any point during the full decade 2001–2010, initially without controls. In Column (2), we add controls for demographic and initial-job characteristics. The coefficient in our preferred specification in Column (2), significant at the 5% level, implies that a one-standard-deviation increase in import exposure increases the probability that a worker retrains by 1.1 percentage points — an 8.1% increase on the mean 10-year retraining rate of 13.5%. In Column (3) we estimate a logit specification using a control function approach and obtain similar results: a one-standard-deviation increase in sectoral import exposure increases a worker's relative odds of retraining by around 6.5%. Finally, Column (4) explores the intensive margin by focusing on the number of days spent retraining. We again find a positive, but in this case statistically insignificant, effect of import exposure on retraining.[7]

In principle increased retraining among more exposed workers could reflect two forces: changes in the distribution of workers across employment and non-employment, and changes in workers' propensity to retrain conditional on their employment status. In Appendix A.5 we provide a decomposition that formalizes this idea and find that both forces play a role. Exposure to import competition shifts workers into non-employment, and, combined with differences in baseline retraining rates between employed and non-employed workers, this shift accounts for 43% of the effect in Table 5. But most of the effect – 57% – is driven by changes in workers' decisions conditional on their employment status. We interpret this breakdown as evidence that retraining decisions are not just mechanically related to a worker's employment status, but instead respond endogenously to economic incentives.

2.4 Taking Stock

Two findings stand out from our empirical analysis. First, in the cross-section, retraining and intersectoral mobility are tightly linked: workers who retrain are 36.7 percentage points more likely to switch sectors than those who do not (Table 2). Second, in response to the China shock, both margins move together—a one standard deviation increase in import competition raises sector switching by 12.8% and retraining by 8.1%. These patterns point towards a complementarity between retraining and intersectoral mobility — and hence a tight link between the availability of retraining and workers' ability to smooth trade shocks.

At the same time, the joint nature of the retraining and sector-switching decisions means that we cannot pin down the true direction of causality from these patterns alone. We now develop a model of workers' retraining and sector switching decisions that will allow us to address the endogeneity of retraining and to explore the interaction of trade, intersectoral mobility, and retraining in equilibrium.

[7] As with the labor market outcomes above, we find quantitatively very similar results using a finer 3-digit sector classification in Appendix Table A1.

Table 5: Chinese Import Exposure and Retraining

	(1)	(2)	(3)	(4)
Outcome variable	Pr(retrain)	Pr(retrain)	Pr(retrain)	Days retraining
Specification	Linear probability model (2SLS)		Logit	2SLS
Sectoral import exposure	4.300***	1.564**	0.094***	2.338
	(1.100)	(0.697)	(0.023)	(1.728)
Demographic controls		✓	✓	✓
Initial job controls		✓	✓	✓
Observations	83,565	83,099	83,099	83,099
Mean of dependent variable	13.5	13.5	0.135	17.030
First-stage *F*-statistic	181.17	237.63		237.63

Notes: Robust standard errors in parentheses, clustered at the sector level, in Columns 1–2 and 4; standard errors in Column 3 bootstrapped. *** indicates p<0.01, ** p<0.05, and * p<0.1. The retraining outcome in Columns 1–3 is a dummy for participation in subsidized retraining during 2001–2010; Column 4 measures the number of days of retraining. Column 3 estimates a logit control function specification. Shares and probabilities are multiplied by 100; these outcomes can be interpreted as percentage points.

3 A Theory of Trade and Retraining

We begin with a stylized model and analyze the effect of retraining on the labor market dynamics and welfare changes induced by a trade shock. We then enrich our model with worker heterogeneity and embed this description of the labor market in a quantitative, general equilibrium model of international trade.

3.1 Simple Model

Environment

Time is discrete and indexed by t. When we quantify the model we will take a period to be five years. We choose this longer timespan to capture the idea that effects of retraining may persist over a number of years.

We study a single small open economy with tradable sectors $i = 1, ..., N$. World prices P_{it} are exogenous. Production in each sector has constant returns to scale, uses only labor, and is carried out by a mass of identical, perfectly competitive firms with productivities normalized to one: the result is that nominal wages $\tilde{w}_{it}$ are equal to world prices. The economy is populated by a unit mass of workers and we denote employment in sector i at time t by l_{it}.

The worker's problem

Focus on a single worker who starts period t in sector i. She begins the period by supplying one unit of labor in exchange for a nominal wage $\tilde{w}_{it}$. The worker is hand-to-mouth, and has Cobb-Douglas

preferences over goods from different sectors with weights α_i. She therefore consumes her real wage,

$$w_{it} \equiv \tilde{w}_{it} P_t^{-1}, \quad P_t = \prod_{j=1}^{N} P_{jt}^{\alpha_j}, \tag{2}$$

where P_t is the aggregate price index. The worker is infinitely lived, has log utility, and discounts the future with a discount factor β. We denote the expected lifetime utility of a worker in sector i in period t by v_{it}.

At the end of the period, the worker must make two decisions: whether or not to switch out of sector i into some other sector j, and whether or not to retrain. To capture the interaction of these two decisions, we combine the model of complementary choices in Gentzkow (2007) with the model of labor mobility developed by Artuç, Chaudhuri, and McLaren (2010). The payoffs to the worker from these different decisions are,

$$\begin{aligned}
\text{Do not switch \& do not retrain} &\implies \beta v_{it+1} + \nu \epsilon_{ii} \\
\text{Switch to sector } j \text{ \& do not retrain} &\implies \beta v_{jt+1} + \nu \epsilon_{ij} - C \\
\text{Do not switch \& retrain} &\implies \beta v_{it+1} + \nu \epsilon_{ii} + (\sigma\eta - F) \\
\text{Switch to sector } j \text{ \& retrain} &\implies \beta v_{jt+1} + \nu \epsilon_{ij} - C + (\sigma\eta - F) + \Gamma.
\end{aligned}$$

In these expressions, ϵ_{ij} are idiosyncratic preference shocks for each destination j (including the current sector), scaled by a dispersion parameter ν; C is a deterministic switching cost; and F is a deterministic retraining cost, offset by an idiosyncratic benefit η scaled by σ.

The key parameter in the expression above is Γ, which captures the interaction between retraining and switching sectors. If $\Gamma > 0$, the two are complements – retraining primarily helps workers acquire skills useful outside their current sector. If $\Gamma < 0$, they are substitutes – retraining is more useful in deepening skills in which the worker already has a foundation. As we will see below, this distinction is crucial for the interaction of retraining and trade shocks.

As is standard in the literature, we assume that the preference shocks ϵ_{ij} are drawn from a Type 1 Extreme Value distribution with mean zero and scale parameter normalized to one. For tractability we also assume that η is drawn from a logistic distribution with mean zero and scale one. We then summarize the problem facing the worker with a Bellman equation,

$$v_{it} = \log w_{it} + \mathbb{E}\Big[\max_j \left\{ \beta v_{jt+1} + \nu \epsilon_{ij} - C\mathbb{1}\{j \neq i\} + \max\{\Gamma \mathbb{1}\{j \neq i\} + \sigma\eta - F, 0\} \right\} \Big], \tag{3}$$

where the expectation is taken over the idiosyncratic shocks ϵ_{ij} and η. The indicator $\mathbb{1}\{j \neq i\}$ ensures that switching costs C and the complementarity benefit Γ apply only when the worker changes sector.

Equilibrium

Real wages w_{it} are exogenous. Given an initial distribution of labor across sectors, an equilibrium of the model is: a sequence of worker values v_{it} which solve the Bellman equation (3); given these worker values, a sequence of switching probabilities μ_{ijt} – denoting the probability a worker in sector i moves to sector j – and retraining rates ρ_{it} implied by (3); and finally a sequence of labor allocations across sectors satisfying,

$$l_{it+1} = \sum_{j=1}^{N} \mu_{jit} l_{jt}.$$

Below we will focus on the economy's dynamics following a permanent shock to world prices, and thus real wages, which we loosely interpret as an import competition shock. Since, following the shock, real wages are constant over time, worker values and choice probabilities are also constant over time. We therefore drop the t subscripts where doing so does not cause confusion.

3.2 Analytical Results

Proofs of all the results in this section can be found in Appendix B.1.

Retraining and worker choices

Workers simultaneously decide whether to switch sectors and whether to retrain. This simultaneity is useful – as we will see in Section 4, it gives the model a natural way of capturing an important endogeneity problem in the data – but it makes workers' choice probabilities intractable. We therefore take a first order approximation around $\Gamma = 0$, where the two decisions are independent and the model can be solved by hand. As Theorem 1 shows, close to these parameter values the model remains tractable but naturally captures the interdependence of retraining and switching.

Theorem 1. *To a first order approximation around $\Gamma = 0$, the probability a worker initially in sector i switches to sector j, relative to the probability of remaining in i, is,*

$$\log\left(\frac{\mu_{ij}}{\mu_{ii}}\right) = \left(\frac{\beta}{\nu}\right)(v_j - v_i) - \left(\frac{C - \Gamma\bar{\rho}}{\nu}\right), \tag{4}$$

and the retraining rate is,

$$\rho_i = \bar{\rho} + \bar{\rho}(1-\bar{\rho})\left(\frac{\Gamma}{\sigma}\right)(1 - \bar{\mu}_{ii}). \tag{5}$$

In these expressions $\bar{\mu}_{ii}$ is the probability of remaining in sector i, and $\bar{\rho}$ is the retraining rate, both evaluated at $\Gamma = 0$. Note that when $\Gamma = 0$ this retraining rate is common across sectors.

Theorem 1 makes the role of retraining in our model clear. The probability a worker switches sectors takes a standard form in (4), but with switching costs shifted by $-\Gamma\bar{\rho}$. If switching and retraining are complements, then switching costs effectively fall as retraining rises, whereas if they are substitutes then the opposite is true. In either case, the key parameter in determining the

effect of retraining is Γ, scaled by the dispersion parameter ν. Finally (5) shows there is a natural link between retraining rates and mobility across sectors, with the sign of this relationship again determined by Γ.

Retraining and welfare

A key motivation for retraining policies is concern over the uneven welfare effects of trade shocks. To understand what retraining can achieve, we study the effects of a small shock to world prices when the economy starts at a symmetric steady state.

It turns out that a sufficient statistic for the role of retraining in this environment is the steady state rate at which workers transition across sectors, which we denote by $\tilde{m}$. It increases in Γ, the complementarity parameter, and when $\Gamma > 0$ it is decreasing in retraining costs F. For Γ close to zero, we can use Theorem 1 to get a closed form expression:

$$\tilde{m} = \frac{N}{e^{(C-\Gamma\bar{\rho})/\nu} + N - 1}, \tag{6}$$

where $\bar{\rho}$ is the baseline retraining rate defined in Theorem 1. With this object in hand, we can compactly describe how retraining alters the welfare effects of trade shocks.

Theorem 2. *Assume the economy is initially in a symmetric steady state with $P_i = P_j$ for all sectors i and j. At $t = 0$ world prices change permanently by $d \log P_i$. Then:*

(i) *Changes in real wages are given by*

$$d \log w_i = d \log P_i - \sum_j \alpha_j d \log P_j. \tag{7}$$

(ii) *The employment-weighted average change in welfare is*

$$dV = \left(\frac{1}{1-\beta}\right) \sum_i (l_i - \alpha_i) d \log P_i. \tag{8}$$

(iii) *The change in the welfare of workers initially in sector i is*

$$dv_i = \left(\frac{d \log w_i}{1-\beta}\right) + \lambda(\tilde{m}) \left(dV - \left(\frac{d \log w_i}{1-\beta}\right)\right), \tag{9}$$

where

$$\lambda(\tilde{m}) \equiv \frac{\beta\tilde{m}}{1-\beta+\beta\tilde{m}} \tag{10}$$

captures the importance of the option value the worker derives from being able to switch sectors in the future.

To unpack this result, let us start with (7), which tells us that changes in real wages take a standard form: changes in world prices affect workers directly, through their effect on nominal wages, and

indirectly, through their effect on the price index. The effect on aggregate welfare in (8) may be positive or negative, and depends on how the changes in world prices load onto employment shares l_i versus consumption shares α_i. Neither of these expressions depends on retraining or worker mobility more broadly.

Instead, (9) shows that mobility, and thus retraining, matters for the distribution of welfare changes across workers. These welfare changes are composed of two terms. First, a direct effect that captures the real wage change facing a completely immobile worker. Second, an option value term that captures the worker's ability to move to a new sector in future. Crucially, this option value term is always negatively correlated with the direct effect of the trade shock and, as long as $\Gamma > 0$, its magnitude rises with the availability of retraining via the effect of retraining on baseline mobility $\tilde{m}$. The result is that the welfare effects of trade shocks are always less dispersed in the economy with retraining.

Retraining and labor market dynamics

A large literature has documented sluggish labor market adjustment to international trade shocks. Our final analytical result looks at how the availability of retraining might speed or slow these transitions. Throughout we assume $\Gamma > 0$, so that retraining and switching are complements and we can be confident that reductions in the cost of retraining or increases in its effectiveness will raise the baseline mobility $\tilde{m}$.

Theorem 3. *Following the shock to world prices described in Theorem 2:*

(i) *The change in employment in sector i in the short run ($t = 1$) is*

$$d \log l_{i1} = \tilde{m}(2 - \tilde{m}) \left(1 - \lambda(\tilde{m})\right) \left(\frac{\beta}{\nu}\right) \left(\frac{d \log w_i}{1 - \beta} - dV\right). \tag{11}$$

A higher $\tilde{m}$ has ambiguous effects on the magnitude of short-run employment reallocation in general, but for $\tilde{m}$ sufficiently small, increases in $\tilde{m}$ always result in more short-run reallocation.

(ii) *The long-run change in employment is*

$$d \log l_{i\infty} = (2 - \tilde{m}) \left(1 - \lambda(\tilde{m})\right) \left(\frac{\beta}{\nu}\right) \left(\frac{d \log w_i}{1 - \beta} - dV\right). \tag{12}$$

A higher $\tilde{m}$ always decreases the magnitude of long-run employment reallocation.

(iii) *The speed of convergence, measured by the fraction of the long-run adjustment complete at time t, is*

$$\frac{d \log l_{it}}{d \log l_{i\infty}} = 1 - (1 - \tilde{m})^t. \tag{13}$$

Thus a fraction $\tilde{m}$ of long-run adjustment is completed one period after the shock: a higher $\tilde{m}$ always speeds up convergence.

Theorem 3 reveals that retraining, through its effect on baseline mobility $\tilde{m}$, has nuanced effects on the employment response to trade shocks.

Focus first on the short-run response in (11). Two forces are at work. Retraining always makes workers more responsive to a given change in values dv_i, but, from Theorem 2, it also dampens the response of those values to real wage changes. The net effect is thus ambiguous, but when baseline mobility is sufficiently low — which turns out to be the relevant case empirically — the first effect dominates and so retraining, by raising baseline mobility, raises the extent of labor reallocation in the short run.

Now turn to the long run in (12). This expression shows that retraining unambiguously lowers the long-run employment changes caused by trade shocks. The reason is twofold. First, the lower sensitivity of worker values to real wage changes disincentivizes moving exactly as in the short run. Second, in contrast to the short run, in the long run higher baseline mobility actually lowers the responsiveness of employment to a given change in worker values. The intuition is that higher baseline mobility makes it harder for a growing sector to retain workers and ultimately shrinks long run employment changes.

The final expression in Theorem 3 combines the short and long run results to provide a sharp characterization of the speed of adjustment. As retraining becomes more widely available, baseline mobility rises and the transition to the new steady state becomes more front-loaded.

3.3 Quantitative model

Three results emerge from the simple model: retraining acts like a reduction in switching costs, it compresses the distribution of welfare changes across workers, and it makes employment reallocation smaller in the long run but more front-loaded. To quantify these effects, we now enrich the model. Motivated by the heterogeneity in retraining rates we found in the data in Section 1, we model workers of different skill levels and ages. We also allow for a non-employment option to capture this margin of adjustment to trade shocks. Finally, to connect our model to the evidence from Section 2 on the effects of import competition, we embed our description of the labor market within a quantitative, general equilibrium model of international trade.

Worker heterogeneity

We model worker heterogeneity along two dimensions. The first is skill, which we identify with a worker's education level (no higher education, vocational training, or a university degree) upon entering the labor market. In the model a worker's skill type is exogenous and fixed over time.

The second dimension of heterogeneity is age, which we capture with a simple overlapping generations structure. Workers are born at an exogenous rate δ as new entrants, indexed by e. New entrants choose a sector and then immediately become young workers, indexed by y. At some exogenous rate χ young workers become old workers, indexed by o. In turn old workers retire at rate ζ and exit the labor market. We assume a constant population, which implies $\delta = \zeta\chi\left(\zeta + \chi\right)^{-1}$.

A worker type is thus a skill-age pair. We denote types with the superscripts k for skill and a for age. A worker of type ka supplies h_i^{ka} units of effective labor when working in sector i and faces switching costs C_{ij}^{ka} and preference shocks ϵ_{ij} if she chooses to move from sector i to sector j. As in the simple model, we assume $C_{ii}^{ka} = 0$, but otherwise allow switching costs to vary across origin-destination pairs. Since new entrants do not have an initial sector, their "switching costs" should be regarded as entry costs: we write these costs as C_j^{ke}.

Motivated by the heterogeneity in retraining rates across age and skill types we saw in the data in Section 1, we allow the costs and benefits of retraining to vary across worker types and denote these by F^{ka} and Γ^{ka}. New entrants cannot retrain before choosing a sector.

Non-employment

We augment our model with a non-employment option indexed by $i = 0$, and model entry into and exit out of this sector in the same way as any other. While in non-employment workers of type ka enjoy a flow of utility b^{ka}. Workers in non-employment may retrain at cost F_0^{ka}, while we denote the costs of retraining for employed workers by F_1^{ka}. Finally, we assume that retraining only affects the cost of entering productive sectors, i.e., excluding non-employment.

Bellman equations

We summarize these various model ingredients with a system of Bellman equations. At time t, a new entrant from skill group k draws preference shocks ϵ and chooses an initial sector j to solve

$$\max_j \{\beta v_{jt+1}^{ky} + \nu\epsilon_j - C_j^{ke}\}, \tag{14}$$

where v_{jt+1}^{ky} is the value of starting the next period as a young worker in sector j.

Once employed, a worker of type ka in a productive sector $i \neq 0$ derives utility from the log of her consumption $\log(w_{it}h_i^{ka})$ plus an exogenous shifter ψ_i^{ka}.[8] Her value function satisfies

$$v_{it}^{ky} = \log(w_{it}h_i^{ky}) + \psi_i^{ky} + (1-\chi)U_{it}^{ky} + \chi U_{it}^{ko}, \tag{15}$$

$$v_{it}^{ko} = \log(w_{it}h_i^{ko}) + \psi_i^{ko} + (1-\zeta)U_{it}^{ko}, \tag{16}$$

where the continuation value U_{it}^{ka} is given by:

$$U_{it}^{ka} = \mathbb{E}\Big[\max_j \Big\{\beta v_{jt+1}^{ka} + \nu\epsilon_{ij} - C_{ij}^{ka} + \max\{\Gamma^{ka}\mathbb{1}\{j \neq i\}\mathbb{1}\{j \neq 0\} + \sigma\eta - F_1^{ka}, 0\}\Big\}\Big], \tag{17}$$

where F_1^{ka} is the cost of retraining for employed workers and Γ^{ka} is the complementarity parameter for workers of type ka. Notice that the worker only gains from this complementarity between switching and retraining if she moves to a new productive sector, i.e., not non-employment and not

[8] Technically we could dispense with the flow utility shifters ψ_i^{ka} and absorb them into switching costs. Including them allows us to impose the natural normalization that $C_{i0}^{ka} = 0$, i.e., entering non-employment is always costless.

her initial sector i. The problem facing non-employed workers is almost identical, with the only differences being in their flow payoffs b^{ka} and retraining costs F_0^{ka}.

We denote the resulting sector-transition and retraining probabilities by μ_{ijt}^{ka} and ρ_{ijt}^{ka}, respectively. Given a distribution of worker types over sectors at time t, denoted l_{it}^{ka}, employment evolves according to,

$$l_{it+1}^{ky} = (1-\chi)\sum_{j=0}^{N}\mu_{jit+1}^{ky}l_{jt}^{ky} + \delta\mu_{it+1}^{ke}, \quad l_{it+1}^{ko} = \sum_{j=0}^{N}\mu_{jit+1}^{ko}\left((1-\zeta)l_{jt}^{ko} + \chi l_{jt}^{ky}\right) \tag{18}$$

for each skill group k. Finally, total effective labor supply in sector i is,

$$L_{it} = \sum_{k}\sum_{a} l_{it}^{ka}h_i^{ka}. \tag{19}$$

Labor supply in other countries

Our model of labor supply in other countries, which we index by n, is simple. A mass of L_n homogeneous workers all supply one unit of labor and are perfectly mobile across sectors. There is therefore a single wage w_{nt} in each country n in each period t. We do not allow for non-employment in other countries.

International trade

The international trade side of our model is standard and closely follows Caliendo and Parro (2015), although we dispense with the spatial dimension. We therefore keep our exposition brief. Since this block of the model is entirely static, we drop time subscripts in what follows.

Firms in sector i in country n produce with constant returns to scale using a Cobb-Douglas bundle of labor, structures, and intermediate inputs from other sectors. We assume that structures are in fixed aggregate supply within a country but perfectly mobile across sectors, implying a common structures rental rate r_n. The resulting unit costs, expressed in logs, are,

$$\log c_{in} = \gamma_{in}((1-\phi_{in})\log w_{in} + \phi_{in}\log r_n) + (1-\gamma_{in})\sum_{j=1}^{N}\xi_{ijn}\log P_{jn}, \tag{20}$$

where P_{jn} is the price index for sector j goods in country n, γ_{in} is the value added share in i, ϕ_{in} is the share of structures in value added in i, and ξ_{ijn} is the share of sector j in the intermediate inputs purchased by sector i in n. Given unit costs c_{in}, trade between countries in sector i is modeled exactly as in Eaton and Kortum (2002) and the resulting trade shares and price indices are,

$$\pi_{inm} = \frac{\left(\tau_{inm}c_{in}\right)^{-\theta_i}T_{in}}{P_{im}^{-\theta_i}}, \quad P_{im} = \left(\sum_{n}\left(\tau_{inm}c_{in}\right)^{-\theta_i}T_{in}\right)^{-\frac{1}{\theta_i}}. \tag{21}$$

Here T_{in} and θ_i are the scale and shape parameters of the distribution from which the productivities

of producers in sector i in country n are drawn: a country with a high T_{in} is relatively productive in sector i on average. Lastly, τ_{inm} represents an iceberg cost of shipping sector i goods from n to m.

Consumers in each country have Cobb-Douglas preferences over different sectors with weights α_{in}. As in Dekle, Eaton, and Kortum (2007), we allow for exogenous deficits D_n that create a wedge between final expenditures and total value added. Market clearing then requires:

$$X_{in} = \alpha_{in} Y_n + \sum_{j=1}^{N} (1 - \gamma_{jn}) \xi_{jin} R_{jn}, \tag{22}$$

$$Y_n = D_n + \sum_{i=1}^{N} \left(\frac{w_{in} L_{in}}{1 - \phi_{in}} \right), \tag{23}$$

$$R_{in} = \sum_{m} \pi_{inm} X_{im}, \tag{24}$$

$$w_{in} L_{in} = \gamma_{in} (1 - \phi_{in}) R_{in}, \tag{25}$$

$$r_n S_n = \sum_{i=1}^{N} \gamma_{in} \phi_{in} R_{in}, \tag{26}$$

where X_{in} and R_{in} denote total expenditures and revenues in sector i in country n, Y_n is total final expenditure, D_n is an exogenous trade deficit, and S_n is the exogenous supply of structures. In Germany L_{in} is predetermined and (25) pins down sector-specific wages. In other countries, labor mobility implies a single wage w_n, determined by aggregating (25) over sectors.

Equilibrium

Following Caliendo, Dvorkin, and Parro (2019), we define the *fundamentals* of an economy as its switching costs C, retraining costs F and complementarities Γ, type-specific units of effective labor h and non-employment utilities b, as well as its input-output coefficients γ and ξ, its trade costs τ, its productivities T, its Cobb-Douglas consumption shares α and its exogenous deficits D. Given a set of fundamentals and a distribution of effective units of labor across sectors in Germany, we then define a *static equilibrium* as wages w, rental rates r, prices P, unit costs c, trade shares π, expenditures X and revenues R that solve (20) – (26). Finally, given an initial distribution of labor across sectors in Germany and a (possibly time-varying) sequence of fundamentals, a *dynamic equilibrium* is a sequence of static equilibria plus a sequence of worker values v, sector transition probabilities μ, retraining decisions ρ, and labor supplies l satisfying (15) – (19) consistent with those static equilibria and fundamentals.

4 Calibration

The model requires four groups of parameters. Table 6 reports the first group: the trade elasticities θ_i, the discount factor β, the parameters of the OLG structure, and the share of each skill group in the population, all of which we calibrate externally. The second group consists of trade-side

fundamentals (productivities, trade costs, input-output coefficients, and so on), which are absorbed entirely by solving the model in changes following Dekle, Eaton, and Kortum (2007).

The remaining parameters are on the labor supply side of the model: switching costs C_{ij}^{ka}, which we recover from observed worker flows, and a vector $\Theta = \{\nu, \sigma, \{\Gamma^{ka}, F_0^{ka}, F_1^{ka}\}_{ka}\}$ of 20 parameters governing preferences over sectors, retraining costs, and the complementarity between retraining and mobility. We calibrate Θ by matching the model's predicted response to the China shock to our empirical estimates from Section 2, along with other moments from the data.

4.1 Hat algebra

Our calibration procedure – like the counterfactual experiments in Section 5 – starts from a baseline equilibrium and solves the model given a sequence of shocks to fundamentals. Exactly as in Caliendo and Parro (2015), given data on the baseline equilibrium and a candidate Θ, the model's static equilibrium can be solved in changes. Trade-side fundamentals – productivities, trade costs, input-output coefficients – either drop out completely or can be read from the World Input Output Tables (WIOT).

4.2 Recovering switching costs

Switching costs C_{ij}^{ka} are recovered by inverting the model's choice probabilities. In principle, data on worker flows across sectors are rich enough to back out a full set of costs without parametric assumptions. In practice, the transition matrix is sparse, and Dingel and Tintelnot (2025) argue that using sparse matrices directly may produce misleading counterfactual predictions. Disclosure restrictions in the SIAB compound the problem by censoring many cells.

We address these challenges in two steps, described in detail in Appendix B.2. First, we parameterize switching costs as a function of origin-sector and destination-sector fixed effects, a measure of skill distance between sectors, and dummies for transitions between manufacturing and

Table 6: Externally Calibrated Parameters

Parameter	Description	Value	Source
θ_i	Trade elasticities	6.638[a]	Caliendo and Parro (2015)
β	Subjective discount factor	0.977[b]	Annual discount factor = 0.97
χ	Young-old transition rate	0.159	SIAB: share aged 21-40
ζ	Retirement rate	0.370	Working life = 45 years
λ_L	Low skill share	0.150	SIAB: share with no degree
λ_M	Medium skill share	0.730	SIAB: share with vocational degree
λ_H	High skill share	0.120	SIAB: share with university degree

Note: [a] We take estimates of sector-specific trade elasticities from Table 1 of Caliendo and Parro (2015). We enforce a lower bound of 3 and an upper bound of 12 on these elasticities. The table reports a simple average. [b] Incorporating the 0.37 probability of exit for old workers results in a population-average discount factor of 0.87 when $\beta = 0.977$, which, annualized, is approximately 0.97.

non-manufacturing. Second, we run PPML regressions in the data that parallel this specification and solve for cost parameters such that the model exactly matches the estimated regression coefficients. This specification describes the data well: the correlation between fitted and actual transition probabilities is 0.99.

The recovered costs C_{ij}^{ka} depend on the candidate Θ, because the mapping from observed flows to implied costs runs through the model's choice probabilities. Therefore switching costs are calibrated jointly with Θ, and to emphasize this we write $C(\Theta)$ below.

4.3 The China shock

Our calibration strategy requires a model analogue of the China shock. We define the shock in manufacturing sector i as the proportional change in Chinese productivity in that sector between 2000 and 2010. Following Caliendo, Dvorkin, and Parro (2019), we choose the vector of shocks such that the model-implied changes in Germany's net imports from China in each sector exactly match those predicted by our first-stage regressions in Section 2. Because the model solution depends on Θ, the implied shock vector CS also varies with the candidate parameters. We write $CS(\Theta)$ to make this dependence clear, although in practice the China shock we infer is almost invariant to Θ.

4.4 Calibrating Θ

Identification

We identify 20 parameters by targeting 23 moments: 12 worker type and employment status specific retraining rates, 4 estimates of labor market effects of the China shock from Table 4 and an estimate of the effect on retraining from Column (2) of Table 5, and the coefficients from the 6 type-specifc retraining-switching regressions in Table 2. Formally, all the parameters are jointly identified by all the targeted moments. However, it is possible to provide a relatively transparent identification argument in three steps.

Step 1: Twelve of the target moments are type- and employment-status-specific retraining rates, which are closely tied to the 12 retraining cost shifters F_0^{ka} and F_1^{ka}. These parameters are effectively pinned down by the corresponding retraining rates, so we set them aside and focus on the remaining 8 parameters – ν, σ, and the 6 type-specific values of Γ^{ka} – which target 11 moments.

Step 2: Four of the remaining target moments are the estimated effects of the China shock on earnings, employment, manufacturing employment, and sector switching from Section 2. These capture the responsiveness of the labor market to trade shocks and are therefore closely tied to ν, the dispersion of sector preference shocks. With ν effectively pinned down by these four moments, the identification problem reduces to 7 parameters – σ and the 6 type-specific Γ^{ka} – targeting 7 moments.

Step 3: The expression for retraining rates in Theorem 1 clarifies the remaining challenge:

$$\rho_i = \bar{\rho} + \bar{\rho}(1-\bar{\rho})\left(\frac{\Gamma}{\sigma}\right)(1-\bar{\mu}_{ii}).$$

Think about i as a sector that is highly exposed to the China shock – noting that in the simple model workers are homogeneous, so Γ has no type superscript. Then our empirical results tell us that workers in this sector will switch out at high rates ($(1-\bar{\mu}_{ii}) \uparrow$) and retrain at high rates ($\rho_i \uparrow$). This observation, combined with the expression above, reveals that we must have $\Gamma > 0$, so that retraining and switching are complements. Crucially, however, the magnitude of the response of retraining to the China shock depends on both Γ and σ, and so this moment alone cannot separately identify these two parameters.

To resolve this, we additionally target the 6 type-specific regression coefficients from Table T. There we noted that, even after controlling for a rich set of observables, it is likely that these regressions confound the causal effect of retraining with selection on unobserved propensity to switch sectors. But our model of the decision to retrain explicitly captures this selection problem: because the two decisions are made simultaneously, workers in the model who draw a strong preference for switching sectors will be more likely to retrain (as long as $\Gamma > 0$) and more likely to switch sectors, regardless of the effectiveness of retraining. By matching these regression coefficients to their model counterparts, we effectively control for selection on unobserved propensity to switch sectors and thus recover useful information about the complementarity between retraining and switching.

Implementation

We collect all target moments into a vector m and denote the corresponding vector of standard errors se.

We calibrate Θ using the following fixed point iteration. First, given a candidate Θ_0, we infer switching costs $C(\Theta_0)$ and the China shock $CS(\Theta_0)$. Second, we feed the model the China shock and solve for the resulting steady state and transition path, yielding wages, transition probabilities, and retraining rates by worker type, sector, and period. Our solution takes the baseline equilibrium to be the German and world economies in 2000. We assume that the China shock is unforeseen in 2000, but workers learn of it between 2000 and 2005 — recall that one model period is five years — and take it into account when making their sector choice and retraining decisions for 2005. Third, using this simulated data we run five regressions that parallel those in Tables 4 and 5 and, for each worker type, compute average retraining rates and estimate (1). All model moments are measured over two periods following the shock (i.e., 2005 and 2010), paralleling the empirical window.

The result is a vector of model-implied moments $m(\Theta_0|C(\Theta_0), CS(\Theta_0))$. Our calibrated value of Θ on this iteration solves:

$$\Theta_1 = \underset{\Theta}{\text{argmin}} \left\{ \sum_i \left(\frac{m_i - m_i(\Theta|C(\Theta_0), CS(\Theta_0))}{se_i} \right)^2 \right\}. \tag{27}$$

We then repeat the steps above, replacing Θ_0 with Θ_1, until the two converge. In practice, the dependence of the model-implied m on Θ via switching costs and the China shock is negligible, and this procedure converges on the second iteration.

4.5 Calibration results

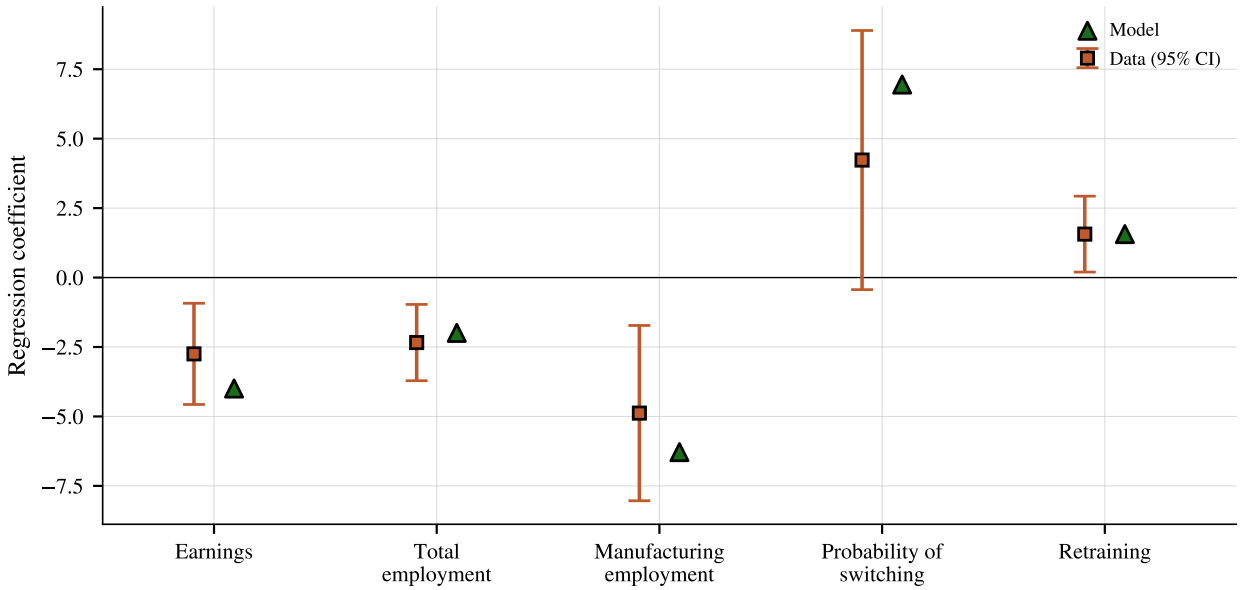
Figure 2 and Table 7 report our calibration results. Figure 2 shows that the model does a good job of matching the effect of the China shock.[9] Table 7 reports the calibrated parameter values, in addition to mean switching costs for each worker type.

Dispersion parameters

The first two rows of Panel A of Table 7 show our estimates of the dispersion parameters ν and σ, which are common to all worker types. The dispersion of sector preference shocks, ν, is 0.272, implying that a transitory 1% increase in real wages in a sector raises the probability that workers switch to that sector by roughly 3.67%. This implies a somewhat higher level of sensitivity than existing estimates, although differences in time horizon across papers make a direct comparison difficult (Artuç, Chaudhuri, and McLaren 2010; Dix-Carneiro 2014; Traiberman 2019; Caliendo, Dvorkin, and Parro 2019).

The dispersion of retraining shocks, σ, is 0.225. This value implies that the retraining decision is quite sensitive to costs: a 10% increase in costs F results in a decline in retraining rates of between 0.67 and 2.21 percentage points, depending on a worker's age, skill, and sector of employment.

Figure 2: China shock effects in model and data



Note: Squares show empirical estimates from Tables 4 and 5 along with 95% confidence intervals. Triangles show model-implied coefficients at the parameter values in Table 7.

[9]The model fits the other 18 target moments perfectly. See Appendix Table A3 for details.

Switching costs

The mean switching cost – averaged across origin-destination pairs, weighted by transition frequency – is 1.07. In the context of our model, this implies that switching costs are equivalent to a 66% reduction in real wages over five years: an economically large effect, but in line with the literature on worker mobility (Artuç, Chaudhuri, and McLaren 2010; Dix-Carneiro 2014). Switching costs are fairly homogeneous across skill groups but roughly 20% higher for old workers.

Costs and benefits of retraining

The final three rows of Panel B report the costs and benefits of retraining. We find that retraining costs are substantial but smaller than switching costs, averaging roughly 60% of switching costs for employed workers. As with switching, retraining costs are larger for old workers. We also find that retraining is less costly for workers in non-employment, consistent with the idea that the opportunity cost of time is lower for this group.

Our calibration finds positive values for Γ^{ka} for all worker types, implying that retraining makes it easier to switch sectors. Averaging across all types, the calibrated values of Γ^{ka} in the final row of Panel B imply that retraining lowers the effective cost of switching by 28%. This effect is fairly homogeneous across worker types, with the notable exception of young, highly-skilled workers, who seem to benefit less.

The result of all this is that workers who retrain are much more likely to move to a new sector. Averaging over all workers, retraining approximately doubles the probability of switching sectors, raising it by 18.5 percentage points from a baseline of 18.6 percentage points. Of course, workers who retrain are positively selected on their propensity to switch – but even within this selected

Table 7: Internally Calibrated Parameters

Panel A: Common parameters

Parameter		**Value**
ν	Sector pref. dispersion	0.272
σ	Retraining pref. dispersion	0.225

Panel B: Type-specific parameters

Parameter		(Y,L)	(Y,M)	(Y,H)	(O,L)	(O,M)	(O,H)	**Avg**
$\bar{C}^{ka}$	Switching cost	0.965	1.069	0.957	1.209	1.202	1.145	1.069
F_0^{ka}	Retraining cost (non-emp.)	0.363	0.435	0.495	0.498	0.463	0.499	0.414
F_1^{ka}	Retraining cost (emp.)	0.393	0.624	0.740	0.786	0.750	0.840	0.599
Γ^{ka}	Complementarity	0.302	0.310	0.188	0.301	0.335	0.342	0.301

Note: Worker types are indexed by age (Y = young, O = old) and skill (L = low, M = medium, H = high). Table reports the parameter values that minimise the loss function defined in (27), as well as the switching costs we infer from observed worker flows at these parameter values. Switching costs in the table are an average over $i - j$ transitions, weighted by the baseline frequency of those transitions.

group, the treatment effect of retraining is 22.6 percentage points, similar to the population-wide average.

In Appendix B.3 we decompose the welfare gain from retraining for an individual worker, $\mathcal{G}_{it}^{ka}$, into three components:

$$\mathcal{G}_{it}^{ka} = \underbrace{(\sigma\eta - F^{ka})}_{\text{Direct}} + \underbrace{S_0 S_1 \Gamma^{ka}}_{\text{Switching: intensive}} + \underbrace{(1-S_0)S_1\left(\beta(v_{j^*t+1} - v_{h^*t+1}) + (\epsilon_{j^*} - \epsilon_{h^*}) - (C_{ij^*}^{ka} - C_{ih^*}^{ka} - \Gamma^{ka})\right)}_{\text{Switching: extensive}} \tag{28}$$

where S_0 indicates whether the worker would switch sectors even without retraining, S_1 indicates switching when retraining is available, and j^* and h^* denote the chosen sectors in each case. Three findings emerge from this decomposition. First, workers who retrain experience welfare gains equivalent to a 25% increase in real wages over five years. Second, direct gains are modest (8%), implying workers benefit mainly from the complementarity between retraining and switching. Third, intensive margin gains (13%) dominate extensive margin gains (4%) – most of the welfare benefit comes from easing transitions that would have happened anyway.

5 Counterfactuals

With the calibrated model in hand, we now turn to our paper's central question: how does retraining shape the effects of trade shocks? We focus on the interaction of retraining and the China shock and begin by studying the effects of this shock in the baseline economy, then re-run the same shock while varying the costs of retraining and thus the aggregate retraining rate. We ask how retraining affects the distribution of welfare across workers and the dynamics of employment reallocation across sectors, and investigate the role of general equilibrium forces in generating these results.

5.1 The China Shock in the Baseline Economy

We start with the baseline economy — where retraining costs are exactly those we calibrated in Table 7 — and feed it the changes in manufacturing productivities in China we obtained as part of our calibration procedure. We model this shock exactly as we did in Section 4: the period zero equilibrium, which need not be a steady state, is the world economy in 2000. Between period zero and period one, German workers learn about the China shock and incorporate it into their retraining and sector-switching decisions. The shock arrives in period one and is permanent.

Panel (a) of Figure 3 shows how employment responds. The overall employment rate rises by 0.29 percentage points, as cheaper imported goods draw workers out of non-employment. Manufacturing employment, by contrast, declines by 0.29 percentage points. These small aggregate shifts mask substantial heterogeneity across manufacturing sectors. Employment in textiles, for

example, collapses (−36%), while employment in computers and electronics also falls sharply (−19%). Growing sectors include chemicals (+8%) and motor vehicles (+6%).

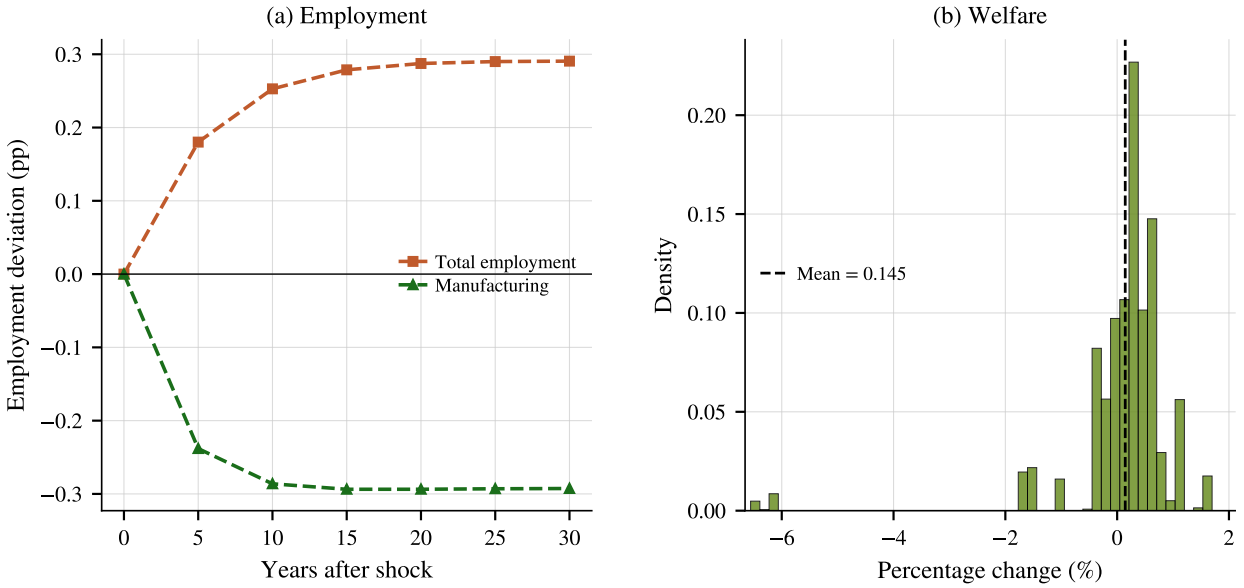
How did this shock affect the welfare of German workers? We measure changes in welfare using equivalent variation (EV), expressed as a fraction of per-period consumption. This depends on a worker's initial sector of employment i, their skill type k, and their age according to:

$$EV_i^{ky} = \left(\frac{(1-\beta(1-\chi))(1-\beta(1-\zeta))}{\beta(1-\beta(1-\chi)(1-\zeta))} \right) \widehat{U}_{i0}^{ky},$$
$$EV_i^{ko} = \left(\frac{1-\beta(1-\zeta)}{\beta(1-\zeta)} \right) \widehat{U}_{i0}^{ko}, \tag{29}$$

where $\widehat{U}_{i0}^{ka}$ is the change in the expected value defined in (15) between the period zero equilibrium with the China shock and the equilibrium without the China shock. The terms preceding $\widehat{U}_{i0}^{ka}$ for each age group simply convert the once-and-for-all changes in $\widehat{U}_{i0}^{ka}$ into per-period changes in consumption.

Weighting by baseline employment shares, we find that the China shock raises average welfare by 0.243%, reflecting the gains from cheaper imports. The histogram in Panel (b) of Figure 3 focuses on workers initially employed in manufacturing and shows the employment-weighted distribution of welfare changes caused by the shock. The average welfare gain remains positive but is smaller among these workers (0.145%). More strikingly, these welfare effects are widely dispersed. About

Figure 3: Baseline effects of the China Shock



Note: Panel (a) shows percentage point changes in total employment (circles) and manufacturing employment (triangles). The difference is taken between the economy with the baseline retraining parameters in Table 7 and the China shock, and the economy with the same parameters but no shock. Panel (b) shows the equivalent variation of the China shock, as defined in (29), among manufacturing workers. Equivalent variation is defined for each age-skill-initial employment cell, and cells are weighted by their baseline employment. The vertical line shows the baseline employment-weighted mean equivalent variation.

23% of manufacturing workers are made worse off and the left tail of the distribution is long: welfare among the worst-affected workers falls by more than 6%.

A worker's age, skill, and initial sector all play a role in shaping the distributional effects of this shock. Average gains vary relatively little by age or skill groups (from 0.181% to 0.272%), but the dispersion of these gains varies substantially. Most strikingly, among young workers initially in manufacturing the standard deviation of EV is 0.442, but among old workers it is 1.492. Old workers discount the future more heavily, and Table 7 also revealed that they face higher switching costs: the result is that the option value of moving in the future is less effective in insuring old workers against exposure to the shock, and its effects are more uneven.

Overall, the effects of the China shock in our baseline economy are broadly similar to those in Caliendo, Dvorkin, and Parro (2019), who study the effects of the same shock in the United States. They find that aggregate employment rises by 0.22 percentage points, manufacturing employment falls by 0.36 percentage points, and that the shock's welfare effects are positive on average but vary substantially across sectors and local labor markets.

5.2 Retraining and the China Shock

How does retraining interact with the China shock? Starting from the baseline economy, we now feed the model two shocks simultaneously: the China shock studied above, and a multiplicative change in retraining costs Δ, applied equally to workers of every age, skill, and employment status. We then follow the trajectory of employment, earnings, and welfare as the economy converges towards a new steady state. To isolate the effect of the China shock at time t, we compare the value of a variable on the path with both shocks to its value on the path with the retraining cost change alone – that is, we difference out the direct effect of the retraining policy and focus on how the presence of retraining alters the impact of the China shock.

We consider four scenarios for retraining costs: $\Delta = \infty$ ("No retraining"); $\Delta = 1$ ("Baseline"); $\Delta = 0.65$, which causes the retraining rate to roughly double ("2x"); and $\Delta = 0.45$, which causes the retraining rate to roughly triple ("3x"). Table 8 reports our main results. The first row shows the counterfactual retraining rate and the second shows the resulting sector switching rate — $\tilde{m}$ from Section 3. Consistent with Theorem 1, as the retraining rate rises, so does the sector switching rate: from just over 28% in the No retraining scenario to just under 36% in the 3x scenario. The rest of the table explores how these changes in mobility alter the effects of the China shock. We focus on welfare and employment dynamics, as well as the role of general equilibrium forces.

Welfare

The first panel of Table 8 shows that Germany's aggregate welfare gains from the China shock are nearly invariant to the retraining rate. This is consistent with Theorem 2, which shows that retraining does not enter the expression for aggregate welfare in the simple model. The small changes that do appear reflect compositional effects absent from that setting: the China shock

reduces non-employment, and non-employed workers benefit more from retraining than employed workers. The result is that the China shock slightly lowers the aggregate gains from retraining, accounting for the negative relationship in Table 8. Among workers initially in manufacturing, this pattern is reversed.

The second panel of Table 8 shows that retraining compresses the distribution of welfare effects of the China shock. As Theorem 2 predicts, the mechanism runs through the option value of mobility: retraining lowers the cost of switching sectors and so compensates workers in adversely affected sectors with the option of moving to a new one. Quantitatively, the effects are moderate. Going from the No retraining column to the 3x column, the standard deviation of welfare changes across all workers falls by 17% and across manufacturing workers by 17%. The solid line in Panel (a) of Figure 4 illustrates this decline. Focusing on the bottom of the distribution, the share of manufacturing workers who are worse off as a result of the shock falls from 24.1% to 22.7%, while the welfare loss of the worst affected workers — old, low-skill workers initially employed in textiles — declines in magnitude from -6.76% to -5.82%.

From these results, we conclude that expanding retraining is an attractive tool for a policymaker concerned about the distributional consequences of import competition shocks. But the magnitudes in Table 8 also suggest that, even in an economy with widely available retraining, some workers

Table 8: Effects of the China Shock Across Retraining Scenarios

	No retraining	Baseline	2x	3x
Retraining rate	0.0%	11.5%	23.0%	34.5%
Switching rate	28.4%	31.1%	33.6%	35.9%
Welfare: aggregate				
Mean EV	0.249	0.243	0.241	0.241
Mean EV (mfg)	0.144	0.145	0.151	0.159
Welfare: distribution				
Std(EV)	0.472	0.450	0.420	0.391
Std(EV) (mfg)	1.004	0.956	0.893	0.832
% of mfg. workers with EV < 0	24.1	22.8	22.7	22.7
Min EV	-6.761	-6.557	-6.204	-5.823
Aggregate employment dynamics				
Aggregate employment (pp change), year 5	0.175	0.180	0.180	0.178
Aggregate employment (pp change), LR	0.290	0.290	0.280	0.267
Mfg. employment (pp change), year 5	-0.237	-0.238	-0.242	-0.246
Mfg. employment (pp change), LR	-0.298	-0.293	-0.294	-0.298
Sectoral employment dynamics (mfg)				
$\|\Delta l\|_1$ at year 5	5.290	5.362	5.445	5.520
$\|\Delta l\|_1$ long run	7.875	7.741	7.646	7.574
% of LR adj. at year 5	67.0	69.1	71.0	72.7

Note: Each column shows effects of the China shock under different retraining cost scenarios. The effects of the China shock are always defined as differences between the economy with and without this shock, so that direct effects of changes in retraining costs are differenced out. Means and standard deviations are weighted by baseline employment. "Mfg" refers to manufacturing.

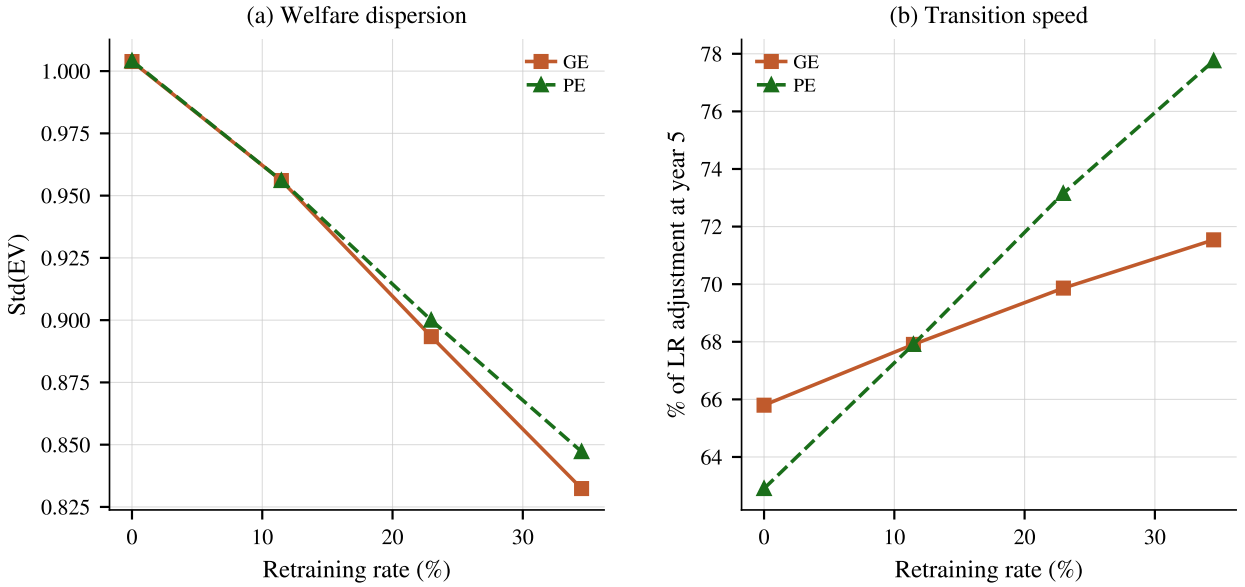
will inevitably lose out.

Employment dynamics

The third panel of Table 8 shows that retraining has small, non-monotone effects on aggregate and manufacturing employment changes in both the short run and the long run. To explore how employment dynamics change at a more granular level, we focus on manufacturing and measure employment reallocation across sectors by calculating the average absolute change in sectoral employment shares within manufacturing at different time horizons. The final panel of Table 8 shows that, under the Baseline scenario, the average sector experiences a 5.362 percentage point change in its employment share in the short run.

In line with Theorem 3, retraining has different effects on reallocation at different time horizons. In the short run, the reduction in effective switching costs caused by retraining makes it easier for workers to exit declining sectors and enter booming ones, resulting in larger employment share changes. But in the long run, the pattern is exactly the opposite: employment shares are actually more stable in economies with higher retraining rates. The intuition is that when retraining rates are higher, workers in low-wage sectors are better compensated by the option value of switching in the future, and given this, their sectoral choices are less responsive to wages. The result is less employment reallocation in the long run.

Figure 4: Results of varying retraining costs



Note: Both panels show how an outcome varies across retraining cost scenarios. In both panels the line with square markers ("GE") shows the full model and the line with triangles ("PE") shows the partial equilibrium model in which the path of real wages in every sector is held constant even as retraining costs vary. Panel (a) shows the baseline employment-weighted standard deviation of equivalent variation across workers initially in manufacturing. Panel (b) shows our measure of transition speed, the fraction of long-run employment reallocation that is complete within five years of the shock.

The combination of larger short-run responses and smaller long-run responses means that the transition to the new steady state is faster when retraining is more widespread, exactly as Theorem 3 predicts. In Table 8, we measure this transition speed as the share of long-run reallocation that is complete within five years: this share rises from 67.0% in the No retraining column to 72.7% in the 3x column. The solid line in Panel (b) of Figure 4 illustrates this shift.

Partial versus general equilibrium

Retraining directly affects the switching costs facing workers, but by altering how the distribution of employment across sectors responds to the China shock it may also have important general equilibrium effects on real wages. We investigate these in Appendix Table B, where we repeat the retraining cost experiments of Table 8 but hold the trajectories of real wages constant at their baseline values (i.e., the same as those generated by the Baseline column of Table 8). The dashed lines in Figure 4 focus on two statistics — the dispersion of welfare effects, and the speed of the transition – and show how these vary with retraining rates in partial equilibrium.

The two lines in Panel (a) are almost identical, implying that general equilibrium effects hardly matter for the relationship between retraining and the dispersion of welfare. But the two very different lines in Panel (b) show that general equilibrium forces do play an important role in how retraining shapes the employment effects of the China shock. We can see that the partial equilibrium model substantially overstates how sensitive the speed of labor reallocation is to retraining: in the full model the share of the transition completed within five years rises from 67.0% under No retraining to 72.7% in the 3x scenario; but the dashed line in Panel (b) shows that in partial equilibrium it rises from 63.6% to 77.8%. The implication is that general equilibrium changes in wages are substantially offsetting the direct effect of retraining on labor mobility, and a partial equilibrium approach overstates the effectiveness of retraining in speeding up transitions following trade shocks.

5.3 Taking Stock

Our counterfactual experiments deliver three main results. First, retraining compresses the distribution of welfare effects of the China shock across workers: as we move from an economy in which retraining is impossible to one in which the retraining rate triples relative to the data, the standard deviation of welfare changes across workers falls by 17% and the share of manufacturing workers who are made worse off by this shock falls from 24.1% to 22.7%. Second, retraining speeds up the transition to the new steady state in the short run but dampens long-run employment reallocation across sectors. And finally, general equilibrium feedback substantially limits the impact of retraining on labor reallocation across sectors.

In general these effects are quantitatively modest. While retraining is certainly a useful tool for a policymaker concerned by the distributional effects of trade shocks or sluggish adjustment to such shocks in the labor market, our results suggest it is not a panacea.

6 Conclusion

This paper studies the role of government-subsidized retraining in helping workers adjust to international trade shocks. Using administrative data from Germany, we document that retraining is tightly linked to transitions across sectors and that workers retrain in response to rising import competition from China. We then develop a model in which the decisions to retrain and to switch sectors are made jointly, and show that when the two are complements, increases in the availability of retraining are isomorphic to reductions in switching costs.

Our calibration confirms that retraining and sector switching are complements for all worker types: a worker who retrains faces effective switching costs 28% lower than one who does not. In a counterfactual in which the aggregate retraining rate triples relative to the data, the standard deviation of welfare changes caused by the China shock falls by 17% and the share of long-run employment reallocation completed within five years rises from 67% to 73%, all without materially affecting aggregate welfare. General equilibrium forces, however, substantially attenuate the effects of retraining on employment reallocation, and the magnitudes we find are quantitatively modest.

These results suggest that retraining is an attractive tool for policymakers concerned about the distributional consequences of sectoral shocks. It evens out the welfare effects of import competition and accelerates labor market adjustment without diminishing the aggregate gains from trade. At the same time, our findings caution against viewing retraining as a panacea: even with widely available retraining, some workers will inevitably lose from large sectoral shocks. Retraining is best understood as a useful complement to other adjustment policies, not a substitute for them.

A Data Appendix

A.1 German Sample of Integrated Labor Market Biographies (SIAB)

We measure labor market outcomes using standard German administrative labor market data, the Sample of Integrated Labor Market Biographies (SIAB) 1975-2021 (Graf et al. 2023), which we accessed on-site at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently via remote data access. The SIAB draws a 2% sample from Germany's primary administrative worker database, known as the Integrated Employment Biographies (IEB). This panel records, for each worker and month between 1975 and 2021, any active employment spells, unemployment benefits, and participation in active labor market programs such as retraining (Schmucker, Seth, and Berge 2023).

A.1.1 General Cleaning and Preparation

We clean and prepare the SIAB for all further analysis using the excellent suite of Stata routines provided by W. Dauth, Eppelsheimer, and Stüber (2023). In particular, we implement their codes which take the raw worker-by-employment or benefit receipt episode panel and then split episodes which span multiple calendar years, correctly account for lump-sum payments, calculate job tenure, merge in firm characteristics, aggregate education levels, merge in values of the contribution assessment ceiling and marginal part-time income threshold for tax and social insurance payments, and deflate monetary values. We then restrict the panel to workers between the ages of 18 and 65, drop employment spells with zero income, and drop employment statuses not observed in all years: marginal employment spells, internships, and a catchall "other" category. Next, we use W. Dauth, Eppelsheimer, and Stüber (2023)'s imputation procedure to correct for top-coding of wages and later apply their final cleaning routine.

A.1.2 Sector Aggregates

Having thus conducted basic cleaning, we compute aggregates 3-digit sectors in the German Classification of Economic Activities, Edition 1993 (WZ 93). Specifically, we use reported earnings per day and episode length of all observed employment episodes to compute the annual wage bill for each year at the sector level. We also take an annual snapshot on 30 June to compute employment counts. To do so, we must define a primary job for each worker; we define the latter as the job held on 30 June with the highest daily earnings and break ties by selecting the job where the worker has the longest tenure in the firm and, if any ties remain, randomly selecting one episode. Based on these yearly primary jobs, we then compute sectoral employment counts for each year. In computing all aggregates, we account for the fact that our data represents a 2% sample of the economy.

A.1.3 Worker Sample

We now prepare a worker-level dataset of labor market outcomes. We start with the data prepared as in Appendix A.1.1 and again build on the Stata routine provided by W. Dauth, Eppelsheimer, and Stüber (2023) to correct for parallel employment episodes. Whenever workers concurrently hold multiple jobs, we keep only a single "primary" job. In particular, we select the job where the worker has the longest tenure in the firm and break ties based on (in order) daily earnings, total length of the episode, and then randomly. We later define a worker's sector based on this primary job but also record the sum of earnings across all jobs held in parallel.

Our sample of workers then comes from a cross-sectional snapshot in the year 2000. Loosely following W. Dauth, Findeisen, and Suedekum (2021), we include all workers who, in their primary job, were full-time employed in manufacturing on 30 June 2000, had at least two years of tenure in their current job, earned above the marginal earnings threshold, and who were aged 24-65 during our whole sample period of 2001-2010.[10]

A.1.4 Retraining Episode Sample

The facts regarding episode length in Section 1.3 are based on a dataset of retraining episodes derived from the raw SIAB panel. As in the rest of the paper, we define retraining as the employment status (*erwstat*) codes 10001 (activation and vocational integration), 10002 (career choice and vocational training), and 10003 (vocational retraining and further education) in the Participants-In-Measures History File (MTH/XMTH) module of the SIAB. Since the SIAB only includes such episodes starting in 2000, we restrict our sample to retraining spells between 2000 and 2019. We then calculate the length of retraining episodes in days.

A.1.5 Quarterly Panel

To characterize retraining rates and calculate aggregates for calibration, we also build a quarterly panel of workers. We begin with the SIAB, cleaned as described in Appendix A.1.1, and correct for parallel employment episodes as described in Appendix A.1.3. We then adapt existing code for a yearly panel from W. Dauth, Eppelsheimer, and Stüber (2023) to instead generate a quarterly panel of workers from 1992 through 2019. In this panel, we measure workers' employment status, earnings, and sector on the midpoint date of each quarter; job characteristics are those of their primary job, as previously defined, on this date. We also define a quarterly retraining dummy which equals one if the worker participated in subsidized retraining at any point during that quarter, not necessarily only on the "sample" date. We classify worker-quarters missing from the data as non-employment. We associate non-employed workers with their last observed occupation observed on the sample date of a quarter.

[10] Manufacturing sectors in the 3-digit German Classification of Economic Activities, Edition 1993 include sectors 151-212 and 241-366.

A.2 UN Comtrade Database

Our trade data comes from the UN Comtrade Database.[11] Comtrade provides primary values by importing and exporting country and SITC Rev. 3 sector; we map these values to the 3-digit sectors in the German Classification of Economic Activities, Edition 1993 (WZ 93) with a crosswalk provided by W. Dauth, Findeisen, and Suedekum (2021). We then convert all values to 2005 USD using the FRED Consumer Price Index for All Urban Consumers: All Items in US City Average (CPIAUCSL), seasonally adjusted, indexed to January 2005 and finally convert to 2005 Euros using December 2005 exchange rates.[12]. Finally, we crosswalk trade flows to a slightly-aggregated version of ISIC Rev. 4 sectors using establishment counts as provided for Germany by Eberle et al. (2014). We then focus on trade flows between Germany and China. We also follow common practice in the trade literature and calculate trade flows between each of eight other high-income countries and China; our "other" high-income countries include the UK, Sweden, Norway, Canada, Australia, New Zealand, Japan, and Singapore.

A.3 Variable Definitions

A.3.1 Retraining Rates

The retraining rates cited in Section 1.3 are based on our SIAB-derived quarterly panel. We restrict the data to the period 2000-2019, as in the case of our retraining episode sample, and calculate the yearly retraining rate as the share of person-years during which a worker participates in subsidized retraining (employment status *erwstat* 10001-10003). We calculate both aggregate rates and rates by nine aggregate sectors delineated by W. Dauth and Eppelsheimer (2020), which correspond to those employed in the IAB Establishment Panel. Finally, we arrive at the lifetime retraining rate by computing the share of workers in this quarterly panel who complete retraining at some point during 1992-2019.

A.3.2 Labor Market Outcomes

We calculate earnings, employment, and retraining in the worker sample discussed in Appendix A.1.3; in doing so, we build on replication code provided by W. Dauth, Findeisen, and Suedekum (2021). First, we calculate earnings across all jobs during the year 2010, divide by total earnings across all jobs during the year 2000, and multiply by 100 to obtain our measure of *earnings growth*. Then, we calculate the share of calendar days in 2010 during which a worker is employed in any job to obtain the *share of days employed* and the *share of* (calendar) *days employed in manufacturing*, defined, for the purposes of employment shares, as 3-digit sectors 151-366. Finally, for our linear probability model and logit specifications for the *Pr(retrain)*, we define a subsidized retraining dummy equal to one if we observe a worker participating in subsidized retraining during 2001-2010, which we

[11] Available at https://comtradeplus.un.org.

[12] CPI available at https://fred.stlouisfed.org/series/CPIAUCSL#0 and USD-Euro exchange rates at https://www.europarl.europa.eu/RegData/etudes/note/join/2007/379231/IPOL-TRAN_NT(2007)379231_EN.pdf.

define as the employment status (*erwstat*) codes 10001 (activation and vocational integration), 10002 (career choice and vocational training), and 10003 (vocational retraining and further education) in the Participants-In-Measures History File (MTH/XMTH) module of the SIAB. We finally define the *number days retraining* as the sum of the lengths (in days) of all episodes of subsidized retraining during 2001-2010.

A.3.3 Controls

Using the SIAB, we also calculate demographic and initial-job-related controls for our worker sample discussed in Appendix A.1.3. We define a female dummy as well as one for foreign nationality. We also define dummy variables for education dummies for three education levels: low (neither vocational training nor degree from university), medium (vocational training), and high (degree from a university or university of applied science). The age bins for which we include dummies include 24-34, 35-44, 45-54, and 55+. We also define controls related to workers' "initial" primary job in the year 2000. These controls include dummies for <1, 2-4, 5-9, and 10+ years of tenure in the initial job, as defined by W. Dauth, Eppelsheimer, and Stüber (2023), dummies for firm (i.e. plant) size bins of 1-9, 10-99, 100-499, and 500+ workers, four broad manufacturing sectoral groups, and a dummy for workplaces in the former East German states. Finally, we record total year-2000 earnings, summed across all jobs.

A.3.4 Trade Exposure

We then compute sector-level trade exposure. We convert Comtrade trade flow values to 2015 Euros and then calculate the change in net imports, $\Delta\text{net imports}_s$, as the raw change in imports minus exports between Germany or the aforementioned other high-income countries and China in a sector from 2001-2010.

To aggregate up to the occupation level, we define the import exposure of a worker initially in occupation t as a weighted average of changes in sectoral net imports from the East, either to Germany or to the set of other high income countries:

$$\text{import exposure}_s \equiv \frac{\Delta\text{net imports}_s}{\text{wage bill}_s},$$

As in W. Dauth, Findeisen, and Suedekum (2021), we normalize net imports by the sector's total year-2000 wage bill in Germany, calculated as in Appendix A.1.2. Note also that, in line with common practice, we focus only on manufacturing trade, which we define, for the purposes of calculating trade flows, as 3-digit sectors 151-212 and 241-366. Thus, $\Delta\text{net imports}_s$ equals zero for all sectors s outside of manufacturing.

Table A1: Labour Market and Retraining Effects of Chinese Import Exposure: 3-Digit Sectors

IV (2SLS)	(1) Share days employed	(2) Share days in manufacturing	(3) Earnings growth	(4) Pr(Switch Sector)	(5) Pr(Retrain)
Sectoral import exposure	-0.023***	-0.049***	-2.748**	0.035**	0.016***
	(0.006)	(0.011)	(1.102)	(0.016)	(0.005)
Demographic Controls	✓	✓	✓	✓	✓
Initial Job Controls	✓	✓	✓	✓	✓
Observations	83,099	83,099	83,099	83,099	83,099
Mean of Dependent Variable	0.761	0.649	80.965	0.236	0.135
First-Stage F Statistic:			736.18		

Notes: Robust standard errors in parentheses, clustered at the sector level; *** indicates p<0.01, ** p<0.05, and * p<0.1. Columns 1–4 present instrumental variables estimates of (1) for workers employed in manufacturing in 2000 in the SIAB data, where our sectors are the 3-digit German Classification of Economic Activities (WZ 93). We measure the share of days employed and share of days employed in manufacturing (unconditional on employment) in 2010, our earnings growth measure equals 100 times total 2010 earnings divided by those in the year 2000, we measure sector switching as employment in 2010 outside of a worker's initial sector, and our retraining outcome is a dummy variable for participation in retraining during 2001–2010 . We instrument for 2001–2010 3-digit sectoral import exposure in Germany with an analogous measure calculated using net imports to other high-income countries. Demographic controls include age bins, gender, education, and foreign nationality, measured in 2000. Initial, year-2000 job controls include tenure and firm size bins, manufacturing sector group indicators, an East Germany dummy, and log earnings, the latter summed across all jobs.

A.4 Finer Sector Classification

Tables 4 and 5 in the main text measure import exposure and switching at the level of 24 slightly-aggregated ISIC Rev. 4 sectors. Table A1 re-estimates our key specifications using 3-digit sectors from the German Classification of Economic Activities (WZ 93). Point estimates are remarkably stable across the two classifications: the employment, manufacturing employment, earnings growth, and retraining coefficients are virtually identical, and the sector-switching coefficient differs only modestly (0.035 versus 0.042 in the main specification). Thus, our findings do not depend on the level of sectoral aggregation.

A.5 Decomposition: Trade, Retraining, and Unemployment

A natural question is whether the positive effect of import exposure on retraining documented in Table 5 operates through a mechanical increase in unemployment—since unemployed workers retrain at far higher rates than employed workers—or whether trade exposure also raises retraining rates, conditional on workers' employment status. Table A2 displays the appropriately-instrumented effects of import exposure on, in Column (1), the share $\Pr(R|N)$ of non-employed days spent in retraining; in Column (2), the share $\Pr(R|E)$ of employed days spent in retraining; and in Column (3), the share of days spent non-employed, all measured over 2001-2010. Import exposure significantly

Table A2: Decomposition of the Trade-Retraining Relationship

IV (2SLS)	(1) $\Pr(R\|N)$	(2) $\Pr(R\|E)$	(3) $\Pr(N)$
Sectoral import exposure	0.003	-0.00006	0.019***
	(0.002)	(0.00001)	(0.005)
Demographic Controls	✓	✓	✓
Initial Job Controls	✓	✓	✓
Observations	83,099	82,427	83,099
Mean of Dependent Variable	0.015	0.001	0.144
First-Stage F Statistic:	237.63	235.62	237.63

Notes: Robust standard errors in parentheses, clustered at the sector level. *** indicates p<0.01, ** p<0.05, and * p<0.1. This table presents linear instrumental variables estimates of (1) for workers employed in manufacturing in 2000 in the SIAB data. Column 1 displays an outcome equal to the share of days spent unemployed during 2001–2010 in which the worker participates in subsidized retraining. The outcome in Column 2 is the analogous share of employed days, while Column 3 displays the share of days during 2001–2010 spent unemployed. Our sectors are a mildly-aggregated version of ISIC Rev. 4. In each case, we instrument for 2001–2010 sectoral import exposure in Germany with an analogous measure calculated using net imports to other high-income countries. Specifications include controls as noted. Demographic controls include age bins, gender, education, and foreign nationality, measured in 2000. Initial, year-2000 job controls include tenure and firm size bins, manufacturing sector group indicators, an East Germany dummy, and log earnings, the latter summed across all jobs.

raises the probability $\Pr(N)$ of unemployment (Column 3), confirming that trade shocks displace workers from their initial jobs. However, the rate of retraining conditional on unemployment also increases with import exposure (Column 1), though the coefficient is imprecisely estimated. Thus, the overall effect of trade on retraining reflects both an extensive margin—more workers entering unemployment—and an intensive margin of higher retraining take-up among displaced workers.

More formally, these results allow us to decompose the overall effect of import exposure ΔM on retraining probability $\Pr(R)$ as follows,

$$\frac{\partial \Pr(R)}{\partial \Delta M} = \underbrace{\Pr(N)\frac{\partial \Pr(R|N)}{\partial \Delta M}}_{66\%} + \underbrace{(1-\Pr(N))\frac{\partial \Pr(R|E)}{\partial \Delta M}}_{-9\%} + \underbrace{(\Pr(R|N)-\Pr(R|E))\frac{\partial \Pr(N)}{\partial \Delta M}}_{43\%}, \tag{30}$$

where, again, $\Pr(N)$ is the probability of unemployment, $\Pr(R|N)$ and $\Pr(R|E)$ are the probabilities of retraining conditional on unemployment and employment, respectively. We then plug in the coefficients from Table A2 as well as the accompanying mean values of $\Pr(N)$, $\Pr(R|N)$, and $\Pr(R|E)$ to calculate the percentage contribution of each channel to the overall effect of imports on retraining, displayed in the equation above. While the "mechanical" increase in unemployment accounts for 43% of the overall effect of import exposure on retraining, the increase in retraining conditional on unemployment accounts for a full 66%. Thus, trade clearly appears to alter the incentives for unemployed workers to retrain.

B Model Appendix

B.1 Proofs of Analytical Results

Proof of Theorem 1. We proceed in three steps: solve the model at $\Gamma = 0$, differentiate with respect to Γ, and evaluate the derivative at $\Gamma = 0$.

Step 1: Solution at $\Gamma = 0$. When $\Gamma = 0$ the retraining decision does not depend on the sector choice. A worker retrains if and only if $\sigma\eta - F > 0$, giving a retraining rate

$$\bar{\rho} = \Pr(\eta > F/\sigma) = \frac{1}{1 + e^{F/\sigma}},$$

which is common across sectors. Since the retraining payoff $\max\{\sigma\eta - F, 0\}$ is the same regardless of destination, it cancels from pairwise comparisons. The remaining sector choice is a standard logit, giving

$$\log\left(\frac{\bar{\mu}_{ij}}{\bar{\mu}_{ii}}\right) = \frac{\beta(v_j - v_i) - C}{\nu}.$$

Step 2: Differentiation. We derive $\frac{\partial}{\partial\Gamma}\log(\mu_{ij}/\mu_{ii})|_{\Gamma=0}$. Conditional on the retraining shock η, the sector choice remains logit, with the payoff of each switching option $j \neq i$ augmented by $\max\{\Gamma + \sigma\eta - F, 0\}$ and the payoff of staying augmented by $\max\{\sigma\eta - F, 0\}$. Differentiating with respect to Γ: the payoff of each switching option $j \neq i$ changes at rate $\mathbb{1}\{\Gamma + \sigma\eta - F > 0\}$, which at $\Gamma = 0$ equals $\mathbb{1}\{\eta > F/\sigma\}$, while the payoff of staying in i does not depend on Γ. Since the payoffs of all switching options change by the same amount, the standard logit derivative gives

$$\left.\frac{\partial\mu_{ij}(\eta)}{\partial\Gamma}\right|_{\Gamma=0} = \frac{\mathbb{1}\{\eta > F/\sigma\}}{\nu}\bar{\mu}_{ij}\bar{\mu}_{ii}, \qquad \left.\frac{\partial\mu_{ii}(\eta)}{\partial\Gamma}\right|_{\Gamma=0} = -\frac{\mathbb{1}\{\eta > F/\sigma\}}{\nu}\bar{\mu}_{ii}(1 - \bar{\mu}_{ii}).$$

At $\Gamma = 0$ the conditional probabilities $\mu_{ij}(\eta) = \bar{\mu}_{ij}$ do not depend on η, so the unconditional derivatives are obtained by taking expectations over η, replacing $\mathbb{E}[\mathbb{1}\{\eta > F/\sigma\}]$ with $\bar{\rho}$. Therefore

$$\left.\frac{\partial}{\partial\Gamma}\log\frac{\mu_{ij}}{\mu_{ii}}\right|_{\Gamma=0} = \frac{1}{\bar{\mu}_{ij}}\frac{\partial\mu_{ij}}{\partial\Gamma} - \frac{1}{\bar{\mu}_{ii}}\frac{\partial\mu_{ii}}{\partial\Gamma} = \frac{\bar{\rho}\bar{\mu}_{ii}}{\nu} + \frac{\bar{\rho}(1 - \bar{\mu}_{ii})}{\nu} = \frac{\bar{\rho}}{\nu}.$$

A first-order expansion around $\Gamma = 0$ then yields (4). Expression (6) follows from evaluating the logit choice probabilities at the effective switching cost $C - \Gamma\bar{\rho}$.

Step 3: Retraining rate. Decompose the retraining probability as

$$\rho_i = \Pr(\text{retrain} \mid \text{stay}) \cdot \mu_{ii} + \Pr(\text{retrain} \mid \text{switch}) \cdot (1 - \mu_{ii}).$$

At $\Gamma = 0$ both conditional probabilities equal $\bar{\rho}$, so $\rho_i = \bar{\rho}$. Differentiating with respect to Γ: the

threshold for retraining conditional on switching is $\eta > (F - \Gamma)/\sigma$, so

$$\frac{\partial}{\partial \Gamma} \Pr(\text{retrain} \mid \text{switch})\Big|_{\Gamma=0} = \frac{1}{\sigma}\bar{\rho}(1-\bar{\rho}),$$

using the logistic density $f(F/\sigma) = \bar{\rho}(1-\bar{\rho})$. The threshold for retraining conditional on staying, $\eta > F/\sigma$, does not depend on Γ. Finally, the composition effect from the changing μ_{ii} vanishes to first order since both conditional retraining probabilities equal $\bar{\rho}$ at $\Gamma = 0$. Collecting terms:

$$\frac{\partial \rho_i}{\partial \Gamma}\Big|_{\Gamma=0} = (1 - \bar{\mu}_{ii}) \cdot \frac{\bar{\rho}(1-\bar{\rho})}{\sigma},$$

yielding (5). □

Proof of Theorem 2. Part (i). Equation (7) follows directly from $w_{it} = \tilde{w}_{it} P_t^{-1}$ with $\tilde{w}_{it} = P_{it}$ and the Cobb-Douglas price index $P_t = \prod_j P_{jt}^{\alpha_j}$.

Part (ii). Following the permanent shock, real wages, worker values, and choice probabilities are all constant over time. The steady-state Bellman equation is $v_i = \log w_i + \mathcal{V}_i(\mathbf{v})$, where $\mathcal{V}_i$ is the continuation value. Differentiating with respect to the shock and applying the envelope theorem:

$$dv_i = d\log w_i + \beta \sum_j \mu_{ij}\, dv_j, \tag{31}$$

where we used $\partial \mathcal{V}_i / \partial v_j = \beta \mu_{ij}$. Summing over i and using $\sum_j \mu_{ij} = 1$:

$$dV = \frac{1}{N}\sum_i d\log w_i + \beta\, dV, \quad \Longrightarrow \quad dV = \frac{1}{1-\beta}\sum_i l_i\, d\log w_i,$$

where $l_i = 1/N$ at the symmetric baseline. Since $\sum_i l_i\, d\log w_i = \sum_i (l_i - \alpha_i) d\log P_i$, this establishes (8).

Part (iii). At the symmetric baseline, $\mu_{ii} = 1 - \bar{m}$ and $\mu_{ij} = \bar{m}/(N-1)$ for $j \neq i$, where $\bar{m}$ is the raw probability of switching sectors. Writing $\sum_{j \neq i} dv_j = N\, dV - dv_i$ and defining $\tilde{m} = \bar{m}N/(N-1)$, equation (31) becomes

$$dv_i = d\log w_i + \beta(1-\tilde{m})\, dv_i + \beta \tilde{m}\, dV.$$

Solving for dv_i and rearranging: add and subtract $d\log w_i/(1-\beta)$ to obtain

$$dv_i = \frac{d\log w_i}{1-\beta} + \lambda(\tilde{m})\left(dV - \frac{d\log w_i}{1-\beta}\right),$$

where $\lambda(\tilde{m}) = \beta\tilde{m}/(1-\beta+\beta\tilde{m})$, establishing (9). □

Proof of Theorem 3. We linearize around the symmetric steady-state baseline ($l_i = 1/N$ for all i) throughout.

Dynamics and front-loading. The law of motion for employment is $l_{it+1} = \sum_j \mu_{jit} l_{jt}$. At the symmetric baseline, $\mu_{ji} = \bar{m}/(N-1)$ for $j \neq i$ and $\mu_{ii} = 1 - \bar{m}$, where $\bar{m}$ is the raw probability of switching sectors. Log-linearizing around the steady state and using the fact that, following a permanent shock, choice probabilities are constant over time:

$$d \log l_{it+1} = (1 - \bar{m}) d \log l_{it} + \frac{\bar{m}}{N-1} \sum_{j \neq i} d \log l_{jt}.$$

Since $\sum_j d \log l_{jt} = 0$ (unit mass of workers), we have $\sum_{j \neq i} d \log l_{jt} = -d \log l_{it}$, giving

$$d \log l_{it+1} = \left(1 - \frac{\bar{m} N}{N-1}\right) d \log l_{it} = (1 - \tilde{m})\, d \log l_{it},$$

where $\tilde{m} = \bar{m} N/(N-1)$. More precisely, the transition matrix has two distinct eigenvalues: 1 (corresponding to the uniform eigenvector, reflecting conservation of total employment) and $1 - \tilde{m}$ (corresponding to any mean-zero eigenvector). Since the perturbation $d \log l_{it}$ is mean-zero for $t \geq 1$, the dynamics are governed entirely by the second eigenvalue, and the gap between current and long-run employment closes geometrically:

$$d \log l_{it+1} - d \log l_{i\infty} = (1 - \tilde{m}) \left(d \log l_{it} - d \log l_{i\infty}\right).$$

With $d \log l_{i0} = 0$, iterating forward gives $d \log l_{it} = \left[1 - (1 - \tilde{m})^t\right] d \log l_{i\infty}$, establishing (13).

Short-run reallocation. Setting $t = 0$ in the expression above gives $d \log l_{i1} = \tilde{m} \cdot d \log l_{i\infty}$, so it suffices to derive the long-run expression.

Long-run reallocation. In the new steady state, the logit choice probabilities are determined by the new values v_i. A first-order expansion of the transition matrix around the symmetric baseline and the steady-state condition $l_{i\infty} = \sum_j \mu_{ji\infty} l_{j\infty}$ yields

$$d \log l_{i\infty} = (2 - \tilde{m}) \frac{\beta}{\nu} (dv_i - dV). \tag{32}$$

To see this, note that the net inflow into sector i in steady state must satisfy $\tilde{m}\, d \log l_{i\infty} = \sum_j \bar{\mu}_{ji} d \log \mu_{ji\infty}$. At the symmetric baseline, $d \log \mu_{ji\infty} = (\beta/\nu)(dv_i - \sum_k \mu_{jk} dv_k)$ for $j \neq i$. Summing over origins and using the symmetry of the baseline gives the result, with the factor $(2 - \tilde{m})$ arising from the interaction of the changed choice probabilities with the changed employment distribution.

Using Theorem 2 to substitute $dv_i - dV = (1 - \lambda(\tilde{m}))\left(\frac{d \log w_i}{1-\beta} - dV\right)$ into (32) establishes (12). Expression (11) then follows from $d \log l_{i1} = \tilde{m} \cdot d \log l_{i\infty}$.

Comparative statics. For part (i), note that $\tilde{m}$ is increasing in Γ when $\Gamma > 0$ (from Theorem 1). The coefficient on $(d \log w_i/(1-\beta) - dV)$ in (11) is $\tilde{m}(2 - \tilde{m})(1 - \lambda(\tilde{m}))(\beta/\nu)$. The factor $\tilde{m}(2 - \tilde{m})$ is increasing in $\tilde{m}$ for $\tilde{m} < 1$, while $(1 - \lambda(\tilde{m}))$ is decreasing. For $\tilde{m}$ sufficiently small the first effect dominates and short-run reallocation rises. For part (ii), the long-run coefficient $(2 - \tilde{m})(1 - \lambda(\tilde{m}))(\beta/\nu)$ is unambiguously decreasing in $\tilde{m}$: both factors fall as $\tilde{m}$ rises. For part (iii), the fraction

of adjustment $1-(1-\tilde{m})^t$ is increasing in $\tilde{m}$ for all $t \geq 1$. □

B.2 Switching costs

We now describe how we parameterize and recover sector switching costs. Since the procedure works entirely within a worker type, we drop the *ka* superscript throughout. We set $C_{ii} = 0$ and $C_{i0} = 0$ for all i, so that remaining in sector and entering non-employment are costless. Letting $M(i) \in \{0, 1\}$ indicate manufacturing, the cost of moving from i to j is

$$C_{ij} = C_i^o + C_j^d + C_{MN} M(i)(1 - M(j)) + C_{NM}(1 - M(i))M(j) + C_\delta \delta(i, j), \tag{33}$$

where $\delta(i, j)$ is a measure of the skill distance between sectors i and j. For workers who are initially non-employed, we leave C_{i0} free.

We measure skill distance using the occupational task content weights developed by Dengler, Matthes, and Paulus (2014) based on a German expert database. In particular, we average their 3-digit-occupation-level weights on analytical non-routine tasks, interactive non- routine tasks, cognitive routine tasks, manual routine tasks and manual non-routine tasks at the sector level using employment shares in 2000 as weights. We then take the log Euclidean distance between the five average task weights of each pair of sectors to obtain $\delta(i, j)$.

Our goal is to infer these costs from the observed transition matrix μ_{ij}. To motivate our approach, first consider a model without retraining. Then the (log) probability a worker switches from sector i to sector $j \neq i$ is:

$$\begin{aligned} \log \mu_{ij} = &\left(\frac{\beta}{\nu}\right)(v_j - U_i) \\ &- \left(\frac{1}{\nu}\right)\left(C_i^o + C_j^d + C_{MN} M(i)(1 - M(j)) + C_{NM}(1 - M(i))M(j) + C_\delta \delta(i, j)\right), \end{aligned} \tag{34}$$

while the probabilities of remaining in i or entering non-employment are:

$$\log \mu_{ii} = \left(\frac{\beta}{\nu}\right)(v_i - U_i), \quad \log \mu_{i0} = \left(\frac{\beta}{\nu}\right)(v_0 - U_i). \tag{35}$$

With the normalization $v_0 = 0$, (35) identifies both v_i and U_i for all i, which pins down the non-cost terms in (34) and allows us to estimate the switching cost parameters — up to the proportional constant ν — via PPML with origin and destination fixed effects, dummies for transitions in and out of manufacturing, and skill distance. The fitted transition matrix matches the data closely (correlation > 0.99) and in particular exactly matches the matrix diagonal and flows into non-employment by construction.

The presence of retraining means that choice probabilities do not take exactly the form in (34). However, retraining does not affect the relative attractiveness of remaining in sector i versus

entering non-employment, so

$$\log \mu_{ii} - \log \mu_{i0} = \left(\frac{\beta}{\nu}\right)(v_i - v_0),$$

which, with the normalization $v_0 = 0$, allows us to recover all the values v_i. Given these values, we adopt an indirect-inference approach to recover switching costs. We run a PPML regression of observed transition probabilities on origin and destination fixed effects, dummies for transitions in and out of manufacturing, and skill distance, and record the resulting coefficients. Then, given a candidate Θ and the values v_i, we solve for the switching cost parameters such that the same regression run on model-implied choice probabilities yields the same coefficients. We repeat this for every new value of Θ, although in practice only ν matters much for the inferred costs.

B.3 Decomposition of retraining gains

Consider an employed worker of type ka in sector i at time t who has drawn retraining shock η and sector preference shocks ϵ, and who chooses to retrain. Define $\mathcal{G}_{it}^{ka}$ as the difference between this worker's expected lifetime utility when retraining is available versus when it is not.

Without retraining, the worker chooses sector h^* to solve $\max_j\{\beta v_{jt+1}^{ka} + \nu\epsilon_{ij} - C_{ij}^{ka}\}$. Let $S_0 = \mathbb{1}\{h^* \neq i\}$. With retraining, switching to a new productive sector $j \neq i, 0$ yields an additional Γ^{ka}, so the worker chooses j^* to solve $\max_j\{\beta v_{jt+1}^{ka} + \nu\epsilon_{ij} - C_{ij}^{ka} + \Gamma^{ka}\mathbb{1}\{j \neq i\}\mathbb{1}\{j \neq 0\}\}$. Let $S_1 = \mathbb{1}\{j^* \neq i\}$. When $\Gamma^{ka} \geq 0$, retraining weakly increases the incentive to switch, so $S_1 \geq S_0$.

Write $V_j = \beta v_{jt+1}^{ka} + \nu\epsilon_{ij} - C_{ij}^{ka}$ for the common payoff component. The gain from retraining is $\mathcal{G}_{it}^{ka} = (\sigma\eta - F^{ka}) + (V_{j^*} + S_1\Gamma^{ka}) - V_{h^*}$. Three cases arise. If neither scenario involves switching ($S_0 = S_1 = 0$), then $j^* = h^* = i$ and the gain is simply $\sigma\eta - F^{ka}$. If both do ($S_0 = S_1 = 1$), then j^* maximizes $V_j + \Gamma^{ka}$ while h^* maximizes V_j; but since Γ^{ka} is common across all $j \neq i$, the ranking is unchanged and $j^* = h^*$, giving a gain of $\sigma\eta - F^{ka} + \Gamma^{ka}$. Finally, if retraining induces switching ($S_0 = 0, S_1 = 1$), then $h^* = i$ and the gain is $\sigma\eta - F^{ka} + (V_{j^*} - V_i) + \Gamma^{ka}$. Combining yields:

$$\mathcal{G}_{it}^{ka} = \underbrace{(\sigma\eta - F^{ka})}_{\text{Direct}} + \underbrace{S_0 S_1 \Gamma^{ka}}_{\text{Switching: intensive}} + \underbrace{(1 - S_0)S_1\left(\beta(v_{j^*t+1} - v_{h^*t+1}) + (\epsilon_{j^*} - \epsilon_{h^*}) - (C_{ij^*}^{ka} - C_{ih^*}^{ka} - \Gamma^{ka})\right)}_{\text{Switching: extensive}},$$

as claimed.

B.4 Full calibration results

Table A3 shows the calibration targets (with standard errors) and corresponding model moments. The calibrated model perfectly fits all the moments apart from those related to the China shock in Panel A.

Table A3: Calibration Results

	Data	SE	Model
Panel A: China shock effects			
Earnings	-2.748	(0.929)	-4.002
Employment	-2.340	(0.701)	-2.006
Manufacturing employment	-4.880	(1.610)	-6.244
Sector switching	4.230	(2.380)	6.863
Retraining	1.564	(0.697)	1.550
Panel B: Retraining rates			
Young			
Low, Non-employed	0.310	(0.002)	0.310
Low, Employed	0.206	(0.001)	0.206
Medium, Non-employed	0.262	(0.001)	0.262
Medium, Employed	0.085	(0.000)	0.085
High, Non-employed	0.162	(0.003)	0.162
High, Employed	0.045	(0.001)	0.045
Old			
Low, Non-employed	0.228	(0.007)	0.228
Low, Employed	0.038	(0.001)	0.038
Medium, Non-employed	0.278	(0.002)	0.278
Medium, Employed	0.047	(0.000)	0.047
High, Non-employed	0.256	(0.006)	0.256
High, Employed	0.034	(0.001)	0.034
Panel C: Retraining-switching coefficients			
Young			
Low	0.384	(0.016)	0.384
Medium	0.375	(0.019)	0.375
High	0.227	(0.038)	0.227
Old			
Low	0.329	(0.035)	0.329
Medium	0.362	(0.013)	0.362
High	0.366	(0.044)	0.366

C Additional Counterfactual Results

C.1 Retraining in partial equilibrium

Table A4 repeats the retraining cost experiments of Table 8 in partial equilibrium, holding the trajectories of real wages constant at the path followed under the baseline retraining cost scenario.

Table A4: Effects of the China Shock Across Retraining Scenarios (Partial Equilibrium)

	No retraining	Baseline	2x	3x
Retraining rate	0.0%	11.5%	23.0%	34.5%
Welfare: aggregate				
Mean EV	0.252	0.243	0.238	0.235
Mean EV (mfg)	0.146	0.145	0.146	0.149
Welfare: distribution				
Std(EV)	0.472	0.450	0.423	0.399
Std(EV) (mfg)	1.004	0.956	0.900	0.847
% of mfg. workers with EV < 0	22.8	22.8	22.8	22.7
Min EV	-6.763	-6.557	-6.245	-5.919
Aggregate employment dynamics				
Aggregate employment (pp change), year 5	0.172	0.180	0.180	0.175
Aggregate employment (pp change), LR	0.283	0.290	0.273	0.250
Mfg. employment (pp change), year 5	-0.230	-0.238	-0.251	-0.267
Mfg. employment (pp change), LR	-0.278	-0.293	-0.318	-0.344
Sectoral employment dynamics (mfg)				
$\|\Delta l\|_1$ at year 5	5.291	5.362	5.496	5.637
$\|\Delta l\|_1$ long run	8.276	7.741	7.330	7.012
% of LR adj. at year 5	63.6	69.1	75.0	80.0

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