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1 Introduction

This dissertation comprises three independent papers on two distinct topics. Chapter 2 is situated in the fields of international trade and development economics. I connect the newly arising literature on the impact of misallocations in inputs on countries' aggregate productivity levels with empirical studies on trade in intermediate inputs. Chapters 3 and 4, both co-authored with Dominik Boddin, analyze previously unreported aspects of structural transformation and a phenomenon that has been gaining more attention recently – 'servitization'.

The first paper, "Do imports alleviate domestic market distortions? Evidence from the removal of small-scale reservation laws" (chapter 2), considers the importance of international trade in presence of distortions on domestic markets. The question of how international trade affects welfare when domestic markets are distorted reaches back at least to Bhagwati & Ramaswami (1963). In simple models, free trade is shown to be second best optimal when there are misallocations on domestic markets. However, studies could not provide conclusive empirical evidence so far. I exploit an ideal quasi-natural experiment to fill this gap and causally show that, in fact, international trade provides a means to reduce distortions and to reach a more efficient state of the economy: I evaluate the removal of a distortionary policy that reserved numerous products for exclusive production by small-scale firms. This policy effectively restricted the supply of affected products as inputs for downstream markets. I focus on the change in imports of intermediate inputs in response to greater availability of these products on the domestic market once the policy is repealed. Once the distortions are removed, imports contract, thereby revealing that imports could indeed counter the reservation policy. In line with the notion that imports are second best in the presence of domestic distortions, however, the contraction of imports should not be seen as declining welfare. Rather it is a byproduct of the removal of a distortion and a move of the economy towards the first best.

I find that out of the group of importing firms the least productive show the strongest contractions in imports. In addition, I observe strong compositional effects: Both the productivity distribution of importers and of purely domestically sourcing firms shift towards higher productivity levels after distortions are removed. Hence, for comparatively many firms it is profitable to import in the presence of domestic market distortions while they would have not imported otherwise. I thus also provide evidence that declining imports are not necessarily a bad sign as it could mean that an economy has moved

towards a more efficient state and welfare has improved. The chapter therefor provides a further argument in favor of demanding developing countries, in particular, to remove their trade impediments.

The remaining two papers are co-authored with Dominik Boddin and reevaluate different aspects of how the German labor market changed in course of structural transformation.

In chapter 3, "Structural Change Revisited: The Rise of Manufacturing Jobs in the Service Sector", we reevaluate the labor market consequences of structural change over the past 43 years. Taking two different ways of defining manufacturing and service employment as point of departure – according to the industry classification of firms or establishments and according to the occupation and hence the tasks of the workers – we show that structural change is far less serious than generally perceived. Manufacturing and service employment numbers based on the occupations of workers deviate remarkably from the employment numbers based on the industry classification of employers. The decline in manufacturing jobs in Germany is far lower if the measurement of employment is based on the occupation of the worker. About 52% of manufacturing jobs that were lost in manufacturing industries between 1975 and 2017 are offset by new manufacturing jobs in service industries. This also has important implications for empirical applications. By way of example, we reestimate the effect of international trade on manufacturing employment based on the occupation of the worker. Contrary to previously identified negative effects, we cannot identify significant effects of import exposure on employment in manufacturing occupations. We show at the worker level that the service sector increasingly acts as a valuable alternative employment option for workers with manufacturing occupations. We estimate the causal effects of a switch to the service sector on employment outcomes by following workers over time after mass layoffs. The results reinforce our claim that structural change is less significant than perceived, as workers who retain their initial occupation and switch to employment in the service sector experience no significant differences in future employment trajectories compared to workers who manage to stay in the manufacturing sector.

In chapter 4, "Servitization, Inequality, and Wages", which is forthcoming at *Labour Economics* (https://doi.org/10.1016/j.labeco.2021.102011) we study the effect of servitization, i.e., within-establishment changes in the labor force composition towards higher shares of workers with service occupations, on within-establishment wage inequality. We identify servitization as being a main driver of increasing within-establishment wage inequality. Servitization accounts for roughly 7% of the observed increase in the within-establishment wage inequality in manufacturing industries between 1994 and 2017. Higher servitization of an establishment's labor force is associated with, on average, a lower wage level for otherwise equal workers across the majority of occupations. The wage decrease is particularly pronounced for workers in low-skilled manufacturing occupations and workers at the lower end of the wage distribution. These heterogeneous wage effects explain

the increase in within-establishment wage inequality.

2 Do imports alleviate domestic market distortions? Evidence from the removal of small-scale reservation laws

Summary: How international trade affects welfare in the presence of domestic distortions is a long standing question. However, so far empirical research could not conclusively answer if and how imports of intermediate inputs can mitigate distortions on the domestic market. I exploit a quasi-natural experiment to causally show that international trade provides a means to alleviate domestic market distortions and to reach a more efficient state of the economy. Specifically, I evaluate how the removal of product reservations for small-scale enterprises in India affects imports of intermediate inputs. Once the distortions are removed, imports contract, thereby revealing that imports could indeed counter the distortionary policy. In line with the notion that imports are second best in the presence of domestic distortions, however, the contraction of imports should not be seen as bad news for welfare. Rather it is a byproduct of the removal of a distortion and a move of the economy towards the first best. I find that the least productive importers show the strongest contractions in imports. In addition, I observe strong compositional effects: Both the productivity distribution of importers and of purely domestically sourcing firms shift towards higher productivity levels after distortions are removed. Hence, for comparatively many firms it is profitable to import in the presence of domestic market distortions while they would have not imported otherwise. This suggests that the initial distortionary policy had a sizable negative tariff equivalent effect. It increased imports of intermediates even though these imports would not have occurred without the distortions being present and shifted the productivity threshold to import to a lower level. This way, importing has additional, previously unreported positive welfare effects.[1]

[1]I am grateful to Horst Raff, Costas Arkolakis, Arnaud Costinot, Keith Head, and Jens Ruhose for their comments and suggestions and Penny Goldberg for her early encouragement. I like to thank Johannes Boehm and Leslie Martin for sharing data. The paper has been presented at the Aarhus-Kiel Workshop 2020. I thank participants for their comments.

2.1 Introduction

The question of how international trade affects welfare in the presence of domestic distortions reaches back at least to Bhagwati & Ramaswami (1963), who theoretically show that international trade can alleviate such distortions and that free trade can be second best optimal. However, so far research could not provide conclusive empirical evidence for this mechanism. While recent empirical advances put emphasis on trade in intermediate inputs and show that trade in intermediates benefits countries, for instance, through the availability of more and higher quality varieties, it remains unexplored if and how imports of intermediate inputs are able to alleviate misallocations on domestic markets.[2]

In this paper, I rely on a suitable quasi-natural experiment to fill this gap and causally show that, in fact, international trade provides a means to offset domestic distortions. The experiment consists of the removal of product reservations in India – a policy that restricted domestic production of more than 1,000 products to firms from small scale industries. I show that when the reservation of a product is lifted, imports of the product contract, thereby revealing that imports were indeed a means to counter the distortionary policy. In line with the notion that imports are second best in the presence of domestic distortions, however, the contraction of imports should not be seen as bad news for welfare. Rather it is a byproduct of the removal of a distortion and a move of the economy towards the first best.

The changed legal background provides an ideal basis for answering the question in this paper. Since before the 1970s, the Indian government tried to shelter its small scale industries (SSI) with the intention to protect a large part of domestic employment and to stabilize household income. Among other policy schemes, the Indian government imposed restrictions on a variety of products to be exclusively produced by firms from the SSI. This policy has led to distortions and slower growth of the economy (Garcia-Santana & Pijoan-Mas (2014) and Martin et al. (2017)). In particular, it had effects along the value chain since firms that were using the affected products as inputs in production faced severe supply shortages (Balasundharam 2020). In addition, before its balance of payments crisis in the first half of the 1990s, India was a very protectionist country with high tariffs strongly impeding the inflow of products and inputs into its domestic market.

Then, in the course of its economic liberalization, two important policy changes were implemented. First, when India was in need for external finance during the 1990s, it was instructed to open its market to foreign suppliers by substantially lowering import tariffs. This period of trade liberalization allowed for cheaper imports and thus allowed firms to gain access to reserved products from international markets.

Second, the Indian government restructured its policies intended to protect the SSI. The above mentioned reservation policy was repealed in stages from 1997 to 2015 with

[2] Cf. Amiti & Konings (2007), Goldberg et al. (2009), Goldberg et al. (2010*a*), Halpern et al. (2015), Blaum et al. (2018)).

India allowing firms outside the SSI to produce formerly reserved products. The vast majority of products were de-reserved between 2002 and 2008. Henceforth, firms could produce these products without further size restrictions. This resulted in significant entry of domestic firms into these product markets and a significant expansion of domestic production of formerly reserved products (Martin et al. 2017).

In the intermediate period between the completion of the trade liberalization in 1996 and the de-reservation of product restrictions, however, these policies meant that expansion of the supply of reserved products to downstream firms had to come either through the entry of small firms (effectively creating new companies – which hardly occurred) or from imports.[3] As a result, once the reservation policy was repealed, firms that imported these products now faced a new alternative, namely to source them domestically.[4]

This timing of events constitutes a unique environment that is ideally suited to study if imports of intermediate inputs indeed offset domestic distortions on input markets. Trade barriers, specifically tariffs, were removed first which allowed for greater imports of intermediate inputs. And only thereafter a specific distortionary policy, the product reservations, was gradually removed. Both events were exogenous to individual firms which allows for precise identification.

This environment thus allows me to provide first clear evidence of how firms are using imports as a strategy to bypass inefficient domestic input markets. I use detailed firm-(product)-level data for the years 2000-2010, hence covering the years around the majority of product de-reservations, and methodologically exploit the sequential de-reservation of products to be exclusively produced by the SSI. The staggered timing of the de-reservation results in a difference-in-difference type estimator, (Callaway & Sant'Anna (2020), Athey & Imbens (2021), Goodman-Bacon (2021)). I find that, once the product reservation is repealed, imports of affected products contract, both on the intensive margin – the quantity sourced by the average firm declines by 14% –, and the extensive margin – fewer firms import the products. The propensity to import is 3 percentage points lower after the de-reservation. Quantities sourced domestically, on the other hand, increase by 20% in response to the de-reservation. For firms that source the same product on both domestic and international markets the reform leads to a decreasing ratio of imported inputs to domestic inputs by about 11%.

When assessing these results in more detail, I find that out of the group of importing firms the least productive show the strongest contractions in imports. In addition, I observe strong compositional effects: The productivity distributions of both importers and

[3]Therefore, the tariff liberalization could have had further benefits in addition to those already studied in the previous literature. Examples include the reduction of inequality (Topalova 2010), increasing productivity, lower mark-ups, lower prices etc. (De Loecker et al. 2016), more varieties (Goldberg et al. 2009) or lower volatility in sales (Görg et al. 2020).

[4]In addition, India as a country is ideally suited for the current study as it is an emerging country that already has a manufacturing share of GDP similar to that of developed countries, but still has an allocative efficiency distance to the efficient frontier 20 percentage points lower than the U.S. (Bils et al. 2021).

purely domestically sourcing firms shift to the right after de-reservation. Average productivity levels for importers increase due to the exit of relatively low productivity firms from international markets. The average productivity level of domestic firms increases for two reasons. The mentioned import-exiting firms have relatively high productivity levels (in comparison to pre-reform domestic firms), and the least productive firms close.

Hence, for comparatively many firms it is profitable to import in the presence of domestic market distortions while they would have not imported otherwise. In relation to theoretical underpinnings in international trade theory the productivity cut-off to import is relatively low as compared to the threshold in the absence of distortions (see e.g., Antràs et al. (2017)).

These results suggest that in presence of domestic market distortions international trade, in particular importing of intermediate products, is welfare improving.[5] Firms are able to source internationally if inputs are domestically not available or only at high cost. Then, once distortions are removed, firms revert to sourcing domestically because of two effects: Goods become cheaper domestically relative to imports and quantities supplied increase significantly. This reversion back to domestic sourcing reveals that imports can only be a second best solution for a significant share of firms. A particular finding of the present paper is that ceteris paribus, i.e., under constant trade costs, international trade flows could be lower when domestic policy becomes more efficient and distortions are reduced while welfare increases.

Related Literature. Fostered by the awakened interest in misallocations and their impact on aggregate productivity and economic growth[6] recently also the relation between international trade and distortions experienced increasing interest.[7] The current paper extends the literature by providing previously missing clear evidence on the effects of international trade in the presence of distortions. An up to date survey on the relation between trade and misallocations in developing countries has been written by Atkin & Khandelwal (2020). Most of the contemporaneous studies rely on quantitative modeling approaches without the ability to exploit (quasi-)natural experiments. For instance, Święcki (2017) studies the welfare gains from trade in the presence of domestic distortions in a Ricardian model where misallocations are introduced as revenue wedges as proposed by Hsieh & Klenow (2009). Likewise, Berthou et al. (2019) examine gains from trade liberalization in the presence of firm heterogeneity and resource misallocation. In

[5] Put alternatively, the initial product reservation policy had a sizable negative tariff equivalent effect. It increased imports of intermediates even though these imports would not have occurred without the distortions being present and firms sourced on international markets despite relatively low productivity levels.

[6] Probably the triggering study for this awakening is Hsieh & Klenow (2009) who use micro-data to quantify the extent of factor misallocation of China and India respective the United States. See also Restuccia & Rogerson (2013), Hopenhayn (2014), and Restuccia & Rogerson (2017) for literature reviews on this topic.

[7] This relationship has been theoretically examined starting in the 1960s; see for instance, Bhagwati & Ramaswami (1963), Johnson (1965) or Eaton & Panagariya (1979).

their framework, import liberalization has ambiguous effects on welfare and productivity. Bai et al. (2019) assess firm-level distortions in a Melitz (2003)-model. In contrast to Berthou et al. (2019), they only consider welfare effects of trade liberalization with respect to exports. In their model, trade liberalizations can even reduce welfare by exacerbating misallocations which are similarly modeled as a revenue wedge which is jointly determined with productivity.

While these studies are able to quantify the gains from trade in the spirit of Arkolakis et al. (2012) they find, however, ambiguous effects of international trade in the presence of distortions. My paper is able to provide first clear evidence in that it identifies imports of intermediates as a channel through which misallocations can be mitigated. Moreover, my results are based on a 'direct' distortionary policy and do not have to rely on unidentified revenue wedges (in the terminology of Restuccia & Rogerson (2013)).

In addition, my paper is related to the literature on imports of intermediate inputs.[8] Several papers have examined the effects of the Indian trade liberalization on imports of higher quality inputs, more varieties of intermediates, and the effects on firm-level and aggregate productivity in India (Goldberg et al. (2009), Goldberg et al. (2010*a*), Goldberg et al. (2010*b*), and Topalova & Khandelwal (2011)). The time period studied in this paper starts significantly after the trade liberalization such that all adjustments reported in these papers are likely to be concluded before the start of the policy change exploited in the present paper. While I identify contracting imports in response to the repeal of the reservation policy, it explicitly does not imply negative welfare consequences as those found by Gopinath & Neiman (2014) or Vandenbussche & Viegelahn (2018).

Other studies are concerned with the substitutability in production between imported intermediates and domestic inputs which I rely on in this paper. For instance, for Hungary, Halpern et al. (2015) find that imports are only imperfect substitutes for domestic inputs and of higher quality. This is not the case in this paper. For a large number of affected products, the substitutability between domestic and foreign products is high. Products are either of very low complexity, e.g. iron and steel products, pipes and tubes, or very standardized, e.g., chemical compounds.[9]

My paper is also related to the literature on input-output linkages in relation to the de-reservation reform. Closely related to the present paper is Balasundharam (2020), who studies effects of the removal of the product reservation on both upstream suppliers' and downstream buyers' productivities. However, the author restricts her analysis to the domestic market only. In addition, Boehm et al. (2019) utilize the reform to study the optimal production portfolio of firms.[10] They find that firms will extend their product scope into products which require similar inputs as those already produced once inputs

[8] E.g., Amiti & Konings (2007) for a seminal empirical study or more recently Defever et al. (2020). Antràs et al. (2017) provide a thorough theoretical model of the global sourcing decision of firms.

[9] Other, recent studies on trade in intermediate inputs are Kasahara & Rodrigue (2008), Kasahara & Lapham (2013), Blaum et al. (2018), Blaum et al. (2019), and Alfaro et al. (2019).

[10] Boehm et al. (2018) study product turnover and diversification in a high growth period in India. Unlike during the 1990s the product inclusion and dropping rates are similar to the those of the US.

become available in greater quantities and at lower prices. I show that international value chains have to be taken into account when assessing these matters.[11]

The paper proceeds as follows. In Section 2.2, I describe the policy and its repeal in more detail. I introduce the data in Section 2.3 and provide descriptive statistics thereafter in Section 2.4. I examine aggregate effects on the product level in Section 2.5 and on the firm-product level in Section 2.6. In Section 2.7 and following, I explain the adjustment mechanism in more detail. I conclude in Section 2.10.

2.2 The small-scale reservation laws and their removal

The Indian government has been concerned with the protection and promotion of small but formal firms for a long time. Mohan (2002) states that the major reason for this is the firms' labor intensity. India is a labor abundant country, and the government hopes to absorb large parts of the labor force into (formal) employment by subsidizing the small-scale industries (SSI). Belonging to the SSI is based on the firm's historical value of "investment in plant and machinery". The categorizing threshold changed several times over the years: until 1991 firms with less than 3.5M rupees investment value were part of the SSI; in that year the level was raised to 6.5M rupees and further to 30M rupees in 1997. The threshold was lowered again in 1999 to 10M rupees and finally raised once more in 2006 to 50M rupees (see Figure 2.1).[12] Throughout my period of observation, the SSI account for 14% of manufacturing output and 4% of total Indian GDP (Garcia-Santana & Pijoan-Mas 2014).

The Indian government created numerous subsidy schemes to support the SSI. One subsidy scheme with large impact on the real economy and whose repeal is subject of the present paper is the reservation of a set of products for exclusive production by the SSI, as per the Industries (Development and Regulation) Act 1951 (65 of 1951), section 29(B) and amended by the Government of India, Department of Industrial Policy, S.O. 447(E) in 1991.[13][14] This policy allowed solely firms of the SSI to produce a particular set of products. This set was extended throughout the years and reached its largest

[11] Several other papers examine the impact of the policy reform. For instance, in an early study, Garcia-Santana & Pijoan-Mas (2014) quantify the long-run effects of the product reservations of the small scale sector in India on aggregate measures of productivity, output, and consumption. Martin et al. (2017) ask whether promotion of small and medium sized enterprises creates jobs. Growth is driven by entrants into the product markets and incumbents which were previously growth constraint by the policy, less productive firms contract upon entry of new competitors. Galle (2020) develops and quantifies a model on competition and financial constraints. Carpena et al. (2021) detect far reaching heterogeneous effects of the reform on geographical labor markets. Another policy change that affected the small-scale industries is studied by Rotemberg (2019) who assesses the performance changes of firms newly eligible to produce the formerly reserved products.

[12] Initially, also employment restrictions were in place but these were already lifted in 1975 (Mohan 2002).

[13] The respective publication in the Gazette of India can be accessed here: https://dipp.gov.in/sites/default/files/EO477-E%20%202.pdf

[14] Another, more widely known, high impact subsidy is a credit program that obliges Indian banks (private and public) to provide firms with access to cheap credit, (Banerjee & Duflo 2014).

extent before 1991. Afterwards the set was stable, plateauing at a number of more than one thousand products. Overall about a quarter of total manufacturing output was subject to the policy at its peak coverage (Tewari & Wilde 2019). The products seem arbitrarily chosen (Mohan 2002) and range across a variety of sectors such as chemicals, leather, metal, and plastics. Most of the reserved products are of low complexity and very homogeneous across producers. This policy remained active even after major industry reforms in the early 1990s and the trade liberalization between 1992 and 1996 in which average tariffs fell from 90% to about 20%.[15]

Only beginning in 1997, did the government begin to gradually de-reserve products. That is, the reservation of the product for exclusive production by the SSI was lifted and consequently all firms were allowed to produce the de-reserved product. The major part of the de-reservations, however, took place between 2002 and 2008 (about 100-250 products were de-reserved every year). As of 2008, only 20 products remained reserved, but all of these were finally de-reserved in 2015, thus concluding the subsidy scheme. Behind the de-reservation is that the Indian government saw growing consumer demand and that the SSI increasingly had to compete with imports (Martin et al. 2017). To objectively manage the gradual repeal of the reservation, an advisory committee was founded. Figure 2.1 shows the timeline of the de-reservation. A particular feature of the reservation was that large firms that formally were not part of the SSI but were producing the products at time of reservation were allowed to retain production, but output quantity was capped at pre-reservation levels.[16] Martin et al. (2017) report that essentially no entry into the product markets occurred during the reservation time. Only after products became de-reserved, did new firms start production. This leaves the quantity of reserved products de factor stable during the reservation period, as firms in the SSI were restricted in growth, and did not grow by much as reported by Martin et al. (2017).

The reservation poses a problem for firms that are dependent on reserved products as inputs in their production process. If no close substitutes are present on the domestic market, these firms will likewise be restricted in growth and the inefficient policy has effects throughout the value chain. One way to circumvent such a supply side capacity problem is for firms to import reserved products.

There was no policy in place that would preclude imports of products on the reservation list throughout the period of observation. India has historically been a rather protectionist country with large tariffs in place throughout all sectors. However, as part of the IMF's intervention in the balance of payment crisis during the late 1980s to early 1990s, India executed a substantial trade liberalization between 1992 and 1996. Import tariffs were lowered significantly and remained at the levels of 1996 thereafter.[17] Dur-

[15] See Figure 2.7 in the Appendix.

[16] If firms wished to expand production of the reserved products any excess quantity had to be exported (Mohan 2002).

[17] Figure 2.7 in the Appendix shows tariffs over the time period studied. The figure also shows trade

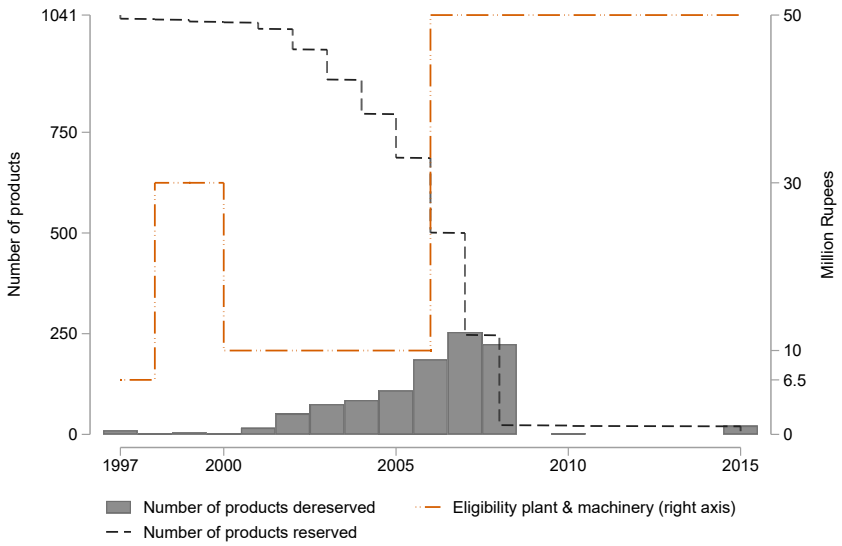


Figure 2.1: Development of the removal of small-scale product reservations and SSI eligibility

The figure shows the number of products reserved in a given year and the number of products de-reserved per year. At the height of the policy 1041 products were reserved. In 2000, 1023 remained reserved. In 2009 (2011) this number was 23 (20). Data compiled from notifications downloadable at https://dcmsme.gov.in/. The graph also depicts the eligibility threshold for the SSI (right-hand side axis). Establishments with historical investment in plant and machinery equal or less than the indicated amount are SSI establishments.

ing the time frame of the de-reservation no large tariff changes and also no significant other industrial policies occurred in India. Due to the gradual de-reservation the setting provides an ideal framework to answer the research questions posed in the introduction, namely if and how imports are able to alleviate misallocations on domestic markets and whether international trade is welfare improving as a second best solution when domestic markets are distorted.

Endogeneity is a potential issue in both the reservation list and the point in time at which particular products were de-reserved. Previous studies have extensively discussed this issue and concluded that it does not constitute a large concern (cf. Garcia-Santana & Pijoan-Mas (2014), Martin et al. (2017), Tewari & Wilde (2019), Galle (2020)). More importantly, my analysis focuses on firms in downstream industries that use the reserved products as inputs. Of course, if they are large enough to exert lobbying power on the advisory committee, the endogeneity concern may still be valid. However, even if downstream firms lobby for a de-reservation, it still remains uncertain to them whether or not supply would increase after de-reservation.

flows (imports and exports) for major trading partners. Trade flows have been increasing over the time period studied with exception of the Great Recession years. I like to argue that the increasing trade integration of India and the ongoing globalization makes my results even more credible as firms would rather 'float with the current' as against it.

2.3 Data

The analysis is based on establishment data for India from the Annual Survey of Industries (ASI) for the years 2000-2010.[18] The ASI is a yearly survey of India's organized manufacturing industries. All manufacturers with more than 20 employees are required to register under sections 2m of the Factories Act (manufacturers with more than 10 employees have to register, if they use electricity in production). The unit of observation is an establishment (plant), large establishments with more than 200 (100, since 2003) employees are surveyed every year, for smaller establishments a sampling approach is taken with weights provided in the data set to create a representative sample.[19] Consequently, smaller firms with more than 10 employees are surveyed approximately every five years.[20] The ASI generally surveys establishments individually. Only when an entity (company or individual) owns two or more establishments in the same state, industry, and sampling scheme (i.e., filing the questionnaire yearly or being sampled randomly) is the owner allowed to file a single answer sheet for these establishments. This is rarely the case: Throughout the years on average less than 2% of observations are joint returns.

The ASI is designed to be the "principal source of industrial statistics in India. It provides statistical information to assess and evaluate, objectively and realistically, the changes in the growth, composition and structure of [the] organized manufacturing sector comprising activities related to manufacturing processes, repair services, gas and water supply, and cold storage." (Instruction Manual ASI, chapter 1, 1.1, p.3, see weblink in footnote 20.) The data cover about 80 percent of total industry output in India but only about 20% of employment (Harrison et al. 2013). Since the ASI only covers organized firms, the data lack information on the prevalent informal firms and hence large parts of employment. However, for the present paper the data set suffices in that mostly large firms engage in international trade, see below and e.g., Bernard et al. (2007) and Antràs et al. (2017), and the majority of industry output is covered. Likewise, most firms that source intermediate inputs source from formal firms so that I also observe the majority of domestic producers of affected products and potential substitutes.

Importantly, in addition to information on fixed assets, capital and debt, employment and labor costs, the ASI provides data on individual inputs: I observe product-wise intermediate manufactured goods, both domestic and imported in quantity and total value, as well as unit values. Firms are required to report domestic and imported intermediate

[18] Previously, this data set had to be acquired, due to a policy which is aimed at facilitating research it is currently possible to download the ASI waves from 1999 onward from the Ministry of Statistics and Program Implementation (MOSPI), http://www.mospi.gov.in/. The data is accessible after creating a user profile and verification by MOSPI at http://microdata.gov.in/nada43/index.php/catalog/ASI/about. However, at the time I requested access to the data, the online portal only provided access to the repeated cross-section of the data. For access to the panel version, i.e., with unique firm identifiers over the different waves, I had to contact MOSPI informally after which the panel version was made available.

[19] Precisely, firms are sampled within districts such that the data set allows to create a regionally representative sample.

[20] For the exact procedure see http://www.csoisw.gov.in/cms/cms/Files/775.pdf.

inputs, so that I observe input usage for all firms. This feature of the data is a particular strength in comparison to other firm-level data sets used in research and allows me to precisely study the effects of the reform in question on intermediate input use and substitution between imports and domestic sourcing.[21]

The ASI is one of two data sources for the manufacturing sector in India. The other is the Prowess database compiled from firms' annual accounts by the Center for Monitoring the Indian Economy. Both of which come with advantages and disadvantages. I like to refer the reader to Martin et al. (2017) for a general comparison between the ASI and Prowess. The ASI has one important advantage over the Prowess database for the current study: It provides detailed information on inputs used and on imports of intermediate inputs; the latter is not the case in the Prowess data.[22]

I use the crosswalk between the NPCMS (the product codes in which the reservation definition is published) and the ASICC (the ASI's product code) made available by Martin et al. (2017) to identify affected products.[23]

In my analysis, I focus on the years 2000-2010. In 2011 a substantial reclassification of the product codes was introduced. The new and old classifications diverge substantially leaving a clear identification and differentiation between products over time infeasible, more so, for a not negligible part the new product class combines (previously) reserved products with never reserved products, leaving it impossible to derive sensible estimates.

2.4 Descriptive statistics

Table 2.1 contains basic descriptive information on establishments in total and differentiated by importing status. All monetary values are deflated using industry specific price indices. I observe in total 144,626 establishments out of which only 21,155, i.e., a fraction of 14.6% import. I observe the usual patterns on age, size (measured by fixed capital or number of workers), number of products produced, etc. Importing firms also

[21] The information of product level input sourcing and the distinction between domestically and internationally sourced inputs is a feature not prominently found in comparable data sets for other countries.

[22] A disadvantage in comparison to Prowess, but outside the scope of the present paper, is that the ASI does not provide information on which products are exported. Unfortunately a matching between the two data sets to create a more encompassing source of information is not possible since, (1) the ASI is anonymous, i.e., does not provide information on the establishment such as name or address, (2) the Prowess data is on firm or enterprise level which complicates a comparison between results across the two data sets further.

[23] Whereas I can readily distinguish between directly sourced indigenous and imported manufactured inputs – a feature that makes the ASI data exceptional in comparison to other firm or firm-product level data sets – the data do not show whether a firm has sourced domestically from wholesalers, that for instance act as export-import-companies. However, I can measure the importance of carry-along-trade in the sampled firms. I.e., I observe when firms source but do not process certain goods that in effect are re-sold on the domestic market. In addition, since the ASI does not sample wholesale or retail firms such as export-import agencies, I revert to the Prowess data set to derive some indications of the importance of import agencies/wholesalers: For the years 2000-2010, the share of imported intermediate inputs sourced by wholesale firms ranges between 1% and 3.8% (with the year 2000 as exception at 3.8%; mean and median during this time period are 1.5% and 1.3%, respectively). This leaves me reassured that imports by wholesalers accounted as domestically sourced inputs constitute only a minor share of total imports of intermediates in India and should not influence the analysis and its results.

source more reserved products than purely domestically sourcing firms, however the cost share of reserved products in total expenditure for inputs is low in either case with .7% and .5% for importing firms and domestically sourcing firms, respectively. Importers source fewer inputs internationally than on home markets, with an average cost share of imported inputs in all inputs of 20%. However, the costs of imports of reserved inputs on average make up a significant part of total expenditures on reserved inputs with about 21%.

Table 2.1: Firm descriptives

	Total		Domestic sourcing		Importer	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Importer of reserved product	.02	.13	–	–	.11	.32
Exporter	.06	.24	.03	.17	.33	.47
Age	15.46	15.22	15.50	15.22	15.23	15.24
Invest. plant & mach. (million ₹)	34.31	859	10.12	178.56	169.78	2162.75
Fixed capital (million ₹)	75.12	1,740	21.767	406	386.48	4431
Loans outstanding (million ₹)	41.71	824	15.48	303	193.49	2013
Total revenue (million ₹)	116.90	1,685	44.40	188	540.00	4358
Total employees	52	255	35	222	152	384
Workers	48	271	30	195	152	517
Average wage per employee (₹)	60,207	1,787,507	49,255	1,697,297	1,241,217	2,133,477
log(TFP)‡	-.019	.11	-.03	.11	.03	.08
Number of products	1.77	1.35	1.64	1.24	2.27	1.77
Multi-product producer	.33	.43	.30	.43	.48	.43
Number of domestic inputs	10.14	3.59	9.69	3.39	12.73	3.62
Cost share of reserved inputs	.005	.03	.005	.03	.007	.02
Number of imported inputs	–	–	–	–	2.24	1.78
Cost share of imports	–	–	–	–	.20	.23
Cost share of reserved imp.	–	–	–	–	.01	.06
Cost share of res. imports in total res. inputs	–	–	–	–	.21	.35
Number of establishments	144,626		122,350		21,155	

Notes: The table shows average descriptives of establishments in total and by importing status. A firm is considered as importer if it ever imported some input. Data: ASI 2000-2010
‡log(TFP) is estimated with the approach of Ackerberg et al. (2015) and normalized within 2-digit industries with mean zero.

Figure 2.9 in the Appendix shows that it is mostly larger firms that source reserved products even domestically. The graphs show the average firm size distribution differentiated by domestic sourcing of reserved products. The median firm sourcing reserved products on the domestic market is 1.9 times as large in total revenue than the median firm not sourcing a reserved product. This might be due to the fact that the policy allowed own production of reserved products only for small firms such that these rely on own production of reserved products even if they only use them in further production of their final goods and do not necessarily sell these products. This strategy will result in a larger 'vertical span' as dubbed by Boehm & Oberfield (2020), i.e., more production steps are performed within the boundaries of the firm.

Table 2.2 shows information on importing firms, differentiated by whether or not they

import reserved products.[24] Importers of reserved products are far fewer in numbers (2381 out of 21,155, about 11.3%) and they are larger and financially more solvent firms. Their investment in plant and machinery is on average higher, as is their fixed capital. Also, firms that import reserved products employ more workers but remuneration per worker is rather similar.

Firms that import reserved products also import more products as compared to firms that do not import reserved products. In addition, firms that import reserved products source more of reserved products domestically than firms that do not import reserved products. The cost share of reserved products imported is higher than that of reserved products sourced domestically. Likewise, the cost share of imported reserved products in total costs of reserved inputs is substantial at 54%.[25]

Table 2.2: Firm descriptives of importers by importing of reserved products

	Reserved products		Only un-reserved products	
	mean	std. dev.	mean	std. dev.
Exporter	.467	.499	.321	.467
Age	16.23	14.47	15.10	15.33
Invest. plant & mach. (million ₹)	283	4744	155	1553
Fixed capital (million ₹)	526	7112	368	3964
Loans outstanding (million ₹)	230	2550	189	1935
Total revenue (million ₹)	886	9654	496	3095
Total employees	211	344	144	389
Workers	218	453	144	524
Wage per employee (₹)	139,795	188,842	122,133	216,180
log(TFP)	.04	.08	.03	.09
Number of products	2.55	1.99	2.24	1.74
Multi-product producer	.52	.42	.48	.43
Number of domestic inputs	14.39	4.10	12.52	3.50
Cost share of reserved inputs	.024	.044	.005	.020
Number of imported inputs	3.50	2.27	2.07	1.64
Cost share of imports	.235	.229	.196	.235
Cost share of reserved imp.	.115	.143	–	–
Cost share of res. imports in total res. inputs	.540	.357	–	–
Number of establishments	2,381		18,774	

Notes: The table shows average descriptives of establishments that import and by importing of reserved products. A firm is considered as importer if it ever imported a specific input. Data: ASI 2000-2010

In combination, these descriptive statistics show that it is mostly large firms that buy reserved products. This may be due to two different reasons: First, even though large firms are allowed to produce reserved products for own use (but not to sell the products), they potentially do not have sufficient internal demand for reserved products that it would pay to start their own production rather than to source them domestically or internationally. Second, market power will crucially influence the price of inputs if

[24] Note that here a firm is considered to be importing reserved products if it ever imported a reserved product. In this definition a consecutive importing of reserved products is not necessary.

[25] Figure 2.10 in the Appendix once more highlights the different firm size distributions of firms across importing of only not-reserved products and reserved products.

the markets for reserved products are not competitive. Then, only large buyers will encounter efficient prices and be willing to source from outside the firm.

Likewise, out of the set of importers, mainly large firms import reserved products. This speaks for the proposed alleviating effect of imports on domestic distortions. Domestic supply is limited in a way that induces sufficiently solvent firms to rely on imports of these products, which they would not do in the absence of distortions. Thus, only large firms are able to cover the costs of importing. Specifically, importing overall larger quantities and a greater number of products, enables them to spread the fixed costs to import and the per-shipment costs on more products.

Next, it is informative to consider how many products are actually used as inputs in production and how many products are imported. Table 2.3, Panel A shows the respective numbers and shares for the product codes in the ASI data. Note that the SSI product codes which determine the reservation status of products are converted into the product classification of the ASI data following Martin et al. (2017). The SSI product classification is very detailed so that a large fraction of the 1041 products that were reserved at some point in time fall into one ASI product category. This results in a maximum number of reserved products in the ASI data of 353. The majority of products observed is both produced and sourced. Less than one percent of all products I observe in the data are only produced but not bought by any firm in any year. Likewise, for less than two percent of products I cannot identify a producer in the data but some firm sources the product.[26] There are three reserved products for which I cannot identify a producer.

For imports, Panel B of Table 2.3 contains the corresponding information. Here as well, the majority of products, both non-reserved and reserved, are produced and imported as inputs. However, there are a sizeable number of products that are not produced domestically and thus have to be imported. These make up 9% of all products observed. There are 34 reserved products that are not produced by sampled firms and that are only observed as imports.

To see if there are specific differences in the sourcing strategy, i.e., importing or domestic sourcing, for specific products, I plot the average quantity share of domestic inputs in total domestic input quantity (of all products) against the share of imported quantities per product in total quantity imported in Figure 2.2. The graph differentiates by reservation status of the products. It shows that for both types of products, reserved and not reserved, there are numerous products that have more weight in domestic inputs and numerous that have a higher weight in imports. However, overall the picture is quite close to the 45-degree line with the exception of two outliers and I cannot identify large differences between products that were reserved at some point and products that were never reserved. The latter point becomes clearer when considering fitted lines of

[26] Be reminded that the ASI only covers the formal sector of production and a large number of small, informal establishments are not sampled.

the correlations between the quantity share in inputs and the quantity share in imports. There is no statistical difference between the correlations, fitted lines almost run on top of another.

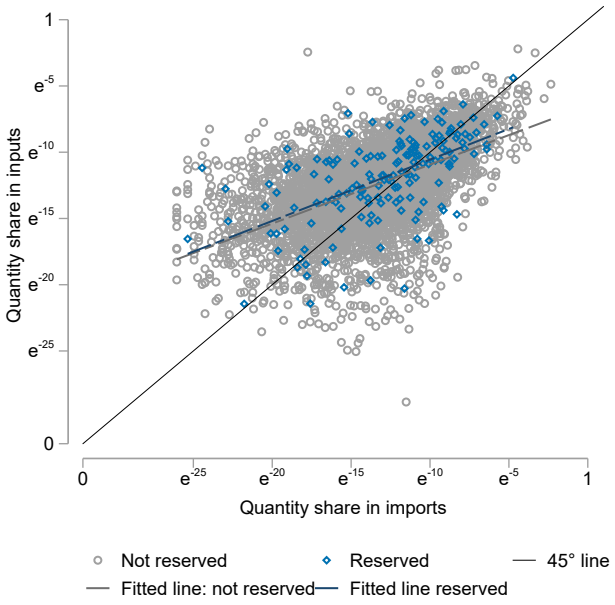


Figure 2.2: Quantity shares of products in total domestic inputs vs. total imports
The graph shows the average shares of each sourced product in total domestic inputs and total imports by reservation status. Displayed on log-scale. Data: ASI 2000-2010

To get a first indication of the effects of the de-reservation policy on imports of reserved products, Figure 2.3 plots the import value relative to total expenditure per reserved product averaged for the three years immediately prior to the respective de-reservation date against the share of the import value in total expenditure as an average for the immediate three years after the de-reservation date for the respective product. It shows a significant number of products for which the import share decreases after the respective product has been de-reserved. In addition, the figure shows that changes occur on both, the intensive and extensive product margin.[27] Some products are no longer imported, for others only the share in total expenditure changes. But the figure also shows a sizable number of previously reserved products that after the de-reservation are imported in higher shares than prior to the de-reservation.

This first look at the dynamics of imports relative to the de-reservation of exclusive production by SSI firms emphasizes again that there are several potential channels through which production factor allocations might be distorted. First, some products simply are not available in sufficient supply prior to de-reservation to meet total demand of domestic firms. Thus, firms resort to more expensive imports. Once products are taken off the reservation list, domestic supply increases and prices stay constant or even

[27] See Das et al. (2007) for a first study on differences along the two margins.

Table 2.3: Products used as inputs

	Number of products	Percentage of total	Percentage in group
Panel A: Domestic inputs			
Total			
Only Output	59	.91	.91
Only Input	116	1.79	1.79
Output and Input	6293	97.29	97.29
Total	6468	100	100
Not reserved			
Only Output	59	.91	.95
Only Input	113	1.75	1.82
Output and Input	6021	93.09	97.22
Total	6193	95.75	100
Reserved			
Only Output	0	0	0
Only Input	3	.046	1.09
Output and Input	272	4.21	98.91
Total	275	4.25	100
Panel B: Imported inputs			
Total			
Only Output	29	.45	.45
Only Import	591	9.18	9.18
Output and Import	5818	90.37	90.37
Total	6438	100	100
Not reserved			
Only Output	29	.45	.47
Only Import	557	8.65	8.98
Output and Import	5615	87.22	90.55
Total	6201	96.32	100
Reserved			
Only Output	0	0	0
Only Import	34	.53	14.35
Output and Import	203	3.15	85.65
Total	237	3.68	100

Notes: The table shows in total and by reservation status the occurrence of products as outputs, inputs or both in Panel A and for imports in Panel B. Percentages are rounded on two decimal places. Data: ASI 2000-2010

fall (cf. the following Sections 2.5 and 2.6, and Martin et al. (2017) and Boehm et al. (2019)). Firms that imported these product will be able to satisfy their total needs for these products by sourcing domestically and exit the importing market altogether. This channel works solely through cost considerations.[28] Second, changes in market structure may be at play. Figure 2.3 also shows that for a number of reserved products the value share in total expenditure of imports increases after the de-reservation.[29] A possible reason for this observation is that in the course of the de-reservation, large firms enter these markets as producers and thus the domestic market structure changes in such a way that smaller buyers face powerful sellers. Then the relative import costs could fall,

[28] In addition to cost considerations, time-to-deliver may play a role (e.g., Muris et al. (2019)) but this is not testable given the data.

[29] This is highly correlated with the quantity share which I do not show here.

so that more is imported.

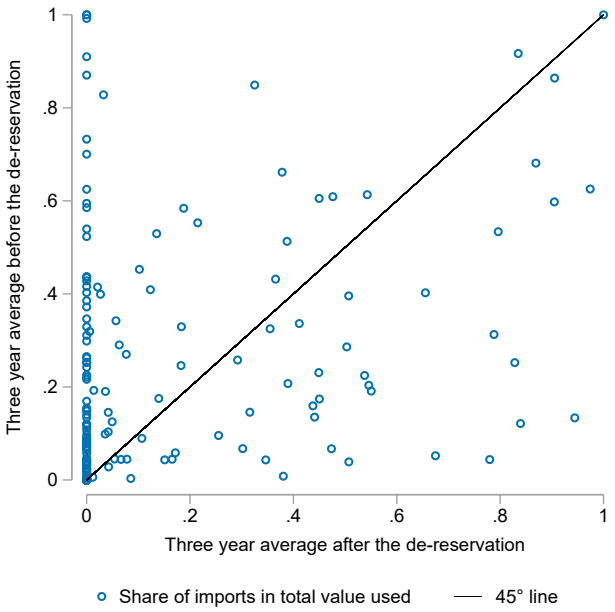


Figure 2.3: Import shares of reserved products pre and post de-reservation

The graph shows three-year average shares of imported value in total expenditure on all reserved products for the immediate three years before and after de-reservation of the products. Data: ASI 2000-2010

Table 2.4 contains information on average product homogeneity proxied by the relationship specificity index of Rauch (1999) as converted to the ASI product classification by Boehm & Oberfield (2020).[30] The homogeneity index is on a continuous scale $\in [0, 1]$, where 1 is most relationship specific and, hence, the lower the number the more homogeneous the product is. Table 2.4 shows that products on the Indian market are rather homogeneous. The table also shows that products subject to the reservation policy on average are more homogeneous than products that are not reserved for production by the SSI. In Panel D, the table lastly shows that out of the reserved products those that are imported are the most homogeneous.

With reference to Figure 2.3, out of the 43 de-reserved products for which the import share post de-reservation is larger than before the de-reservation, 16 are classified as relationship specific and the remaining 27 as homogeneous. Whereas in numbers this figure is larger for more homogeneous products, reverting to shares the picture changes: For a share of 20% of all relationship specific inputs that are affected by the reform, imports increase post reform. For the homogeneous inputs this share is lower, at about 16%. In addition, for a share of 77% of the homogeneous products, imports fall to zero post de-reservation, for relationship-specific products this share is 60%.

[30] I thank Johannes Boehm for sharing the index-data with me.

Table 2.4: Product homogeneity

	# of products	mean homogeneity index	std. dev. of homogeneity index
Panel A: Outputs			
Total	5343	.304	.449
Not reserved	5030	.308	.450
Reserved	313	.253	.424
Panel B: Inputs			
Total	5293	.308	.450
Not reserved	5033	.310	.451
Reserved	260	.260	.427
Panel C: Imports			
Total	4890	.317	.454
Not reserved	4691	.319	.454
Reserved	199	.273	.436
Panel D: Only reserved inputs by importing status			
Total	286	.247	.421
Only domestic	81	.239	.418
Only imported	29	.132	.337
Domestic and imported	176	.270	.434

Notes: The table shows average product homogeneity indexes according to Rauch (1999) as converted to the Indian ASI data by Boehm & Oberfield (2020) and made available by the authors. Products are classified on a continuous scale on the interval [0, 1] where a larger number indicates more relationship specificity of the product, i.e., less homogeneous products. Data: ASI 2000-2010

2.5 Product level effects

First, I use the staggered removal of products from the reservation list to provide aggregate evidence on the impact of the reform on changes in sourcing strategies. It is illustrative to first consider changes on the aggregate product level to get a broad picture.[31]

The empirical strategy makes use of the fact that products on the reservation list have been sequentially taken off the list and that not all products have ever been on the reservation list. This leaves me with general treatment and control groups where treatment occurs at different points in time. Put more technically, I am faced with a setting of staggered treatment adoption where a unit changes treatment status at most once. In my case this means that a product that is taken off the reservation list remains in that status. This allows me to derive treatment effects of the reform on both domestic inputs and imports at the product level via a difference-in-difference strategy (Callaway

[31] While previous studies have already assessed the impact on aggregate misallocations and changes in aggregate productivity (Garcia-Santana & Pijoan-Mas (2014), Martin et al. (2017), and Tewari & Wilde (2019)), studies on changes in sourcing are limited to date, notable exceptions are Balasundharam (2020) and Boehm et al. (2019).

& Sant'Anna (2020), Athey & Imbens (2021)). The estimation follows Equation (2.1).

$$\ln(y)_{pt} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \delta_p + \delta_t + \epsilon_{pt} \tag{2.1}$$

The outcome of interest, y, is aggregated at the product level (observations are weighted by their initial labor share in downstream production, i.e., where the product is consumed as input) and regressed on an indicator set equal to one in and after the year the product has been taken off the reservation list ($\mathbb{1}\{t \geq t^*\}$, t^* indicates the year of de-reservation). I include product and year fixed effects (δ_p and δ_t, respectively) to establish the difference-in-difference estimator and simultaneously control for more aggregate macro-trends and time invariant product specificity.[32]

I evaluate the effect of the de-reservation on total quantity sourced, total spending on inputs, and unit values, i.e., input prices, for both domestic inputs and imports for the period of 2000-2010.[33] Panel A of Table 2.5 shows results on domestic inputs and Panel B for imports. It becomes apparent that the policy repeal leads to changes in sourcing strategies although imprecisely estimated. Domestically sourced quantity of de-reserved products almost doubles ($\approx e^{0.70} - 1$, column (1)) and total spending seems to decline slightly by 3% (column (2)). This may be because of declining average prices after the reform by about 32% (see column 3).

The quantity of imported intermediates, on the other hand, exhibits strong negative treatment effects of -56%, again imprecisely estimated. The unit values of imported intermediates increase by 20% (column (3), Panel B).

This finding on aggregate sourcing strategies and unit prices of domestic and international intermediate inputs may come out of different reasons. On the domestic market, the de-reservation reform led to increased and more efficient production of de-reserved products (Martin et al. (2017), Boehm et al. (2019), and Balasundharam (2020)).

But the de-reservation also allowed firms to start producing their own inputs at sufficient scale, i.e., to meet their own demand and to sell additional quantity at market prices to achieve sufficiently low average costs. Overall, the domestically sourced quantity increased in response to the reform and average domestic prices declined. The greater availability of inputs on domestic markets allows firms to source these domestically. This is confirmed by the product-level average treatment effects on imports. But the increasing unit costs of imports indicate a second mechanism. Products on the reservation list are very heterogeneous, some are very relationship specific, others are homogeneous across producers and quality differences are small in general. For newly entering producers it

[32] I thereby acknowledge recent methodological advances for difference-in-difference settings with different treatment or adaption (Borusyak et al. (2021), Callaway & Sant'Anna (2020), Han (2020), Sun & Abraham (2020), Athey & Imbens (2021)). I assume (and in Appendix Section A.2.1 test for) two types of parallel trends: (i) Expected outcomes of not-yet-treated and never-treated units conditional on observable characteristics are equal, and (ii) expected outcomes of not-yet-treated across different adoption dates (here: de-reservation years) are equal.

[33] Section A.2.4 in the Appendix contains robustness exercises confirming that the results presented are not driven by the trade collapse following the Great Recession.

is rather easy to offer homogeneous products or products of lower quality. These are potentially the products increasingly sourced on the domestic market. More relationship intensive products or products of higher quality will be sourced through established international buyer-seller relations.

Panel C of Table 2.5 further shows results at the product level for relative values of imports over domestic inputs. It shows that total expenditure on imported intermediates relative to spending on the same domestic input increased by 80% ($\approx e^{0.59} - 1$). However, this is not because firms actually source in greater quantity on foreign markets but rather it is due to a strong relative price effect. The relative quantity sourced on international markets decreased in fact, cf. column 1.

I perform additional robustness exercises in the Appendix. In Section A.2.1, I estimate a dynamic difference-in-difference framework (or event study) to check for (i) non-zero pre-trends and (ii) dynamic adjustment effects. Reassuringly, I do not find anticipation effects on the aggregate product level. Also, treatment effects are relatively stable over time following the de-reservation.

Table 2.5: Impact of the reform on product level domestic inputs and imports

	(1) log(Quantity cons)	(2) log(Total Costs)	(3) log(Price)
Panel A: Domestic inputs			
$\mathbb{1}\{t \geq t^*\}$	0.705	-0.0342	-0.384
	(0.452)	(0.208)	(0.466)
N	28,213	28,213	28,213
R^2	0.132	0.087	0.385
Number of inputs	2,787	2,787	2,787
Panel B: Imported inputs			
$\mathbb{1}\{t \geq t^*\}$	-0.810	0.491	0.184
	(0.503)	(0.507)	(0.241)
N	14,248	14,314	14,940
R^2	0.202	0.042	0.013
Number of inputs	1,695	1,695	1,909
Panel C: Imported inputs/Domestic inputs			
$\mathbb{1}\{t \geq t^*\}$	-0.575	0.585*	0.105
	(0.660)	(0.301)	(0.167)
N	13,534	13,610	14,119
R^2	0.129	0.076	0.092
Number of inputs	1,674	1,674	1,674
Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The table reports average treatment effects of the de-reservation from a difference-in-difference estimation on the product level on indicators of domestically sourced inputs in panel A and on imported inputs in panel B. Panel C shows treatment effects on the ratio of imports relative to domestically sourced inputs. t^* indicates the year a product is taken off the reservation list. Data: ASI 2000-2010. Standard errors in parentheses and clustered at product level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

2.6 Firm-product level imports of de-reserved products

Since selection into importing typically depends strongly on firm characteristics, such as productivity, I now turn to firm-product-level effects of the de-reservation. These allow me to infer the impacts of the reform on input misallocation more properly by controlling for the overall structure of the firm and to study adjustments at the firm level. This exercise will enable me to make statements about the underlying mechanisms and the decision to import as a second best solution when domestic input markets are distorted.

Intensive margin of imports

Similarly to the empirical strategy of the previous section, I rely on a difference-in-difference estimation at the firm-product level. I estimate equation (2.2):

$$\ln(y)_{ipt} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \delta_{ip} + \delta_t + \epsilon_{ipt}, \tag{2.2}$$

where, again, $\mathbb{1}\{t \geq t^*\}_{pt}$ is an indicator for whether product p has been taken off the reservation list at time t. Given firm-product level and year fixed effects (δ_{ip} and δ_t, respectively) coefficient β is the difference-in-difference effect (ATT). Errors ϵ_{ipt} are clustered at the firm level for this and any following estimations on the firm-product level.[34] For these estimations, I use inverse sample weights given in the ASI data to derive representative results. Table 2.6 summarizes the results.

In fact, for importers the de-reservation policy leads to a decrease in imports (Panel A of Table 2.6). Imported quantity falls in response to de-reservation by about 14% ($(e^{-.146} - 1)100\%$; column 1), whereas the unit price of imported intermediates shows no change (column 3), which in combination results in lower spending on imports of intermediate inputs by -35% (column 2). For domestic intermediate inputs, on the other hand, the quantity sourced increases by 20% while unit prices decrease by 11% resulting in slightly higher total spending by about 6% (Panel B).[35]

This first take shows that firms rely less on imports upon impact of the de-reservation reform and use more domestic intermediates.[36] As expected, once a product is taken off the reservation list, firms refrain from imports of that product. In parallel, I observe falling unit prices on the Indian market and firms extending their sourcing from that market. Here, I do not condition on dual sourcing so that the results raise the question if firms also shift their sourcing from importing to domestic sourcing. I will tackle this question in the following section.

In Appendix Section A.2.2, I test for pre-trends and dynamic effects on sourcing decisions after the de-reservation. As already shown at the aggregate level, there are no anticipation effects, especially not at the firm level of either importing or domestic sourcing. This exercise also reveals that the adjustments appear to be immediate and not prone to readjustments several years after the de-reservation occurred.

[34] This allows for heteroscedasticity across firms and serial correlation of errors within firms.

[35] As a robustness exercise, I repeat the estimation including firm-year trends (δ_{it}) instead of year trends (δ_t), and I account for the trade collapse during the Great Recession by restraining the sample to the period of 2000-2008. Both exercises confirm these results and are elaborated in more detail in Appendix Sections A.2.3 and A.2.4, respectively.

[36] In addition, firms produce and sell more of affected products. Confirmed by previous findings from, e.g., Martin et al. (2017) and Balasundharam (2020).

Table 2.6: Firm-product level effects: DiD

	(1) quantity	(2) costs	(3) unit price
Panel A: Imports			
β: $\mathbb{1}\{t \geq t^*\}$	-0.146*	-0.437***	-0.0856
	(0.076)	(0.130)	(0.0849)
N	501,231	501,231	501,231
R^2	0.225	0.194	0.718
Number of firm-product observations	63,025	63,025	63,025
Panel B: Domestic inputs			
β: $\mathbb{1}\{t \geq t^*\}$	0.182***	0.0662***	-0.114***
	(0.0468)	(0.0242)	(0.0416)
N	623,805	623,805	623,805
R^2	0.873	0.920	0.865
Number of firm-product observations	353,013	353,013	353,013
Firm-Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The table reports the difference-in-difference coefficient β from estimation of Equation (2.2). Data: ASI 2000-2010. Standard errors in parentheses and clustered at firm level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

Extensive margin of imports

Having documented that the policy repeal led to declining imports of previously reserved products, I next investigate whether the reform has effects on the extensive margin to import a specific product. Specifically, I test whether firms are less likely to import an affected product once the domestic market distortions are removed, domestic prices decline, and the availability of inputs at home increases. To do so, I regress an import dummy on the reservation time-dummy as a difference-in-difference estimation. The estimation is run in a logit format and the usual fixed effects for firm-product and year are included (δ_{ip} and δ_t, respectively):

$$\mathbb{1}\{\text{import}\}_{ipt} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \delta_{ip} + \delta_t + \epsilon_{ipt} \tag{2.3}$$

$\mathbb{1}\{\text{import}\}_{ipt}$ is equal to one if firm i imports product p at time t and zero otherwise. I report marginal effects in Table 2.7 which show that the probability to import a product decreases by about 3 percentage points once it is lifted off the reservation list. Thus, not only is the intensive margin affected, but firms also exit the import market altogether once availability of intermediate products on the domestic market increases.

I find that the reform, which has led to increasing supply of intermediate inputs at cheaper costs on the domestic market, had effects on both the intensive and extensive margin to import the respective product. The observed adjustments lead to the assumption that firms' reactions to the de-reservation are based on efficiency aspects, which are

Table 2.7: Extensive margin of importing a product relative to de-reservation

	(1)
$\mathbb{1}\{t \geq t^*\}$	-0.0303***
	(0.00493)
N	501,155
Firm-Product FE	Yes
Year FE	Yes

Notes: Table reports marginal effects of DiD-coefficient β from equation (2.3). Data: ASI 2000-2010. Standard errors in parentheses and clustered at firm level. Significance levels:* p<0.1, ** p<0.05, *** p<0.01

connected either to per period fixed costs to import or to sufficiently small sunk costs to enter the import market.

If firms face either of these constraints, prices of imports relative to domestic products changed by enough such that after de-reservation domestic products are cheaper than imports including all costs. However, it might also be the case that imports were more expensive than domestic products already before the policy removal but firms had to rely on imports to be able to produce sufficient quantity themselves to satisfy demand for final (or more downstream) products. Hence, I next explore different explanations for the effects on imports.

2.7 Changes in the sourcing strategy and withdrawal from input markets

Within-firm shifts of sourcing

First, I ask the question of whether firms also shift sourcing away from imports to more domestic intermediates. To answer this question, I re-estimate equation (2.2) where I change the dependent variable to the within-firm-product ratio of imports to domestic inputs, and imports to output sold, respectively. I also check for differential effects on domestic sourcing, distinguishing whether a company has ever imported a product. To this end, I introduce an interaction effect in the difference-in-difference equation and estimate Equation (2.4):

$$\ln(y)_{ipt} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \xi \mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\{\text{ever imported product}\}_{ip} + \delta_{ip} + \delta_t + \epsilon_{ipt}, \tag{2.4}$$

where $\mathbb{1}\{\text{ever imported product}\}_{ip}$ indicates if a firm i ever imported product p and the remaining variables are unchanged from before. Equation (2.4) is estimated for all firm-product input combinations observed irrespective of the market sourced from whereas Equation (2.2) is only estimated for firm-product observations where I ever observed a non-zero import value. Results are reported in Table 2.8.

In Panel A, I study the impact of the reform on within firm-product relative quantities, expenditure, and prices of imported intermediates against domestically sourced intermediates defined as $\ln(y_{ipt}^{\text{imported}}/y_{ipt}^{\text{domestically sourced}})$. The quantity imported relative to the quantity sourced domestically declines in response to the de-reservation by 11%, the relative price surprisingly also declines by 17% and relative total spending declines by about 25%.

I make a similar observation when I study the relative effects of imported intermediates against production of de-reserved products for completeness (Panel B). Note that only sales of products produced are recorded, the data do not yield information on total production, in particular not on production for own consumption. The left-hand-side variables are defined as $\ln(y_{ipt}^{\text{imported}}/y_{ipt}^{\text{sales of own production}})$. Point estimates are in similar ranges as those in Panel A – imports fall by about 11% relative to own production (albeit not statistically significant), and the ratio of spending on imported intermediates to revenue of products sold declines by 28%.

Lastly, I look at differential effects of the de-reservation reform on domestic sourcing distinguishing between if firms source these products on domestic markets only or also on international markets (Panel C). This approach reveals that for firms that also source (or have sourced) products on international markets, domestically sourced quantities decline somewhat (interaction effect ξ plus difference-in-difference effect β) as opposed to for firms that only source on domestic markets. The opposite holds true for the unit price.[37]

Collectively, these results indicate that firms revert back to domestic sourcing of intermediates once products are taken off the reservation list and domestic supply increases.

[37] As a robustness exercise, I repeat the estimation including firm-year trends (δ_{it}) instead of year trends (δ_t), and I account for the trade collapse during the Great Recession by restraining the sample to the period of 2000-2008. Both exercises confirm these results and are elaborated in more detail in Appendix Sections A.2.2 and A.2.4, respectively.

Table 2.8: Firm-product level effects: DiD

	(1) quantity	(2) costs	(3) unit price
Panel A: Imports / Domestic inputs			
β: $\mathbb{1}\{t \geq t^*\}$	-0.115*	-0.288***	-0.172**
	(0.0641)	(0.0982)	(0.0701)
N	501,231	501,231	501,231
R^2	0.204	0.173	0.689
Number of firm-product observations	63,025	63,025	63,025
Panel B: Imports / Output sold[‡]			
β: $\mathbb{1}\{t \geq t^*\}$	-0.113	-0.325**	-0.0913
	(0.0822)	(0.136)	(0.0871)
N	501,231	501,231	501,231
R^2	0.225	0.195	0.712
Number of firm-product observations	63,025	63,025	63,025
Panel C: Interaction effects for indigenous sourcing and importing			
β: $\mathbb{1}\{t \geq t^*\}$	0.208***	0.0648**	-0.140***
	(0.0507)	(0.0257)	(0.0448)
ξ: $\mathbb{1}\{t \geq t^*\}$ $\times \mathbb{1}\{$ever importing product $p\}$	-0.263**	0.0135	0.263***
	(0.124)	(0.0701)	(0.101)
N	623,805	623,805	623,805
R^2	0.873	0.920	0.865
Number of firm-product observations	353,013	353,013	353,013
Firm-Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The table reports the difference-in-difference coefficient β from estimation of Equation (2.2) in panels A and B and difference-in-difference coefficient β as well as interaction with an indicator if a firm ever imported a respective product, ξ, from Equation (2.4) in panel C. Data: ASI 2000-2010. Standard errors in parentheses and clustered at firm level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01
[‡]Column (2) of Panel B shows the regression on changes in costs over revenue within firm.

Changes in sourcing strategy and product range

To get a deeper understanding of the mechanisms at play that lead to the observed effects on imports, I next test whether firms become more likely to produce a reserved product once it becomes de-reserved. Firms potentially found it optimal to produce a product even before the de-reservation and were restricted to do so by the policy.[38] Likewise, the decision to produce a product can differ depending on whether the company sourced the product before the reform or even had to resort to imports in order to meet its factor demand. Hence, I estimate Equation (2.6) as a logit-function and include respective interaction effects. Relatedly, I also test if firms start to source a product domestically and whether this decision differs by previous import activity; Equation (2.5).

$$\begin{aligned}\mathbb{1}\{\text{domestic sourcing}\}_{ipt} =& \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \xi \mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\{\text{imported}\}_{ip}^{pre} + \\ & \delta_{ip} + \delta_t + \epsilon_{ipt}\end{aligned} \tag{2.5}$$

$$\begin{aligned}\mathbb{1}\{\text{own production}\}_{ipt} =& \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \xi \mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\{\text{imported}\}_{ip}^{pre} + \\ & \zeta \mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\{\text{domestic sourcing}\}_{ip}^{pre} + \\ & \chi \mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\{\text{domestic sourcing}\}_{ip}^{pre} \times \mathbb{1}\{\text{imported}\}_{ip}^{pre} + \\ & \delta_{ip} + \delta_t + \epsilon_{ipt}\end{aligned} \tag{2.6}$$

Here $\mathbb{1}\{\text{domestic sourcing}\}_{ipt}$ is an indicator showing if firm i sourced product p on the domestic market at time t and $\mathbb{1}\{\text{own production}\}_{ipt}$ is an indicator equal to one if the firm starts to produce a product p at year t. As before, β is the difference-in-difference effect. $\mathbb{1}\{\text{imported}\}^{pre}$ and $\mathbb{1}\{\text{domestic sourcing}\}^{pre}$ are indicator functions indicating if a firm imported or sourced a product domestically before the de-reservation date, respectively, so that ξ, ζ, and χ are the respective interaction difference-in-difference effects. The usual time and firm-product fixed effects are included. Results are shown in Table 2.9, column (1) for Equation (2.5) and column (2) for Equation (2.6).

Indeed, firms start to include products into their portfolio once a product is de-reserved, as previously shown by Martin et al. (2017) and Boehm et al. (2019); see row 1 of column (2). Firms are also more likely to source on the domestic market upon de-reservation; see row 1 of column (1). More interesting are the interaction effects, which here are transformed so that their size can be interpreted independently. Focusing on the propensity to source a product upon de-reservation on the domestic market (column (1)

[38] Firms motivation to include products might be caused by the fact that production of the product requires similar inputs as the remainder of the firm's product range (Boehm et al. 2019) or it serves as a crucial input in production of some of the products the firm is already producing such that the firm would ideally keep it within its boundaries (Holmstrom & Roberts 1998).

of Table 2.9) it becomes clear that a firm that previously has not sourced a product on the Indian market but did so on international markets is more likely to begin sourcing on the domestic market than a firm that has not sourced the product altogether ($.744 > .704$).

This result is not surprising as it confirms the previously reported results once more. As domestically produced products become more readily available at lower prices (cf. Section 2.6) firms that had to resort to imports to be able to satisfy demands – and fully did so – will, at least in part, shift to domestic sourcing.

In addition, firms are more likely to start producing a product if they have previously imported the product as the estimated interaction effect ξ in column (2) line 2 reveals. However, if firms previously only sourced the product on domestic markets, firms are not as likely to start producing the product as if the firm had not sourced the product at all ($.149 < .168$). There is only a minor difference in the propensity to start producing if firms sourced a product on both, domestic and international markets.

In summary, these results can be brought into alignment with theoretical considerations. Firms that import are generally more productive than firms that are only active on domestic markets.[39] These firms also have a higher production capability, (Boehm et al. 2019), such that it is generally easier or more efficient for these firms to produce additional products and adjust their product range as compared to firms that only source domestically. Additionally, since domestic supply shifted right-wards, for firms that already have established a domestic supply network it might not be optimal to start production themselves which potentially explains the different effects reported.

Table 2.9: Extensive margin relative to de-reservation

	(1) Input	(2) Production
$\mathbb{1}\{t \geq t^*\}$	0.704***	0.168***
	(0.00420)	(0.00180)
$\mathbb{1}\{t \geq t^*\}\times\ \mathbb{1}\{\text{imported}\}$	0.744***	0.195***
	(0.00377)	(0.00188)
$\mathbb{1}\{t \geq t^*\}\times\ \mathbb{1}\{\text{domestic sourcing}\}$		0.149***
		(0.00152)
$\mathbb{1}\{t \geq t^*\}\times\ \mathbb{1}\{\text{imported}\}\times\ \mathbb{1}\{\text{domestic sourcing}\}^{\ddagger}$		0.164***
		(0.00164)
Observations	337,865	253,340
Firm-Product FE	Yes	Yes
Year FE	Yes	Yes

Notes: Table reports marginal effects of DiD-coefficient β and the interaction effect ξ from Equation (2.5) in column (1) and marginal effects of DiD-coefficient β and the interaction effects ξ, ζ, and χ from Equation (2.6) in columns (2). Data: ASI 2000-2010. Standard errors in parentheses and clustered at firm level. Significance levels:* p<0.1, ** p<0.05, *** p<0.01

‡Note that this line shows the transformed effect, i.e., the marginal effect of $\xi + \zeta + \chi$ of Equation (2.6).

[39] See Figure 2.11 in the appendix and the following section.

2.8 Heterogeneity

Figure 2.4 reveals what has been shown in numerous studies and is at the heart of the 'new' new trade theory: Firms participating in international trade have a higher productivity level than firms that are only active on domestic markets.[40][41]

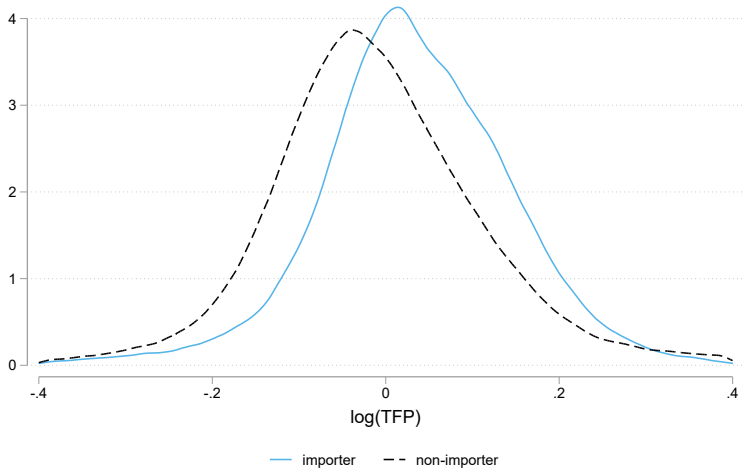


Figure 2.4: Firm productivity by importing status

The figure shows log(TFP) by importing status estimated using the approach of Ackerberg et al. (2015) pooled across all years. Data: ASI 2000-2010

However, the evidence shown so far has not taken into account differential effects by firm heterogeneity. In the course of the paper I have suggested efficiency considerations of firms as a mechanism that can explain the observed aggregate effects: Firms are constrained by too little supply on domestic markets which effectively impedes efficient output levels and ultimately firm growth. Other than in typical models of trade participation considerations that suggest that firms import to minimize costs this is not necessarily the case in the current setting (e.g., Antràs et al. (2017)). Rather, firms import to circumvent constrained domestic input markets.

Still, in a typical Melitz (2003)-type world, mirrored to import markets, with heterogeneous firm-productivity levels and fixed costs to participate in international trade, only relatively productive firms will be able to efficiently import. These firms will be

[40] Firms are inherently heterogeneous and their participation in international trade depends on their ability to do so, typically modeled as a Hick's neutral productivity term (Melitz (2003), Antràs et al. (2017)).

[41] For the following exercises, I rely on firm-level productivity estimates based on the non-parametric procedure proposed in Ackerberg et al. (2015). I estimate production functions with a revenue based approach assuming Cobb-Douglas technology. Intermediate inputs are assumed to be substitutable across domestic or international markets in concordance with the general argument made in this paper. Inputs are total labor, capital stock, and as proxy I use the total spending on intermediate inputs. I estimate production functions for 25 2-digit industries. Table 2.18 in the Appendix contains estimated production function coefficients. In addition, Appendix Figure 2.12 confirms the differences between distributions and that the productivity of importers is for the most part of the distribution larger than for non-importers.

able to distribute fixed costs and trade costs over sufficiently large quantities.[42] However, in the presence of distortions on domestic markets, as is arguably the case before the de-reservation, domestic inputs will be inefficiently expensive or even not available in sufficient quantity. This will make foreign intermediates relatively cheaper and, at given prices, induce more firms to import. This implies that, in comparison to an equilibrium without distortions, the productivity cut-off to import is shifted to the left such that firms with relatively low productivity levels will import.

Once the distortions are removed, i.e., after the de-reservation reforms when products are becoming available in larger quantities and at lower costs domestically, the optimal sourcing strategy of firms will change.[43] In particular, out of the set of formerly importing firms the least productive will exit international markets and rely on home market sourcing.[44] This implies that the average productivity level of importing firms increases, and the whole productivity distribution of importers will contract at the left and potentially shift rightward. Likewise, as firms with relatively high productivity are observed as purely domestic after the reform and firms with low productivity leave the market completely, as shown by Martin et al. (2017), the productivity distribution of domestic firms will also shift to the right.

In this section, I examine the effects of the de-reservation reform on aggregate productivity distributions. Figure 2.5 shows the cumulative density functions of firm-level productivity by importing status and relative to the de-reservation reform. Both the productivity distribution of importers and the productivity distribution of non-importers are situated further to the right after the reform.[45]

These shifts in the distributions could result from general TFP-growth in India during the sample period. However, I also observe a distinct effect of the de-reservation on firms' productivity level: I estimate $\ln(\text{TFP})_{it} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{it} + \delta_i + \delta_t + \epsilon_{it}$, where $\mathbb{1}\{t \geq t^*\}_{it}$ indicates the post de-reservation period if a firm consecutively sourced a product affected by the de-reservation irrespective of the sourcing market. For firms that source several affected products, I follow Martin et al. (2017) and Balasundharam (2020) and set this indicator equal to one once the first product becomes de-reserved. The difference-in-difference estimate is .0093 and statistically significant at conventional levels.[46]

[42] In this discussion, I abstract from the combinatorial discrete choice problem discussed in Antràs et al. (2017) and subsequent papers, where importers face a choice set of where from to source their inputs to minimize marginal costs of production. To bring my argument in line with these types of models, one may assume that the firm has already solved the choice problem facing the final decision to import or not, or for the matter and alignment with the data, that there are only two countries, home and foreign. Generally, fixed costs to export or import are found to be significant, e.g., Das et al. (2007)

[43] Figuratively speaking, the supply curve shifts outward and becomes less steep.

[44] Assuming sourcing of only one (aggregated) input.

[45] In fact, the productivity distributions of importers (non-importers) are different from another pre and post reform. The pre and post reform distributions of importers and non-importers are distinct from another, as indicated by Kolmogorov-Smirnov tests and a test across the complete distribution proposed by Goldman & Kaplan (2018). Appendix Section A.1.1 contains additional tests of stochastic dominance between the distributions based on results of Davidson & Duclos (2000) and Araar et al. (2009).

[46] Clustered standard error .0009; $p < 0.01$; Number of observations: $160,259$; $R^2 : .11$.

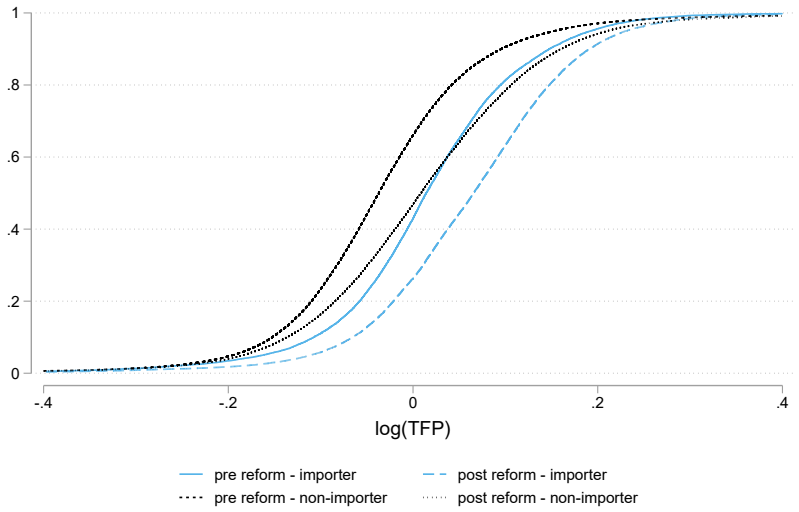


Figure 2.5: Changes in the TFP distribution of importers and non-importers relative to the reform

The graph shows cumulative density functions of the logged productivity values of importing and non-importing firms relative to the de-reservation. Productivity is estimated assuming a Cobb-Douglas production function and accounting for endogeneity of variable inputs with the control function approach of Ackerberg et al. (2015). Data: ASI 2000-2010

In light of the economic mechanism behind the shifts in the productivity distributions discussed above, it remains an empirical question for which type of firm the shift in the productivity distribution is stronger. To assess this question, I perform a procedure similar in spirit to difference-in-difference estimations. In particular, I assess the difference in the differences of TFP-distributions between importing firms and those that are only active on the domestic market before and after the de-reservation of product markets.[47]

To do so, I compare the pre and post reform difference in the difference between importer and non-importer TFP distributions as shown in Panels (c) and (d) of Appendix Figure 2.13. I plot both difference-distributions in Figure 2.6.[48] A proper statistical comparison is technically not feasible, but the figure clearly shows that the difference in TFP-distributions of importers to non-importers post-reform is more dispersed than that before the reform. Their left tails are statistically not different from each other while the right tail of the post-reform-difference distribution is further to the right. This indicates that the overall effect of the de-reservation and subsequent sourcing adjustments on the TFP-distribution of importers is larger than on the TFP-distribution of non-importers.

Even though relatively productive firms fall out of the set of importers into the set of non-importers (and there are some adjustments along the extensive margin of active firms), the remaining importers are more productive than before the de-reservation with a significantly larger shift in the productivity distribution as compared to non-importers.

[47] Acknowledging that there cannot be a clear identification since I observe shifts in TFP for both types of firms which I cannot exclude to potentially be caused by the reform.

[48] Note that the difference of two normal distributions is again normally distributed.

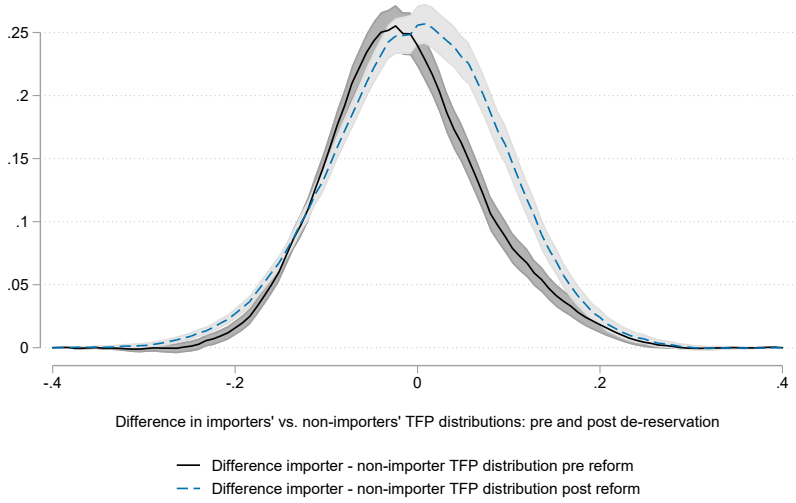


Figure 2.6: Changes in the TFP distribution of importers to non-importers relative to the reform

The graph shows the differences and 95% confidence intervals of importer-non-importer TFP-distributions before and after the de-reservation. Differences are estimated based on Araar (2007) and Araar & Duclos (2013). Data: ASI 2000-2010

Based on the results from this exercise, which show that there are shifts in the productivity distribution of importers in response to the de-reservation reform, I next study heterogeneous effects on the firm-product level along the productivity distribution of firms. I estimate Equation (2.7) where I interact the difference-in-difference indicator with the firm's TFP-level fixed at its value in the initial year in which I observe the firm and particularly before the de-reservation occurs ($\ln(\text{TFP})_i^{pre}$) to minimize simultaneity concerns:

$$\ln(y)_{ipt} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \xi \mathbb{1}\{t \geq t^*\}_{pt} \times \ln(\text{TFP})_i^{pre} + \delta_{ip} + \delta_t + \epsilon_{ipt} \tag{2.7}$$

To allow for non-linear effects along the TFP distribution, I also perform a difference-in-difference estimation on the tertiles of pre-reform TFP levels of firms.[49]

$$\ln(y)_{ipt} = \alpha + \sum_{q=1}^{3} \beta_q \left[\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{ \ln(\text{TFP})_{q(i)}^{pre} \right\} \right] + \delta_{ip} + \delta_t + \epsilon_{ipt}, \tag{2.8}$$

where $\mathbb{1}\left\{ \ln(\text{TFP})_{q(i)}^{pre} \right\}$ is an indicator function equal to one if firm i's pre-reform TFP level, i.e, the TFP level in the first year the firm is observed, falls within the qth tertile of the TFP distribution. Results for both approaches are reported in Table 2.10 and Appendix Figure 2.19.

The findings strongly corroborate the mechanism presented before. Firms at the lower

[49] I rely on tertiles for statistical power, however results are qualitatively in equal ranges when I use quartiles or even deciles of the TFP distribution.

end of the productivity distribution are affected most strongly by the de-reservation of products. Imports for relatively low productivity firms contract strongest whereas I do not find significant effects on imports of the most productive firms (cf. the third row of Panel B in Table 2.10). In particular, it is the most productive firms which show no response to the greater availability of intermediate inputs on the domestic market. From a theoretical perspective, these differences can be reconciled with the presence of fixed costs to import – potentially even per period costs – or per shipment costs. Given that prices on the domestic market decline, for low productivity firms the relative price of sourcing on the domestic market decreases so far that after the de-reservation imports are more costly than domestically bought inputs.

That I observe no adjustments for highly productive firms may be for a variety of reasons. Importing can remain cost efficient because (i) prices on international markets are still cheaper than on the Indian market and these firms have large enough demand for the affected products to distribute fixed (per shipment) costs over larger quantities. Or because (ii) they have demand for a larger variety of products which allows for distribution of fixed costs across different inputs. Or (iii) for these firms, which source a large variety of inputs, the solution to the choice problem of where to source from is still such that imports are optimal, even though, for the affected products, domestic prices are in absolute terms lower than prices on foreign markets. Since different trade partners – or sourcing channels – require (pecuniary) effort to be established and maintained, more productive firms may continue to rely on imports.

Changes in domestic sourcing activity in response to the de-reservation are in line with this argument. I re-estimate Equations (2.7) and (2.8) for domestic inputs. Results reported in Table 2.11 show that firms in both tails of the productivity distribution are affected relatively strongly by the policy change. Specifically, the strong increases in sourcing activity in combination with modest price declines speak in favor of the mechanism outlined before. The set of low-productive firms contains mainly domestic firms that have been constrained by the reservation policy. For these firms it is never optimal to import so that they expand by a lot in the post-reform period. Medium-productive firms, on the other hand, may not have been constrained that much since some were able to efficiently import or produce the products themselves. These are also firms that actively enter the product markets and start production of affected products. Lastly, high-productivity firms have imported and now revert back to domestic inputs in large, significant amounts. These firms might also be sufficiently large to be able to exert market power over their suppliers, see, for instance, Morlacco (2020) or Alviarez et al. (2020).[50]

[50]Papers studying misallocations triggered by incomplete markets are, for instance, Weinberger (2020), who explains misallocated resources through a non-homothetic preferences and hence non-constant mark-up-Melitz (2003) framework, or Peters (2020), who studies firms that compete à la Bertrand but invest into product specific productivity as they get older.

Table 2.10: Heterogeneous effects by productivity levels of firms: Imports

	(1) log(Quantity consumed)	(2) log(Costs)	(3) log(Price)
Panel A: linear, continuous effects			
$\mathbb{1}\{t \geq t^*\}_{pt}$	-0.149*	-0.442***	-0.0878
	(0.0763)	(0.130)	(0.0849)
$\mathbb{1}\{t \geq t^*\}_{pt} \times \ln(\text{TFP})_i^{pre}$	0.492**	1.025***	0.415*
	(0.216)	(0.352)	(0.251)
N	501,155	501,155	501,155
R^2	0.225	0.194	0.718
Number of firm-product observations	63,025	63,025	63,025
Panel B: tertile effects			
1st tertile: $\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{\ln(\text{TFP})_{q(i)=1}^{pre}\right\}$	-0.279**	-0.698***	-0.184
	(0.126)	(0.233)	(0.165)
2nd tertile: $\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{\ln(\text{TFP})_{q(i)=2}^{pre}\right\}$	-0.214	-0.576**	-0.204
	(0.147)	(0.224)	(0.138)
3rd tertile: $\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{\ln(\text{TFP})_{q(i)=3}^{pre}\right\}$	0.102	0.0554	0.175
	(0.125)	(0.217)	(0.128)
N	501,155	501,155	501,155
R^2	0.225	0.194	0.718
Number of firm-product observations	63,025	63,025	63,025
Firm-Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Table reports DiD-coefficient β and interactions effect ξ from Equation (2.7) in Panel A and the DiD-effects β_q on TFP-tertiles from Equation (2.8) in Panel B on importing activities. Data: ASI 2000-2010. Standard errors in parentheses and clustered at firm level. Significance levels:* p<0.1, ** p<0.05, *** p<0.01

Table 2.11: Heterogeneous effects by productivity levels of firms: Domestic inputs

	(1) log(Quantity consumed)	(2) log(Costs)	(3) log(Price)
Panel A: linear, continuous effects			
$\mathbb{1}\{t \geq t^*\}_{pt}$	0.181***	0.0674***	-0.112***
	(0.0468)	(0.0241)	(0.0415)
$\mathbb{1}\{t \geq t^*\}_{pt} \times \ln(\text{TFP})_i^{pre}$	0.0495	0.209**	0.0811
	(0.162)	(0.0851)	(0.109)
N	623,805	623,805	623,589
R^2	0.873	0.920	0.865
Number of firm-product observations	353,013	353,013	352,879
Panel B: tertile effects			
1st tertile: $\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{\ln(\text{TFP})_{q(i)=1}^{pre}\right\}$	0.283***	-0.0323	-0.307***
	(0.0899)	(0.0424)	(0.0804)
2nd tertile: $\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{\ln(\text{TFP})_{q(i)=2}^{pre}\right\}$	0.0466	0.0663	0.0166
	(0.0778)	(0.0443)	(0.0689)
3rd tertile: $\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{\ln(\text{TFP})_{q(i)=3}^{pre}\right\}$	0.239***	0.167***	-0.0704
	(0.0729)	(0.0373)	(0.0624)
N	623,805	623,805	623,589
R^2	0.873	0.920	0.865
Number of firm-product observations	353,013	353,013	352,879
Firm-Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Table reports DiD-coefficient β and interactions effect ξ from Equation (2.7) in Panel A and the DiD-effects β_q on TFP-tertiles from Equation (2.8) in Panel B on domestic sourcing activities. Data: ASI 2000-2010. Standard errors in parentheses and clustered at firm level. Significance levels:* p<0.1, ** p<0.05, *** p<0.01

2.9 Additional results

In Appendix Section A.3, I study additional differentiating channels that may influence the adjustments in response to the de-reservation and resulting decreasing misallocations and distortions. In Section A.3.1, I study if results differ by product homogeneity. As already mentioned in the descriptive section above, most products from the reservation list are rather homogeneous presumably because firms of the SSI have to be able to produce these products while being small, of low ability or poorly equipped with machinery etc.

As one would expect, adjustments are less strong for more relationship specific products (products are classified as relationship specific according to the Rauch (1999)-index as adapted for the product classification of the current data set by Boehm & Oberfield (2020)). For these products, firms will presumably continue to rely on existing business relations. Adjustments to the greater availability at lower costs as effect of the de-reservation will only take place slowly. Hence, I do not expect to observe immediate switching from imports to domestic sourcing for relationship specific products, if at all.

On the other hand, the effects of the de-reservation are particularly pronounced for homogeneous products. The quantity sourced internationally decreases by 20% while the imported quantity for relationship specific products does not change by much. For homogeneous products the import price declines by about 28%, whereas the price increases for heterogeneous products. This implies declining overall spending on homogeneous imports and increasing spending on relationship specific products. For homogeneous products domestic purchases increase strongly by 27% while domestic purchases for relationship specific products rise by just about 14%.

In Section A.3.2, I study if results differ by (a) the market concentration in domestic input markets and (b) the firms' buyer share in total sourcing by Indian firms. The market structure of the supply side is only of minor importance for the post de-reservation importing behavior. There are no strong differences in adjustments in imported quantity or total spending on imports between differently concentrated domestic input markets. The concentration of domestic markets is more important for changes in domestic demand after the de-reservation. For more concentrated markets, the treatment effects in sourcing are considerably lower than for less concentrated markets. Sourcing of intermediate inputs from domestic markets increases by about 6 percentage points less for more concentrated markets, whereas the total spending increases significantly because there are no significant price adjustments in these markets.

Hence, for more concentrated domestic markets, imports contract less strongly and domestic sourcing increases less strongly than for less concentrated markets. Market power and pass-through are important statistics for adjustments as already shown by Balasundharam (2020). For markets where sellers are more concentrated, firms that rely on the respective products as inputs profit less from the de-reservation reform since

market imperfections remain high. Quite intuitively, distortions may still be significant for more concentrated domestic markets which is why inputs show smaller adjustments.

Buyer size and implied buyer power is of greater importance. In particular, prices of imported inputs decline for larger buyers whereas the effect for smaller firms is negligible. For domestic sourcing, somewhat puzzlingly, changes post de-reservation are lower for larger firms. However, this may be because it is these firms that take up production of the affected product.

2.10 Conclusion

By examining a policy repeal in India, which led to greater and more cost efficient availability of intermediate inputs on the domestic market and hence reduced misallocations, this paper reveals an additional, previously unreported channel through which imports are welfare enhancing. I show that the presence of distortions on intermediate input markets leads to higher import levels as compared to a first best world without misallocations. Firms use imports to circumvent distorted input markets.

The paper makes apparent that the misallocations introduced by the initial small-scale industry reservation had a negative tariff-equivalent effect in the sense that imports are increased. I find strong evidence that, in response to the policy repeal, imports contract at both the extensive and intensive margin. Firms adjust their sourcing strategies to greater sourcing from the domestic market once distortions are removed.

The findings reveal that some firms were importing only because either intermediate inputs were unavailable on the domestic market at appropriate quantities or prices or both. As soon as products are available at better conditions, these firms reduce or stop their imports and source more from the domestic market.

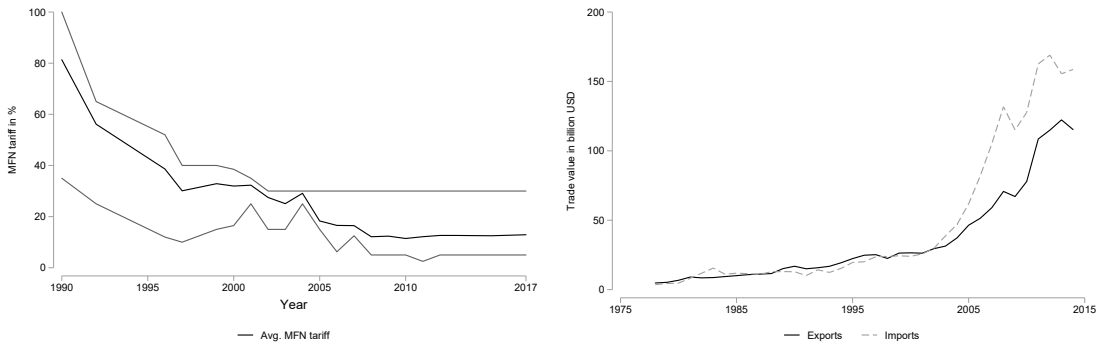
The existence of distortions or misallocations in the markets for intermediate inputs before the policy was lifted lowered the productivity threshold for imports. I show that firms source from international markets despite low productivity levels. Without distortions, firms would not have undertaken any (relatively expensive) import activities in order to at least partially overcome the inefficient domestic markets.

The finding that imports can mitigate domestic distortions should be relevant especially for developing countries that are still characterized by inefficient institutions or industrial policies (see for instance Alfaro & Chari (2014), Midrigan & Xu (2014) or Boehm & Oberfield (2020) for other examples of causes of misallocations).

The present paper thus provides a further argument in favor of demanding developing countries in particular to remove their trade impediments. In addition to the previously reported positive effects on firm-level and aggregate productivity (e.g., Goldberg et al. (2010*a*) or Topalova & Khandelwal (2011)), imports of intermediate inputs are a channel through which misallocations on the input markets can be overcome without the need to determine the cause of misallocations which in some circumstances can be infeasible.

A Appendix

A.1 Additional descriptives



(a) Tariff levels

(b) Trade flows

Figure 2.7: Indian MFN tariffs and trade flows

The figure shows Indian MFN tariff levels and imports and exports over time. Panel (a) shows the average MFN tariff level across 6-digit HS products as well as 10th and 90th percentiles. Data: UNCTAD Trade Analysis Information System (Trains). Panel (b) shows Indian imports and exports with major trading partners over time. Partner countries are Australia, Canada, Germany, France, Indonesia, Japan, Malaysia, New Zealand, rem. Europe, Rep. of Korea, Russian Federation incl. former USSR, Singapore, South Africa, USA, UK. Data: UN Comtrade

Figure 2.8 shows the average firm size distribution by total revenue. Mean and median of total revenue for importing firms are considerably larger than for domestically sourcing firms – the mean importing firm earns about 5 times as much as the mean domestic firm (for the median firm this factor is 13).

Figure 2.9 shows the average firm size distribution differentiated by domestic sourcing of reserved products. The median firm sourcing reserved products on the domestic market is 1.9 times as large in total revenue than the median firm not sourcing a reserved product.

Figure 2.10 highlights the different firm size distributions of firms that import only not-reserved products and firms that import reserved products. The figure shows two Panels, in Panel (a) the total revenue is taken as measure of firm size and in Panel (b) the total expenditure on imports is taken as measure of importer size. For both measures the right tails of the distribution for firms that import reserved products are thicker. Also, the median firms are larger for this type of firms.

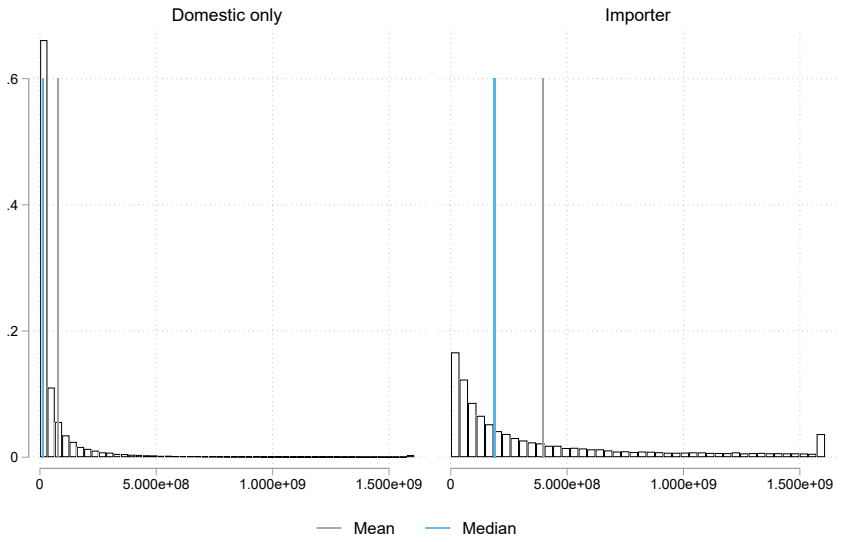


Figure 2.8: Firm size distribution by importing status

The graph shows the average firm size distribution differentiated by importing status of firms. Firm size is measured by total revenue and is winsorized at 5% and 95% levels. The mean (median) of domestic and importing firms' revenues are 77.2M rupees (13.9M rupees) and 397M rupees (189M rupees), respectively. Data: ASI 2000-2010

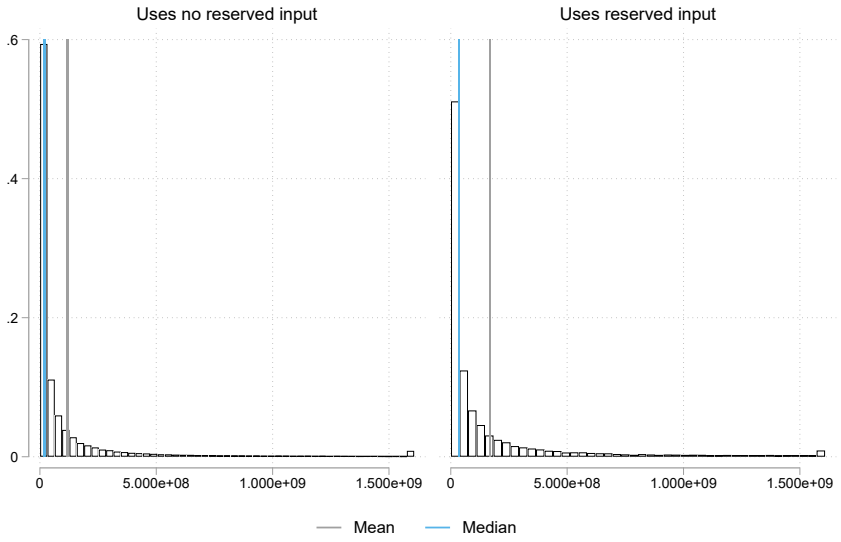
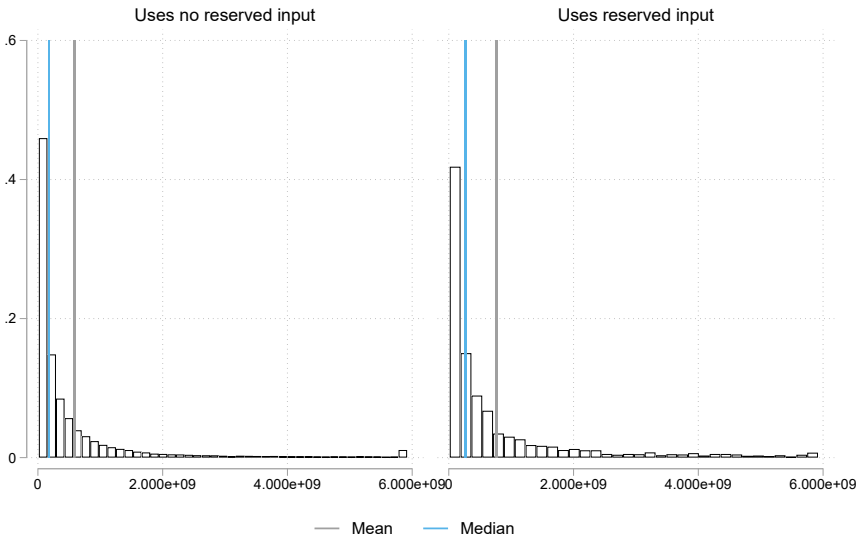
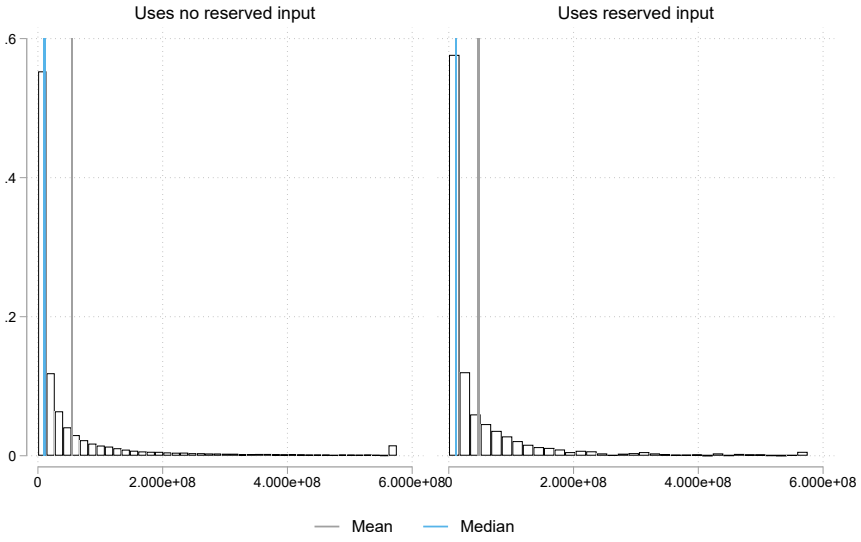


Figure 2.9: Firm size distribution by domestic sourcing of reserved products

The graph shows the average firm size distribution differentiated by firms domestically sourcing reserved products. Firm size is measured by total revenue and is winsorized at 5% and 95% levels. The mean (median) of no-reserved-input and reserved-input firms' revenues are 119M rupees (18.9M rupees) and 169M rupees (35.2M rupees), respectively. Data: ASI 2000-2010



(a) By production value



(b) By importing value

Figure 2.10: Importer size distribution by importing of reserved products

The graph shows the average importer size distribution differentiated by importing of reserved products. Panel (a) shows revenue distribution and Panel (b) shows importing value distribution. Revenue and expenditure values are winsorized at 5% and 95% levels. Mean (median) of no-reserved-import and reserved-import firms' revenues are 584M rupees (181 M rupees) and 765M rupees (266M rupees), respectively (Panel (a)). Mean (median) of no-reserved-import and reserved-import firms' imports are 54.5M rupees (10.3M rupees) and 47.9M rupees (11.6M rupees), respectively (Panel (b)). Data: ASI 2000-2010

A.1.1 Firm-level productivity distributions

This section provides additional information on the changes in productivity distributions of firms in response to the de-reservation reform. Figure 2.11 shows the average productivity distributions (PDFs) of importing and non-importing firms as log (TFP) estimated using the approach of Ackerberg et al. (2015).

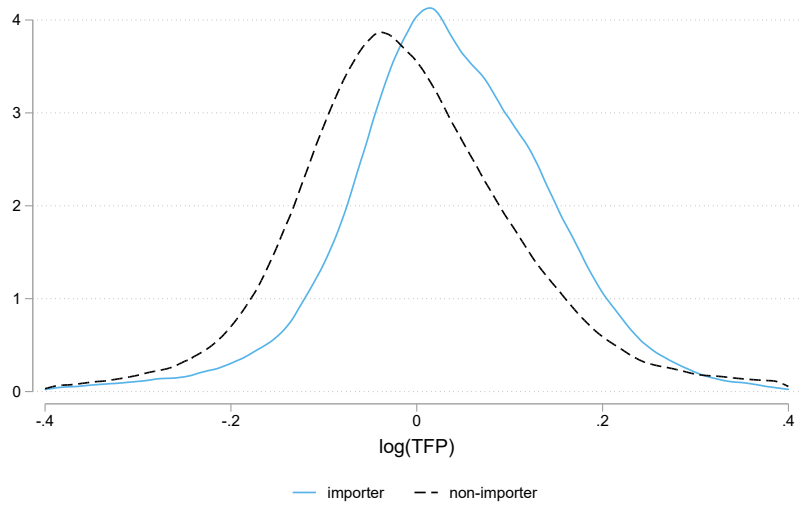


Figure 2.11: Firm productivity by importing status
The figure shows log(TFP) by importing status estimated using the approach of Ackerberg et al. (2015) pooled across all years. Data: ASI 2000-2010

Figure 2.12 shows the difference in TFP-distributions between importers and non-importers. This difference is estimated based on results of Davidson & Duclos (2000), Davidson & Duclos (2013). The difference and confidence intervals are estimated using the DASP-Stata package (Araar & Duclos 2013) which is based on the methodology proposed in Araar (2007).

The figure confirms statistical differences between the distributions shown in Figure 2.11 and confirms that for the most part productivity levels of importing firms are larger than productivity levels of domestic-only firms.

In Figure 2.13, I report differences in TFP distributions of importers (respectively non-importers) before and after de-reservation (Panels (a) and (b)) and differences in TFP-distributions of importers and domestic firms for the time periods before and after the de-reservation, respectively (Panels (c) and (d)). These graphs show the differences of the underlying pdf-distributions of Figure 2.5.

From Panels (a) and (b) it becomes apparent that there is overall TFP-growth for either type of firm between the periods before and after the de-reservation reform. Likewise, Panels (c) and (d) show that importers are more productive than non-importers, both before and after the de-reservation. As mentioned in the main body of the paper, this is also tested via Kolmogorov-Smirnov tests and across the complete distribution as

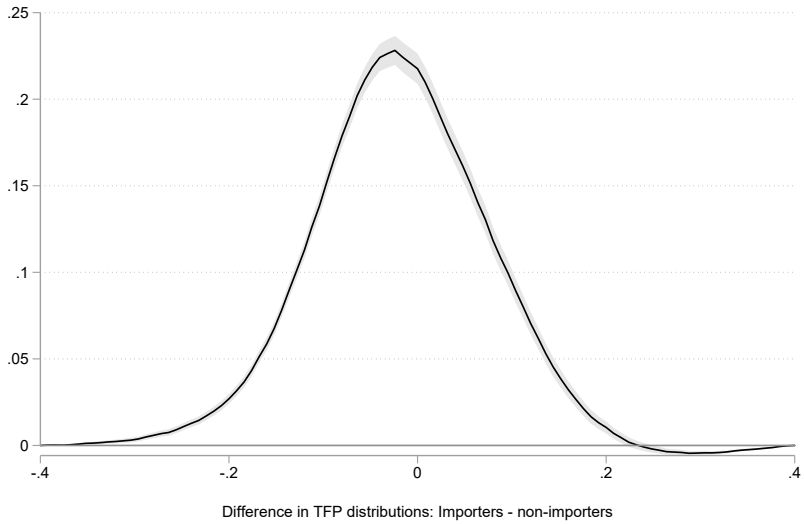
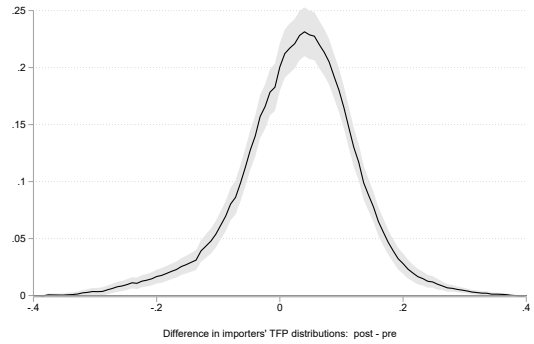


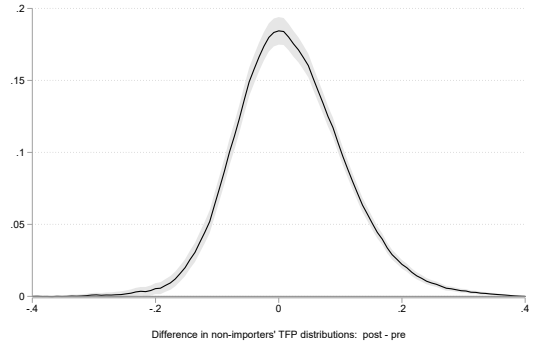
Figure 2.12: Firm productivity differences by importing status

The figure shows the estimated differences and 95% confidence intervals in log(TFP) of the distributions reported in Figure 2.11 by importing status estimated using the approach of Ackerberg et al. (2015) pooled across all years. Differences and confidence intervals are estimated based on the results of Araar (2007) using the Stata package described in Araar & Duclos (2013). Data: ASI 2000-2010

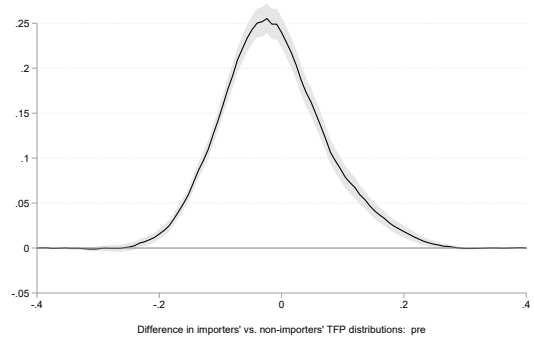
proposed by Goldman & Kaplan (2018).



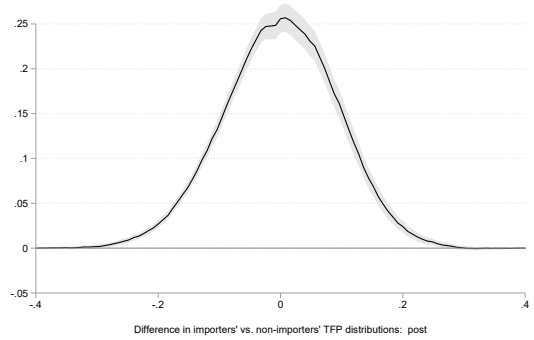
(a) Importers: post-pre difference



(b) Domestic only: post-pre difference



(c) Pre reform: Importers - Domestic firms' TFP difference



(d) Post reform: Importers - Domestic firms' TFP difference

Figure 2.13: Differences in TFP distributions of importing and non-importing firms before and after the reform

The figure shows estimated differences in TFP-distributions and 95% confidence intervals before and after the de-reservation reform for importing and non-importing firms. Panels (a) and (b) show the differences in the TFP-distributions before and after the policy change of importers (Panel (a)) and only domestically sourcing firms (Panel (b)). Panel (c) shows the difference in TFP-distributions of importers to non-importers for the time period before the de-reservation reform. Panel (d) shows the difference in TFP-distributions of importers to non-importers for the time period after the de-reservation reform. Differences and confidence intervals are estimated based on the results of Araar (2007) using the Stata package described in Araar & Duclos (2013). Data: ASI 2000-2010

A.2 Robustness

A.2.1 Dynamic effects: Product level

In this section, I present additional results on the product level. First, I estimate an event study regression on product level to test for any dynamic effects and likewise to report on the absence of pre-trends on product level. Specifically, I estimate

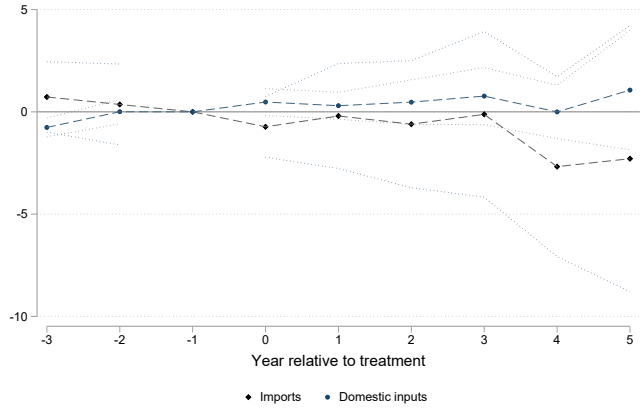
$$y_{pt} = \alpha + \sum_{\kappa=-3}^{5} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} + \delta_p + \delta_t + \epsilon_{pt}, \tag{2.9}$$

where $\mathbb{1}\{t = t^* + \kappa\}$ indicates the relative time to the reservation year of the respective product and δ_p and δ_t are product and year fixed-effects respectively. Because I deal

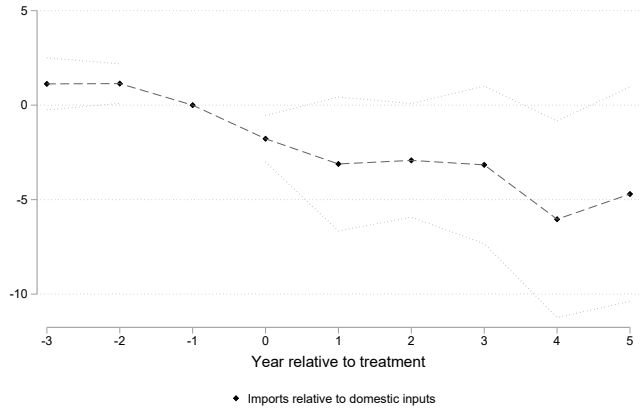
with a potentially unbalanced panel of product observations and staggered treatment adoption, I bin observations outside the interval around the de-reservation year and do not report their estimated coefficients since they do not identify treatment effects as shown by Borusyak et al. (2021). As before, standard errors are clustered at the product level and observations are weighted by their initial labor share.

Results for input quantity sourced are shown in Figure 2.14. It confirms the results of Section 2.5: There is hardly a change in domestic products sourced while the quantity sourced by importing decreases over time. I do not observe pre-trends rendering me assured that the dereservation policy can be considered exogenous and constitutes a suitable environment for the research question answered in this paper. Panel b of Figure 2.14 shows the change in relative imported quantity to quantity sourced domestically. Here as well, the relative quantity per product subject to dereservation imported decreases significantly more than the quantity sourced on Indian markets even though firms start producing these products as shown by Martin et al. (2017).

I relation to important assumptions for the difference-in-difference estimator as put forward by Athey & Imbens (2021), (i) expected outcomes of not-yet-treated and never-treated units conditional on observable characteristics have to be equal and (ii) expected outcomes of not-yet-treated units across different adoption dates (here: de-reservation years) have to be equal, I can confirm both to be valid. Assumption (i) is confirmed by the absence of pre-trends in the whole sample of products also including products that were never treated. The absence of pre-trends confirms that expected outcomes of both units are equal or at least statistically not distinguishable. When restricting the sample for the event study estimation of Equation (2.9) to only products that were at some time reserved for production by the SSI, I find similarly to the shown effects no significant treatment effects *in the years before* the de-reservation date confirming assumption (ii). The same holds true for estimations at the firm-product level as shown in the following section.



(a) Imported inputs and domestic inputs



(b) Imported inputs / domestic inputs

Figure 2.14: Dynamic changes of quantity sourced on aggregate product level

The graph shows treatment effects from a event study estimation on aggregated quantities per product: $y_{pt} = \alpha + \sum_{\kappa=-3}^{5} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} + \delta_p + \delta_t + \epsilon_{pt}$ following Borusyak et al. (2021). The figure shows point estimates and 95% confidence intervals. Standard errors are clustered on the product level. Data: ASI 2000-2010

A.2.2 Dynamic effects: Firm-product level

For results on firm-product level, I also estimate a dynamic difference-in-difference structure to test for pre-trends and check on dynamically different effects in the periods following de-reservation. I estimate equations (2.10) and (2.11) to confirm results of Tables 2.6 and 2.8.

$$\ln(y)_{ipt} = \alpha + \sum_{\kappa=-5}^{5} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} \times \text{reserved}_p + \delta_{ip} + \delta_t + \epsilon_{ipt}, \tag{2.10}$$

$$\begin{aligned}\ln(y)_{ipt} =&\alpha + \sum_{\kappa=-5}^{5} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} \times \text{reserved}_p \\ &+ \sum_{\kappa=-5}^{5} \xi_\kappa \mathbb{1}\{t = t^* + \kappa\} \times \text{reserved}_p \times \mathbb{1}\{\text{ever imported product}\}_{ip} \\ &+ \delta_{ip} + \delta_t + \epsilon_{ipt},\end{aligned} \tag{2.11}$$

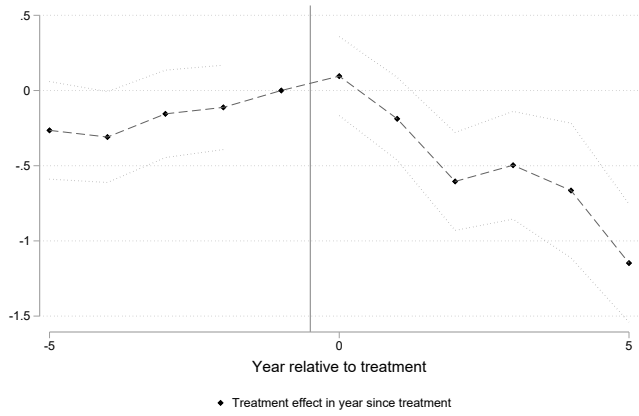
Results are shown in Figures 2.15 for imports, 2.16 and 2.17 for domestic inputs, and 2.18 for the interaction-regression (2.11). As for the aggregate effects on product level, I do not find significant pre-trends confirming the validity of the difference-in-difference approach. Likewise, when restricting the sample to treated products only, I also find no significant effects on β_κ for $\kappa < 0$. Hence, the assumptions hold that (i) expected outcomes of not-yet-treated and never-treated units conditional on observable characteristics have to be equal and (ii) expected outcomes of not-yet-treated units across different adoption dates (here: de-reservation years) have to be equal (Athey & Imbens 2021).

Further, the results of the dynamic approach largely confirm those presented in the main body of the paper. For imported inputs, quantity sourced declines significantly and steadily for the years following de-reservation. Likewise, total spending declines and I observe a slightly declining trend in prices of imported intermediates but as for the static difference-in-difference approach this effect becomes significant only in year 5 after the de-reservation.

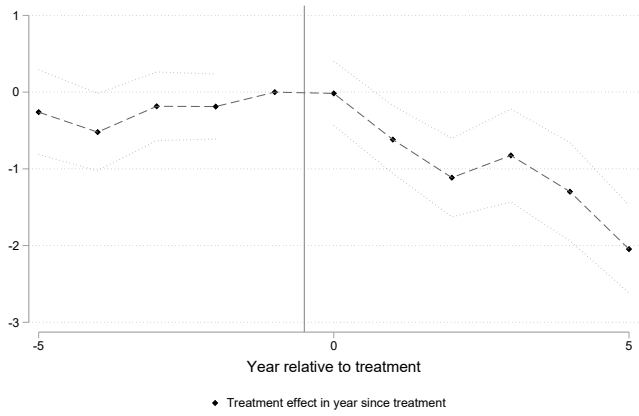
In addition, I observe that imports react with a slight delay of one year to the de-reservation. This is not the case for domestically sourced inputs as shown in Figure 2.16. Here as well, the event study estimation confirms the main results. Reactions to the de-reservation are faster than for imported inputs, I find significant effects already in the year immediately post de-reservation.

Interestingly, there appear to be slight increases in the price of domestic intermediates in the years *before* the de-reservation (Panel (c) of Figure 2.16). This is in line with the overall restriction on entry into the product markets and little growth of incumbent producers. Due to the growing economy demand rose and equilibrium prices increased accordingly. When I restrict the sample to firm-product observations that were directly affected by the reservation policy, i.e., products that were restricted for exclusive production by the SSI, these effects are no longer present, see Figure 2.17. Hence, for all treated products demand increased even before the de-reservation but due to limited growth of incumbent producers and no entry into these product markets there was no increase in supply and in return prices increased relative to never-reserved products. That there are no such trends when restricting the sample to treated products only is also in light of this observation and once again reassuring that the identification strategy is valid. As

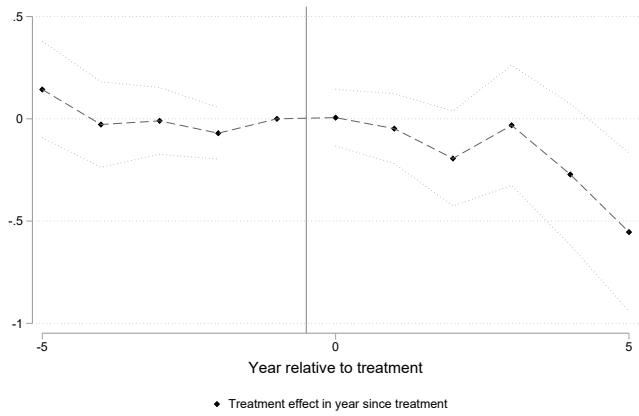
shown by Borusyak et al. (2021), already the staggered treatment adoption allows for clear identification of the average treatment effect on the treated even if all observations will be treated at some point in time.



(a) Import quantity



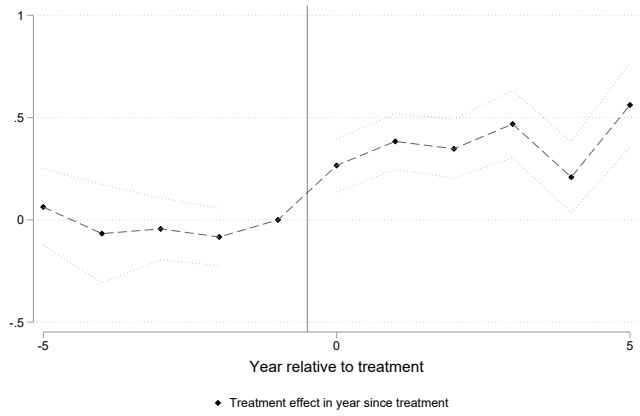
(b) Import costs



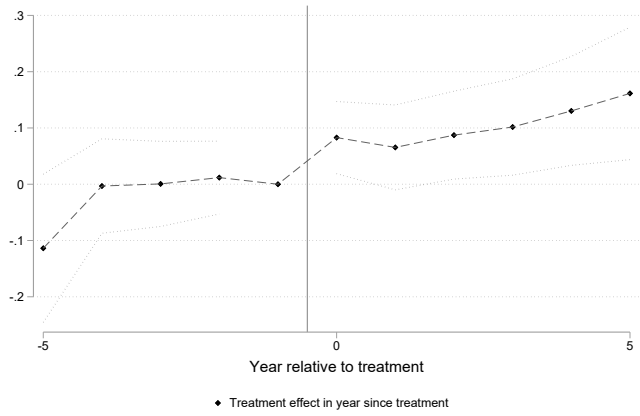
(c) Import unit price

Figure 2.15: Dynamic treatment effects of de-reservation on imports

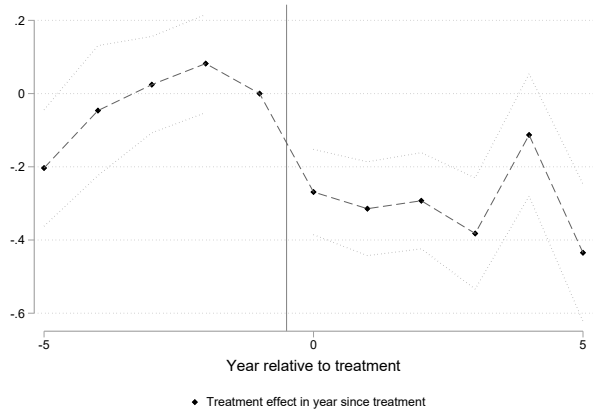
The graph reports the difference-in-difference coefficients β_κ from estimation of Equation 2.10. Panel (a) shows treatment effects of the de-reservation on import quantity, Panel (b) shows treatment effects on total import costs, and Panel (c) reports treatment effects on unit prices of imports. Graphs show point estimates and 95% confidence intervals. Standard errors are clustered on the firm level. Data: ASI 2000-2010



(a) Domestic input quantity



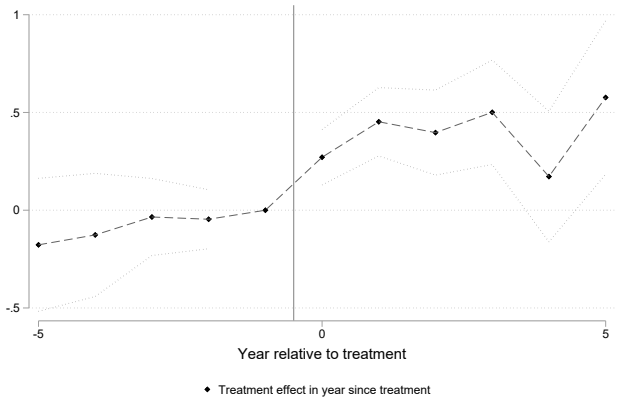
(b) Domestic input costs



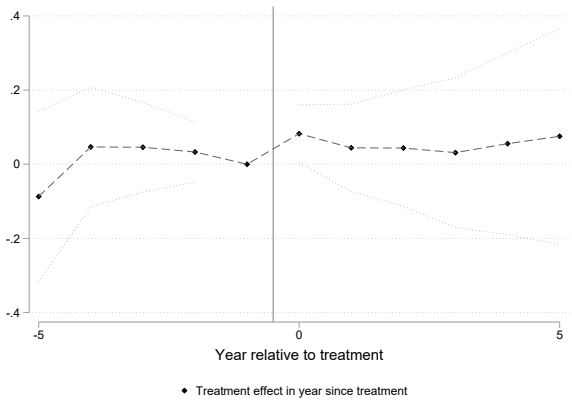
(c) Domestic input unit price

Figure 2.16: Dynamic treatment effects of de-reservation on domestic inputs

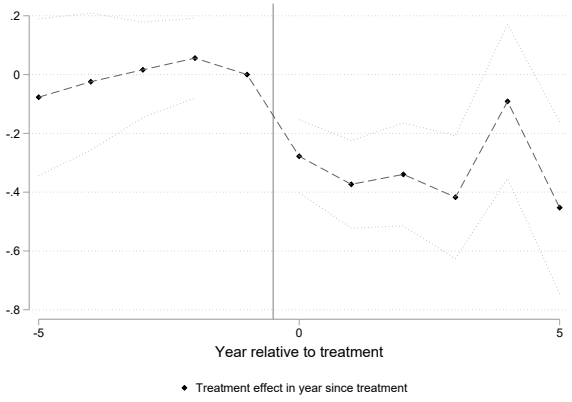
The graph reports the difference-in-difference coefficients β_κ from estimation of Equation 2.10. Panel (a) shows treatment effects of the de-reservation on domestic input quantity, Panel (b) shows treatment effects on domestic input costs, and Panel (c) reports treatment effects on unit prices of domestic inputs. Graphs show point estimates and 95% confidence intervals. Standard errors are clustered on the firm level. Data: ASI 2000-2010



(a) Domestic input quantity



(b) Domestic input costs



(c) Domestic input unit price

Figure 2.17: Dynamic treatment effects of de-reservation on domestic inputs – only products that were on the reservation list

The graph reports the difference-in-difference coefficients β_κ from estimation of Equation 2.10. The sample is restricted to firm-product observations for products that were affected by the reform, i.e., products that were at some point in time reserved pro exclusive production by the SSI. Panel (a) shows treatment effects of the de-reservation on domestic input quantity, Panel (b) shows treatment effects on domestic input costs, and Panel (c) reports treatment effects on unit prices of domestic inputs. Graphs show point estimates and 95% confidence intervals. Standard errors are clustered on the firm level. Data: ASI 2000-2010

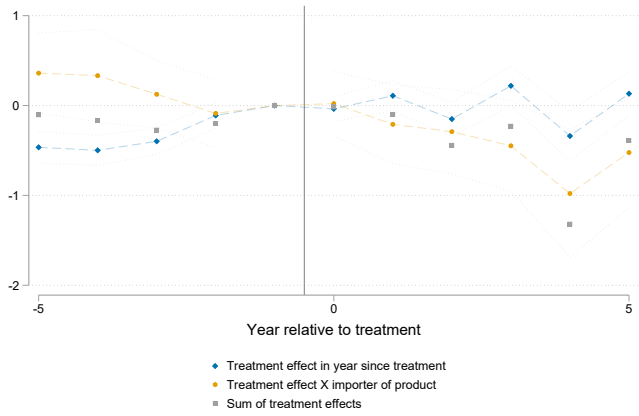


Figure 2.18: Dynamic treatment effects of de-reservation on indigenous sourcing for all and importers of respective product

The graph reports the difference-in-difference coefficients β_κ and interactions with an indicator if a firm ever imported the respective product ξ_κ from estimation of Equation 2.11. Reported are the treatment effects and interactions of treatment effects with and indicator equal to 1 if the firm ever imported product p, in addition the sum of treatment and interaction coefficients are shown. Graphs show point estimates and 95% confidence intervals. Standard errors are clustered on the firm level. Data: ASI 2000-2010

A.2.3 Firm-year trends

For additional robustness, I repeat the estimation of Section 2.6 but include firm specific time trends in the regression. I estimate equations (2.12) and (2.13) with same notation as before.

Results are presented in Table 2.12 and largely confirm the results of the less restrictive estimation.

$$\ln(y)_{ipt} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \delta_{ip} + \delta_{it} + \epsilon_{ipt} \tag{2.12}$$

$$\ln(y)_{ipt} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \xi \mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\{\text{ever imported product}\}_{ip} + \delta_{ip} + \delta_{it} + \epsilon_{ipt} \tag{2.13}$$

Table 2.12: Firm-product level effects: DiD

	(1) quantity	(2) costs	(3) unit price
Panel A: Imports			
β: $t \geq t^*$	-0.0822	-0.378***	0.0459
	(0.0743)	(0.126)	(0.0770)
N	477,303	477,303	477,303
R^2	0.397	0.385	0.787
Panel B: Domestic inputs			
β: $t \geq t^*$	0.221***	0.0547**	-0.160***
	(0.0520)	(0.0244)	(0.0448)
N	592,614	592,614	592,614
R^2	0.934	0.961	0.927
Panel C: Imports / Domestic inputs			
β: $t \geq t^*$	-0.0566	-0.181*	0.00141
	(0.0636)	(0.0953)	(0.0739)
N	477,303	477,303	477,303
R^2	0.363	0.353	0.763
Panel D: Interaction effects for indigenous sourcing and importing			
β: $t \geq t^*$	0.218***	0.0508*	-0.161***
	(0.0562)	(0.0265)	(0.0484)
ξ: $t \geq t^* \times \mathbb{1}\{\text{ever importing product } p\}$	0.0228	0.0375	0.00960
	(0.134)	(0.0583)	(0.109)
N	592,614	592,614	592,614
R^2	0.934	0.961	0.927
Firm-Product FE	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes

Notes: The table reports the difference-in-difference coefficient β from estimation of Equation (2.12) in panels A-D and difference-in-difference coefficient β as well as interaction with an indicator if a firm ever imported a respective product, ξ, from Equation (2.13) in panel E. Data: ASI 2000-2010. Standard errors are clustered on the firm level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

A.2.4 Effects of the financial crisis?

Towards the end of the time period studied a strong shock to international trade and global value chains in particular occurred. To verify that the results presented in the main section of the paper are not driven by the Trade Collapse in the aftermath of the financial crisis, I present results for the restricted time period of 2000-2008. Note that trade flows fell only in 2009 (cf. Figure 2.7) so that I can include the year 2008 in this exercise.

Table 2.13 confirms that the aggregate results on product level are indeed already present for the time before the trade collapse even though for a large fraction of treated products treatment has only just occurred, cf. Figure 2.1.

When repeating the estimation at firm-product level, I again can confirm the results presented in Section 2.6. Table 2.14 contains the results for the 2000-2008 time period. While at times imprecisely estimated, signs and size of estimated coefficients are in equal ranges to those found for the period 2000-2010.

Table 2.13: Impact of the reform on product level domestic inputs and imports – 2000-2008

	(1) log(Quantity cons)	(2) log(Total Costs)	(3) log(Price)
Panel A: Domestic inputs			
$t \geq t^*$	0.780***	0.171	-0.452
	(0.302)	(0.155)	(0.371)
N	23,419	23,451	23,419
R^2	0.137	0.130	0.461
Number of inputs	2,787	2,787	2,787
Panel B: Imported inputs			
$t \geq t^*$	-0.479**	0.720**	0.113
	(0.199)	(0.289)	(0.210)
N	11,984	12,015	12,582
R^2	0.211	0.036	0.008
Number of inputs	1,695	1,695	1,906
Panel C: Imports/Domestic Inputs			
$t \geq t^*$	-0.177	0.845***	0.149
	(0.766)	(0.276)	(0.200)
N	11,369	11,369	11,369
R^2	0.165	0.097	0.113
Number of inputs	1,661	1,661	1,661
Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

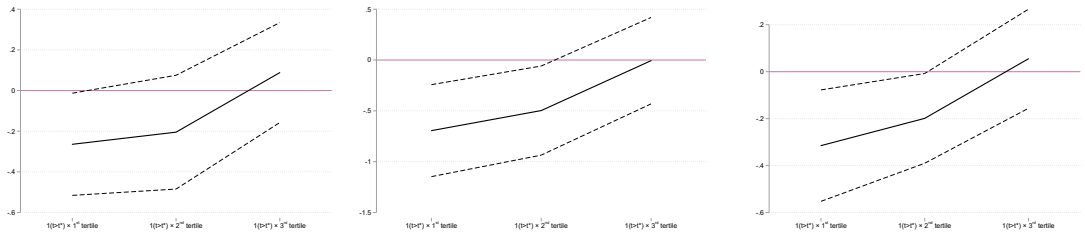
Notes: The table reports average treatment effects of the de-reservation from a difference-in-difference estimation on the product level on indicators of domestically sourced inputs in panel A and on imported inputs in panel B. t^* indicates the year a product is taken off the reservation list. Standard errors are clustered on the product level. Data: ASI 2000-2008

Table 2.14: Firm-product level effects: DiD – 2000-2008

	(1) quantity	(2) costs	(3) unit price
Panel A: Imports			
β: $t \geq t^*$	-0.150**	-0.445***	0.0617
	(0.0646)	(0.107)	(0.0587)
N	423,498	423,498	423,498
R^2	0.280	0.252	0.275
Number of firm-product observations	61,497	61,497	61,497
Panel B: Domestic inputs			
β: $t \geq t^*$	0.141***	0.0328	-0.108**
	(0.0538)	(0.0263)	(0.0492)
N	561,424	561,424	561,424
R^2	0.873	0.924	0.863
Number of firm-product observations	61,497	61,497	61,497
Panel C: Imports / Domestic inputs			
β: $t \geq t^*$	-0.143***	-0.254***	0.00107
	(0.0525)	(0.0856)	(0.0560)
N	423,498	423,498	423,498
R^2	0.247	0.217	0.208
Number of firm-product observations	61,497	61,497	61,497
Panel D: Imports / Output sold			
β: $t \geq t^*$	-0.177***	-0.401***	0.000438
	(0.0618)	(0.103)	(0.0609)
N	423,498	423,498	423,498
R^2	0.279	0.250	0.271
Number of firm-product observations	61,497	61,497	61,497
Panel E: Interaction effects for indigenous sourcing and importing			
β: $t \geq t^*$	-0.0533***	-0.0394**	-0.858***
	(0.00902)	(0.0157)	(0.0133)
ξ: DiD interaction effect $\times \mathbb{1}\{$ever importing product $p\}$	0.109	-0.359*	2.175***
	(0.114)	(0.184)	(0.0868)
N	420,832	420,832	420,832
R^2	0.873	0.924	0.863
Number of firm-product observations	61,497	61,497	61,497
Firm-Product FE	Yes	Yes	Yes
Firm-Year FE	Yes	Yes	Yes

Notes: The table reports the difference-in-difference coefficient β from estimation of Equation (2.2) in panels A-D and difference-in-difference coefficient β as well as interaction with an indicator if a firm ever imported a respective product, ξ, from Equation (2.4) in panel E. Data: ASI 2000-2008. Standard errors are clustered on the firm level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

A.2.5 Productivity effects



(a) Quantity (b) Total costs (c) Price

Figure 2.19: Heterogeneous effects by productivity levels of firms
The figure shows estimated DiD-effects β_q on TFP-tertiles from Equation (2.8). Data: ASI 2000-2010

A.3 Additional results

A.3.1 Product homogeneity

To supplement the main analysis, I differentiate further by product homogeneity. I use Rauch (1999)'s results and differentiate between relationship specific products, i.e., products which for instance are made to order and customized to the buyers specifications, and homogeneous products, i.e., mostly such products that are traded or tradable on official exchanges. For this exercise, I use the Rauch index as converted to the ASI product classification by Boehm & Oberfield (2020).[51] As already shown in the descriptive part of the paper, the majority of products subject to the reservation policy are classified as homogeneous. The products are in general of relative low complexity such that it reasonable for firms of the SSI to have the know-how and capital or machinery to produce the products. Nevertheless, some products are of higher complexity and classified as relationship specific. One would expect that buyer-supplier relationships are relatively strong for these products and that adjustments after the de-reservation shock will be slow. In combination with lock-in effects due to sunk costs to importing one would expect differences in treatment effects in response to the reform between different homogeneity levels of products.[52]

As before, I employ a difference-in-difference estimation strategy but interact the difference-in-difference indicator with an indicator that is equal to one for relationship specific products ($\mathbb{1}\{\text{heterogeneous}\}_p$); Equation (2.14).

$$\ln(y)_{ipt} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \xi \mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\{\text{heterogeneous}\}_p + \delta_{ip} + \delta_t + \epsilon_{ipt} \quad (2.14)$$

Results are shown in Table 2.15. The effects of the de-reservation are particularly pro-

[51] I thank Johannes Boehm for sharing the index-data with me.

[52] See Ramanarayanan (2017) and Ramanarayanan (2020) for studies stressing the importance of irreversible importing activity caused by lock-in effects.

nounced for homogeneous products. Panel A shows that the quantity sourced internationally decreases by 20% for homogeneous products while the imported quantity for relationship specific products does not change by much ($e^{\beta+\xi}$, however, the interaction effect is imprecisely estimated). For homogeneous products the import price declines by about 28% while the price increases for heterogeneous products which in combination lead to declining overall spending on homogeneous imports and increasing spending for relationship specific products.

The results for relative imports to domestic sourcing are in line with these findings and qualitatively equal (see Panel B). Panel C shows this once more. Domestically sourced quantity increases strongly by 27% for homogeneous products while demand for domestic relationship specific products rises by just about half of that effect. Total spending does not change since prices decline.

Table 2.15: Product homogeneity

	(1) quantity	(2) costs	(3) unit price
Panel A: Imports			
β: $\mathbb{1}\{t \geq t^*\}$	-0.228**	-0.714***	-0.333***
	(0.0943)	(0.160)	(0.0948)
ξ: $\mathbb{1}\{t \geq t^*\}$ $\times \mathbb{1}\{$heterogeneous$\}$	0.230	0.776***	0.694***
	(0.164)	(0.273)	(0.174)
N	501,231	501,231	501,231
R^2	0.225	0.194	0.718
Number of firm-product observations	63,025	63,025	63,025
Panel B: Imports / Domestic inputs			
β: $\mathbb{1}\{t \geq t^*\}$	-0.183**	-0.481***	-0.227***
	(0.0805)	(0.120)	(0.0843)
ξ: $\mathbb{1}\{t \geq t^*\}$ $\times \mathbb{1}\{$heterogeneous$\}$	0.191	0.542***	0.153
	(0.131)	(0.203)	(0.154)
N	501,231	501,231	501,231
R^2	0.204	0.173	0.689
Number of firm-product observations	63,025	63,025	63,025
Panel C: Domestic inputs			
β: $\mathbb{1}\{t \geq t^*\}$	0.238***	0.0319	-0.199***
	(0.0717)	(0.0338)	(0.0644)
ξ: $\mathbb{1}\{t \geq t^*\}$ $\times \mathbb{1}\{$heterogeneous$\}$	-0.108	0.0681	0.165*
	(0.0955)	(0.0467)	(0.0849)
N	623,805	623,805	623,805
R^2	0.873	0.920	0.865
Number of firm-product observations	353,013	353,013	353,013
Firm-Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: The table reports the difference-in-difference coefficient β as well as the interaction for product heterogeneity, ξ, from Equation (2.14). A product is considered heterogeneous if the Rauch-heterogeneity index is weakly larger than 0.5. Data: ASI 2000-2010. Standard errors are clustered on the firm level. Significance levels: * p<0.1, ** p<0.05, *** p<0.01

A.3.2 Market structure

The substitution effects studied in this paper may depend on both, the market structure of the domestic market of intermediate goods and the market shares and hence potential buyer power of downstream markets' firms. In particular, if the domestic market of intermediates is severely concentrated, firms sourcing the intermediate inputs will face sellers with substantial market power. If this is the case, firms' reaction to the de-reservation – relying less on imports and more on domestic sourcing – might be lower than what would be observed if the upstream markets were perfectly competitive.

Contrary, if the downstream market exhibits strong concentration, Indian suppliers, including entrants into de-reserved product markets, might be faced with buyers that have buyer power. Such a market structure could lead to a stronger shift away from imports because domestic prices of intermediate inputs can be depressed through buyer power. However, exercising buyer power also results in compressed supply and firms that are not large enough to put pressure on domestic input prices might still find it optimal to source internationally because supply on the domestic market does not increase sufficiently to serve all buyers.

Hence, in this section, I study whether the effects of the de-reservation are homogeneous throughout all product markets or whether significant differences prevail by market structure of the product or by market share of the firm.

Figure 2.20 shows a box plot of the average number of buyers to number of suppliers ratio before and after de-reservation by product markets. While very heterogeneous and of limited meaningfulness the figure indicates that the buyer to supplier ratio on domestic markets increases after products become de-reserved. This may be for a variety of reasons but it suggests that potential supplier power decreases with the reform. Buyers of intermediate inputs face more, potential suppliers and can thus substitute between suppliers more easily. This may also imply that the bargaining power of large buyers will increase as more alternative sourcing options apart from the current buyer-supplier relation exist.

For the following exercises, I measure market concentration with the Herfindahl-Hirschman-Index (HHI) and potential buyer power with the firm's share in total quantity sourced by Indian firms on both the domestic or international markets. Herfindahl indices are constructed on market shares by firm's supply, i.e., quantity sold, and normalized to be between 0 and 1.

To determine whether supplier power is an important feature of the affected markets, I repeat the difference-in-difference estimations of the previous sections but include interactions with the initial market structure of the supply side measured as the HHI in the last year before the de-reservation.[53] I estimate the relation between supply side market

[53]Technical remark: As I fix the HHI in the last year before the policy change, only the interaction with the 'post-reform' indicator is identified. This also implies that I cannot identify differentials in levels between more or less concentrated product markets apart from the difference-in-difference effect or for

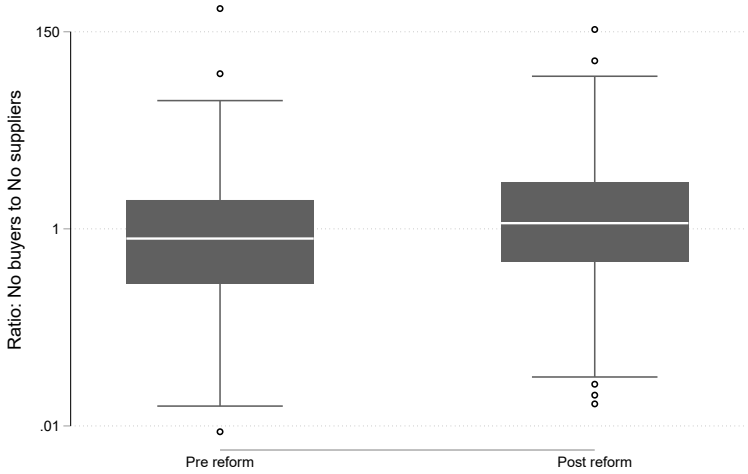


Figure 2.20: Buyers to suppliers

The figure shows the relative buyer-to-supplier ratio (in numbers) relative to the de-reservation of a particular product on log scale. Boxes show median, 25th and 75th percentile. Whiskers extend to 3/2 of the 75th-25th range. Data: ASI 2000-2010

concentration and the impact of the reform on imports with a continuous interaction as per Equation (2.15) and split by the median initial market concentration (Equation (2.16)). Notation remains unchanged, the usual firm-product and year fixed effects are included and standard errors are clustered at the firm level.

$$\ln(y)_{ipt} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \xi \mathbb{1}\{t \geq t^*\}_{pt} \times \text{HHI}_p^{pre} + \delta_{ip} + \delta_t + \epsilon_{ipt} \tag{2.15}$$

$$\ln(y)_{ipt} = \alpha + \sum_{q=1}^{2} \beta_q \left[\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{ \text{HHI}_{q(p)}^{pre} \right\} \right] + \delta_{ip} + \delta_t + \epsilon_{ipt}, \tag{2.16}$$

Results are shown in Table 2.16. This exercise reveals that the market structure of the supply side is somewhat important for the post de-reservation importing behavior. There are no strong differences in adjustments in imported quantity or total spending on imports between differently concentrated domestic input markets (see Panels A and B). What appears to be affected, though, is the price of imported intermediates. For initially more concentrated domestic markets, I find a declining unit price of imported inputs by 4% for a by 10 percentage points higher Herfindahl index ($(e^{-.511} - 1)\% \times 0.1$, see Panel A of Table 2.16).

The concentration of domestic markets is more important for the changes in domestic demand after the de-reservation. Panels C and D of Table 2.16 contain results. It becomes apparent that for more concentrated markets changes in sourcing are considerably less strong than for less concentrated markets, see in particular Panel D, where I split at the

not treated markets.

median market concentration. Sourcing of intermediate inputs from domestic markets increases by about 6 percentage points less for more concentrated markets, whereas the total spending increases significantly because there prices do not adjust significantly.

In summary, for more concentrated domestic markets, imports contract less strongly and domestic sourcing increases less strongly than for less concentrated markets. Market power and pass-through are important statistics for adjustments as already shown by Balasundharam (2020). For markets where sellers are more concentrated firms that rely on the respective products as inputs profit less from the de-reservation reform and declining misallocations. Quite intuitively, distortions may still be significant for more concentrated domestic markets which is why inputs show lower adjustments.

As discussed previously, buyer power may also be important in determining the strength of the observed adjustments. Hence, I interact the indicator with the domestic buyer concentration level before the reform to test whether the individual firm's buyer share plays a role. I estimate Equations (2.17) and (2.18) where I include the individual firm's buyer share in a respective product market. As before, I fix this level to the pre-de-reservation level and remaining terms are unchanged. Results are shown in Table 2.17.

$$\ln(y)_{ipt} = \alpha + \beta \mathbb{1}\{t \geq t^*\}_{pt} + \xi \mathbb{1}\{t \geq t^*\}_{pt} \times \text{Mkt Shr}_{ip}^{pre} + \delta_{ip} + \delta_t + \epsilon_{ipt} \tag{2.17}$$

$$\ln(y)_{ipt} = \alpha + \sum_{q=1}^{2} \beta_q \left[\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{ \text{Mkt Shr}_{q(ip)}^{pre} \right\} \right] + \delta_{ip} + \delta_t + \epsilon_{ipt}, \tag{2.18}$$

As expected, buyer size and implied buyer power is important for the adjustments in response to the de-reservation reform. In Panels A and B, I show results for imported intermediates. In Panel A, I interact the difference-in-difference indicator with the firm's buyer share immediately before the de-reservation to mitigate simultaneity concerns. In Panel B, I split by the median buyer share firms have in respective product markets measured as total quantity sourced by Indian firms on both domestic and international markets. In particular, I observe that prices of imported inputs decline for larger buyers whereas the effect for smaller firms is negligible.

For domestic sourcing, somewhat puzzling, changes post de-reservation are lower for larger firms. However, this may be because it is these firms that take up production of the affected product.

Table 2.16: Firm-product level effects by supply-side market concentration

	(1) log(Quantity consumed)	(2) log(Costs)	(3) log(Price)
Panel A: Imports			
$\mathbb{1}\{t \geq t^*\}$	-0.154	-0.320	0.230
	(0.119)	(0.205)	(0.149)
$\mathbb{1}\{t \geq t^*\} \times \text{HHI}^{pre}$	-0.0336	-0.0795	-0.511**
	(0.185)	(0.331)	(0.237)
N	504,234	504,234	504,234
R^2	0.226	0.194	0.718
Number of firm-product observations	63,036	63,036	63,036
Panel B: Imports – by median			
below median: $\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{\text{HHI}^{pre}_{q(i)=1}\right\}$	-0.170**	-0.389***	0.0517
	(0.0805)	(0.135)	(0.0859)
above median: $\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{\text{HHI}^{pre}_{q(i)=2}\right\}$	-0.175*	-0.303	-0.247*
	(0.103)	(0.189)	(0.128)
N	504,234	504,234	504,234
R^2	0.226	0.194	0.718
Number of firm-product observations	63,036	63,036	63,036
Firm-Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Panel C: Domestic inputs			
$\mathbb{1}\{t \geq t^*\}$	0.265***	0.0452	-0.213***
	(0.0791)	(0.0390)	(0.0717)
$\mathbb{1}\{t \geq t^*\} \times \text{HHI}^{pre}$	-0.229*	0.0466	0.264**
	(0.134)	(0.0744)	(0.117)
N	623,805	623,805	623,805
R^2	0.873	0.920	0.865
Number of firm-product observations	353,013	353,013	353,013
Panel D: Domestic inputs – by median			
below median: $\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{\text{HHI}^{pre}_{q(i)=1}\right\}$	0.191***	0.0385	-0.147***
	(0.0611)	(0.0301)	(0.0554)
above median: $\mathbb{1}\{t \geq t^*\}_{pt} \times \mathbb{1}\left\{\text{HHI}^{pre}_{q(i)=2}\right\}$	0.130*	0.113***	-0.0216
	(0.0711)	(0.0396)	(0.0580)
N	623,805	623,805	623,805
R^2	0.873	0.920	0.865
Number of firm-product observations	353,013	353,013	353,013
Firm-Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Data: ASI 2000-2010. The table reports event study estimates of a dereservation dummy regressed on the domestic market concentrations on product level (Equation (2.15)). Imports: Median HHI= .477, mean HHI= .531, s.d. HHI= .329. Domestic Inputs: Median HHI= .350, mean HHI= .445, s.d. HHI= .327. Standard errors clustered on firm level. Significance levels:* p<0.1, ** p<0.05, *** p<0.01

Table 2.17: Firm-product level effects by buyer share: DiD

	(1) log(Quantity consumed)	(2) log(Costs)	(3) log(Price)
Panel A: Imports			
$\mathbb{1}\{t \geq t^*\}$	-0.221***	-0.405***	-0.0270
	(0.0730)	(0.127)	(0.0864)
$\mathbb{1}\{t \geq t^*\} \times$ Market share^{pre}	0.00192	0.00406	-0.00956***
	(0.00292)	(0.00437)	(0.00237)
N	504,234	504,234	504,234
R^2	0.211	0.202	0.709
Number of firm-product observations	63,036	63,036	63,036
Panel B: Imports – by median			
below median: $\mathbb{1}\{t \geq t^*\}_{pt}$	-0.111	-0.181	0.140
$\times \mathbb{1}\left\{\text{Market share}^{pre}_{q(i)=1}\right\}$	(0.0843)	(0.151)	(0.105)
above median: $\mathbb{1}\{t \geq t^*\}_{pt}$	-0.313***	-0.585***	-0.515***
$\times \mathbb{1}\left\{\text{Market share}^{pre}_{q(i)=2}\right\}$	(0.120)	(0.189)	(0.0974)
N	504,234	504,234	504,234
R^2	0.211	0.202	0.709
Number of firm-product observations	63,036	63,036	63,036
Firm-Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Panel C: Domestic inputs			
$\mathbb{1}\{t \geq t^*\}$	0.220***	0.0739***	-0.141***
	(0.0487)	(0.0252)	(0.0437)
$\mathbb{1}\{t \geq t^*\} \times$ Market share^{pre}	-0.0168***	-0.00338**	0.0126***
	(0.00270)	(0.00149)	(0.00233)
N	623,805	623,805	623,805
R^2	0.873	0.920	0.865
Number of firm-product observations	353,013	353,013	353,013
Panel D: Domestic inputs – by median			
below median: $\mathbb{1}\{t \geq t^*\}_{pt}$	0.537***	0.220***	-0.302***
$\times \mathbb{1}\left\{\text{Market share}^{pre}_{q(i)=1}\right\}$	(0.0625)	(0.0328)	(0.0589)
above median: $\mathbb{1}\{t \geq t^*\}_{pt}$	-0.277***	-0.129***	0.138***
$\times \mathbb{1}\left\{\text{Market share}^{pre}_{q(i)=2}\right\}$	(0.0632)	(0.0320)	(0.0516)
N	623,805	623,805	623,805
R^2	0.873	0.920	0.865
Number of firm-product observations	353,013	353,013	353,013
Firm-Product FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Data: ASI 2000-2010. The table contains the event study estimates of a dereservation dummy regressed on the domestic market share on product level (Equation (2.17)). Imports: Median Mkt Shr= .92, mean Mkt Shr= 15.47, s.d. Mkt Shr= 29.55. Domestic Inputs: Median Mkt Shr= .16, mean Mkt Shr= 7.20, s.d. Mkt Shr= 20.62. Standard errors clustered on firm level. Significance levels:* p<0.1, ** p<0.05, *** p<0.01

A.4 Production function coefficients

Table 2.18: Production function coefficients: Ackerberg et al. (2015)

NIC 2dgt	minig & quarrying	food products and beverages	tobacco	textiles	apparel	leather items	wood products	paper products	printing
k	0.056	0.063	-0.032	0.211	0.006	-0.038	0.001	0.109	0.087
	(0.096)	(0.075)	(0.078)	(0.092)	(0.086)	(0.064)	(0.098)	(0.167)	(0.128)
m	0.828	0.750	1.098	0.585	0.655	0.814	0.514	0.576	0.608
	(0.096)	(0.088)	(0.133)	(0.073)	(0.117)	(0.066)	(0.071)	(0.215)	(0.149)
l	0.002	0.032	0.494	0.007	0.022	0.141	0.269	0.185	0.223
	(0.150)	(0.036)	(0.492)	(0.059)	(0.094)	(0.050)	(0.119)	(0.092)	(0.177)
N	1,445	29,735	1,445	29,735	2,910	20,035	6,858	3,505	2,419
NIC 2dgt	coke, fuel refinement	chemicals	rubber, plastic	oth. non-metal	basic metals	metal products	machinery	office equipment	
k	0.141	0.132	0.202	0.036	0.103	0.191	0.093	0.141	
	(0.078)	(0.690)	(0.093)	(0.070)	(0.073)	(0.067)	(0.053)	(0.051)	
m	0.560	0.452	0.540	0.666	0.856	0.576	0.747	0.558	
	(0.104)	(0.923)	(0.116)	(0.063)	(0.135)	(0.194)	(0.069)	(0.065)	
l	0.248	0.213	0.151	0.132	-0.038	0.002	0.117	0.191	
	(0.102)	(7.143)	(0.088)	(0.041)	(0.182)	(0.485)	(0.050)	(0.035)	
N	3,796	3,577	1,795	16,356	5,826	12,317	9,831	7,483	
NIC 2dgt	electrical machinery	radio, telecom equ't	medical, optical instruments	motor vehicles	oth. transport equ't	furniture	recycling	electricity, water supply	
k	0.145	0.261	0.230	0.094	0.271	0.056	0.287	0.078	
	(0.086)	(0.158)	(0.080)	(0.150)	(0.100)	(0.074)	(0.096)	(0.121)	
m	0.527	0.410	0.569	0.554	0.417	0.540	0.551	0.486	
	(0.072)	(0.249)	(0.066)	(0.235)	(0.182)	(0.057)	(0.107)	(0.121)	
l	0.257	0.087	0.163	0.169	0.069	0.215	0.251	0.423	
	(0.243)	(0.335)	(0.061)	(0.246)	(0.378)	(0.052)	(0.115)	(0.106)	
N	11,059	595	6,444	2,427	2,776	5,756	3,733	4,603	

Standard errors in parentheses.

3 Structural Change Revisited: The Rise of Manufacturing Jobs in the Service Sector

Summary: This paper reevaluates the labor market consequences of structural change over the past 43 years. Taking two different ways of defining manufacturing and service employment as point of departure – according to the industry classification of firms or establishments and according to the occupation and hence the tasks of the workers – we show that structural change is far less serious than generally perceived. Manufacturing and service employment numbers based on the occupations of workers deviate remarkably from the employment numbers based on the industry classification of employers. The decline in manufacturing jobs in Germany is far lower if the measurement of employment is based on the occupation of the worker. About 52% of manufacturing jobs that were lost in manufacturing industries between 1975 and 2017 are offset by new manufacturing jobs in service industries. This also has important implications for empirical applications. By way of example, we reestimate the effect of international trade on manufacturing employment based on the occupation of the worker. Contrary to previously identified negative effects, we cannot identify significant effects of import exposure on employment in manufacturing occupations. Using detailed, comprehensive German social security data, we show at the worker level that the service sector increasingly acts as a valuable alternative employment option for workers with manufacturing occupations. We estimate the causal effects of a switch to the service sector on employment outcomes by following workers over time after mass layoffs. The results reinforce our claim that structural change is less significant than perceived, as workers who retain their initial occupation and switch to employment in the service sector experience no significant differences in future employment trajectories compared to workers who manage to stay in the manufacturing sector.[1]

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3.1 Introduction

Structural change is seen as one of the most pressing challenges for labor markets in many industrialized economies. Concerns about rapidly shrinking manufacturing employment triggered not least by increasing trade exposure and skill-biased technical change (e.g., through digitalization and robotization) are omnipresent.[2]

We show, using data for Germany, that structural change and the associated loss of jobs in manufacturing are less serious than has generally been perceived. Manufacturing jobs that disappear from the manufacturing sector reappear in the service sector in large numbers. These jobs offer an alternative employment option and strongly mitigate the employment decline in the manufacturing sector. A switch to the service sector after being displaced is associated with only a moderate income loss as long as the workers retain their initial manufacturing occupation. The income loss is in a similar range to that of workers who remain employed in the manufacturing sector without changing their occupations after being displaced. Our findings come out of investigating two different concepts of manufacturing and service employment: According to the industry classification of firms or establishments (concept I) and according to the occupation and hence the tasks of the workers (concept O).

Traditionally, the economic literature uses the industry classification of firms or establishments, i.e., concept (I), when discussing structural change and identifying manufacturing and service employment.[3] The industry classification of a particular firm, which is generally based on the (primary) output produced by the firm, determines whether it belongs to the manufacturing or the service sector. In consequence, all workers of that firm are counted as either manufacturing or service employees – regardless of their actual occupation and tasks performed.

Accordingly, in the context of concept (I), an assessment of the labor market consequences of structural change does not permit any statements to be made about the number of specific jobs in the economy as a whole. Instead, a shrinking number of manufacturing jobs means that there are fewer jobs in firms that mainly produce manufacturing goods. However, the loss of a job in a firm, industry or sector does not mean that the job is generally lost in the economy as a whole. We show that jobs with the same job description appear elsewhere in the economy. This possibility of changing jobs

[2]For instance, studies consider international trade as a driver see, e.g., Pierce & Schott (2016), Autor et al. (2013), or Dauth et al. (2014). Digitalization is studied by Autor et al. (2003), Frey & Osborne (2017) and robotization by Acemoglu & Restrepo (2020) and Dauth, Findeisen, Südekum & Wössner (2021).

[3]For instance, Pierce & Schott (2016) use the U.S. Census Bureau's Longitudinal Business Database that categorizes establishments according to 4-digit SIC or 6-digit NAICS industries. Autor et al. (2013) use employment by industry from the County Business Patterns data, while Acemoglu & Restrepo (2020) rely on the same data and enrich them with data on wages and employment of all workers in the manufacturing sector from the NBER-CES dataset. Dauth et al. (2014) and Dauth, Findeisen, Südekum & Wössner (2021) measure manufacturing employment across 222 distinct industries (including 101 manufacturing industries) using administrative data from the German Institute of Employment Research (IAB).

between industries and sectors without major frictions has been largely overlooked so far and instead, the manufacturing sector and the service sector are often treated and viewed as two separate and independent labor markets.

Concept (O) focuses on the occupation of the worker and accounts for the occupational distribution and shifts at the intensive margin, i.e., changes in the workforce composition within the manufacturing or service sector. Occupations are based on the actual tasks a worker performs. In the context of this paper this implies that an occupation is labeled as 'manufacturing' if workers in that occupation by nature of their tasks can directly be involved in the production of physical goods. The official German classification of occupations in our data is based on the same foundations as that of the International Standard Classification of Occupations (ISCO) of the International Labour Organization (ILO).[4]

Usually, workers can perform the same tasks in either sector – one can drive a truck in any industry, one can be an office clerk in any industry, and one can even produce a hard-drive in any industry.[5] We document that both service occupations and, in particular, manufacturing occupations are found in large numbers in establishments for which the industry categorization (service or manufacturing) is opposite to the categorization of the worker's occupation. In 2017, the number of workers with manufacturing occupations in the manufacturing sector was only about 1.3 times higher than the number of workers with manufacturing occupations in the service sector.[6] In 1975 the service sector employed 26% of all workers with manufacturing occupations. By 2017, this share had grown to 42%, and the trend indicates that this growth will continue in the future. The total number of manufacturing jobs in the service sector grew during this time period. Workers with manufacturing occupations are increasingly finding work in service industries.[7]

Concept (O) accounts for these facts by determining manufacturing and service employment at the worker level conditioning on their occupation. Accordingly, the work duties, tasks, and in some cases skills, education, and/or training required for the occu-

[4]ILO states that "the basis of any classification of occupations should be the trade, profession or type of work performed by an individual, irrespective of the branch of economic activity to which he or she is attached or of his or her status in employment." Source: http://www.ilo.org/public/english/bureau/stat/isco/intro2.htm

[5]Table 3.8 in the Appendix serves as further motivation of the importance of the distinction between concepts (I) and (O). For the anecdotal example on hard-drive production, consider IBM corporation: Starting as a traditional hardware manufacturer, IBM increasingly focused on the provision of customer services from the 1990s onwards (see Ahamed et al. (2013)). In 1990, IBM's service segment only accounted for approximately 16% in total revenues, whereas it reached a share of 63% in 2017 (Spohrer 2017). Eventually, IBM was reclassified to a service firm after a particular threshold was met.

[6]Likewise, in 2017, more than 33% of the workers in the German manufacturing sector held service occupations. Boddin & Kroeger (2021*b*) go into a more detailed discussion on servitization – manufacturing firms are increasingly offering service activities, for instance, after-sales services such as maintenance and repair, and are therefore exhibiting shifts in their employment composition towards a higher share of service jobs.

[7]Keeping in mind the previous example, and think, for instance, of large technology firms that mainly offer software solutions but also produce hardware, or of logistics firms that need technicians to set up a logistics infrastructure, etc.

pation define whether a worker is a manufacturing or service worker.[8] We argue that this concept is better suited for analyzing structural change than the industry classification of firms or establishments. Focusing on the actual occupation regardless of the industry classification of the firm offering the position also appears to be critical in assessing the impact of shocks on the labor market, especially on types of employment such as manufacturing. Our findings have important implications pretty much whenever it comes to both discussions of labor market consequences, be it, for instance, through trade exposure, computerization, digitization or skill-biased technical change, and the assessment of (the need for) labor market policies (e.g., identification of workers at risk of layoffs, assessment of the need for retraining through labor market programs, etc.).

In the first part of the paper, we revisit structural change and consider it as a shift in occupational employment shares within the economy and not as a shift of total employment between sectors, thereby contrasting concepts (I) and (O). Using unique, detailed matched employer-employee data in combination with establishment data for the years 1975 to 2017 for Germany, we provide new stylized facts and show that standard definitions of service and manufacturing employment based on the firms' or establishments' industries considerably overestimate deindustrialization. Based on concept (O), we document that about 52% of manufacturing jobs that were lost in the German manufacturing sector between 1975 and 2017 are offset by new manufacturing jobs in the service sector. Overall, the discrepancy between the manufacturing employment share measured according to concept (I) – defined by the sector of the employing establishment – and concept (O) – measured by occupation or task of the worker – is increasing over time and reaches a maximum of 5.3 percentage points in 2017.

Based on these new stylized facts, we carry out an empirical application to show that, in addition to the descriptive deviations, empirical results differ fundamentally depending on whether manufacturing and service employment is defined according to the occupation of the worker or according to the sector of the firm. Trade exposure is often discussed as a potential driver of the decline in manufacturing employment (e.g., Autor et al. (2013), Caliendo et al. (2019), Dauth et al. (2014), or Pierce & Schott (2016)), making it a well-suited topic for this purpose. We estimate the impact of import and export exposure from China and Eastern Europe on the employment of workers in manufacturing occupations in Germany and compare the results with the impact of trade exposure on workers employed by manufacturing firms, as studied by Dauth et al. (2014) (cf. Autor et al. (2013) for the U.S. case). Following precisely their identification strategy, we show that the results are different: While exposure to trade from China and Eastern Europe reduces employment in manufacturing establishments (cf. Dauth et al. (2014)), employment in manufacturing occupations is not affected. This supports

[8]Note to clarify the terminology: In this paper, the term "jobs" is shorthand for the number of workers in different occupations. "Manufacturing jobs" are thus the total number of workers in a manufacturing occupation. We use this term throughout to refer to the different occupations independent of the employer.

our claim that the employment decline in the manufacturing sector is moderated by employment opportunities for workers with manufacturing occupations in the service sector.

Then, we explicitly show that workers switch from the manufacturing to the service sector in significant numbers. Roughly 60% of workers who hold a manufacturing occupation and leave the manufacturing sector find new employment in the service sector while keeping a manufacturing occupation. This pattern of movement is increasing over time and occurs for all manufacturing occupations. The share of all manufacturing occupations in the service sector is increasing and the numbers of jobs in the service sector is growing for the vast majority of manufacturing occupations.

Based on these observations, we assess a switch from the manufacturing to the service sector by following workers with manufacturing occupations that are affected by an exogenous mass layoff over time. A substantial share of these workers are reemployed in the service sector while retaining their occupation. To evaluate this alternative employment option, we match laid-off workers with non-laid-off counterparts with the same initial occupation within the same initial industry. We then compare employment paths to provide estimates of the causal effect of a sector switch on wages, accumulated income, etc. in a difference-in-difference setting (similar to Goldschmidt & Schmieder (2017) and Schmieder et al. (2020)). The initial treatment effect of a sector switch to the service sector on yearly income is a decline of about 4,000 euros in the first two years after dismissal, irrespective of the occupation at the new job. Subsequently, the effect diminishes over the following years and converges to 1,000 euros towards the end of the sample frame ten years after the layoff.

Once we differentiate between workers who retain a manufacturing occupation in the service sector and workers who (have to) take up a service occupation the picture, however, changes. For workers who keep a manufacturing occupation, the initial treatment effect on yearly income is 2,000 euros lower compared to workers with a new service occupation. For the latter the initial treatment effect is a decline of 5,000 euros in yearly income. The difference in treatment effects is persistent in subsequent years but declines over time. Keeping the original occupation is thus beneficial for workers as they experience lower wage cuts and a faster recovery compared to workers who change their occupation in addition to switching sectors. More so, the drop in income is in a similar range as the decline in income for workers who keep a manufacturing occupation and find new employment in the manufacturing sector after being laid off.

Related Literature

This paper adds to a recent set of papers that deal with new aspects of structural change. For instance, Duernecker & Herrendorf (2019) document that economies during the course of structural transformation show a shift in employment numbers based on occupation categories (manufacturing or services) for a broad set of countries. Contrary

to this paper, we evaluate the role of the service sector as an outside employment option for workers with manufacturing occupations and investigate the effect of cross-sectoral job switches at the worker level.

Fort et al. (2018) and Ding et al. (2019) analyze the decline in U.S. manufacturing and find that most of the decline in manufacturing employment (about 75%) occurs at continuing firms, i.e., the intensive margin, and that non-manufacturing employment at manufacturing firms is increasing until about 2000. The articles show that, in fact, about 38% of the increase in non-manufacturing employment is caused by growing non-manufacturing establishments of manufacturing firms.[9] Bernard et al. (2017) consider changes in aggregate employment numbers caused by firms for which the industry classification changes and also call for rethinking deindustrialization. Contrary to our paper, these papers, however, rely on concept (I) and thus regard manufacturing employment based on the manufacturing classification of firms. Hence, the finding of increasing non-manufacturing employment in manufacturing is due to new or growing establishments within the boundaries of firms that belong to the manufacturing sector. To the best of our knowledge, the current paper is the first to reevaluate structural change by focusing on the occupation of the worker.

Naturally, this paper adds to the diverse economic literature on the employment structure of firms (e.g., Caliendo et al. (2015) and Caliendo et al. (2020)) and its changes in response to a variety of shocks. This includes (but is not limited to) studies that discuss (a) reasons for structural change (using industry-based classifications) mentioned above[10], (b) task-based employment changes (see, for instance, Grossman & Rossi-Hansberg (2008) or Baldwin & Robert-Nicoud (2014)), (c) job polarization (e.g., Bárány & Siegel (2018), Goos & Manning (2007), Goos et al. (2014)), (d) skill-bias changes of the workforce (e.g., Spitz-Oener (2006)), and (e) the firm's (re-)organization in response to trade shocks (e.g., Davidson et al. (2017), Caliendo & Rossi-Hansberg (2012)).

Contrary to our paper, the vast majority of these studies are, however, not concerned with the change in the labor composition within firms and sectors per se, and the link to structural change is seldom established. Instead, measures such as tasks or skills are used to distinguish between different types of workers. Our paper is concerned with neither the performance of firms during adjustments in the employment composition nor their reasons, but instead puts emphasis on the fact that the standard approaches may fail to evaluate structural change properly.

In doing so, the current paper extends the literature on the occupational specificity of human capital by adding the perspective of changes across sectors that were previously thought to be widely different, i.e., manufacturing and services. Like the present paper, Kambourov & Manovskii (2009) argue for the use of occupations when studying employment dynamics and revisit the issue of strongly decreasing earnings after a job

[9] In this context, a firm can consist of multiple establishments or plants.

[10] See Herrendorf et al. (2014) for a summary of the macroeconomic literature.

loss for the U.S. Related work has been carried out by Gathmann & Schönberg (2010), who study the mobility of accumulated skills in the labor market based on a task approach. Task-specific human capital accounts for more than half of overall wage growth. Their paper backs our understanding of occupational definitions in the sense that most workers move between related occupations that demand very similar tasks. Neal (1995), on the other hand, argues that industry specific human capital is important. However, the underlying data are limited and the author cannot control for occupational changes of workers.

Our exercise of following workers after displacements adds to the literature on occupational mobility and switching costs or earnings losses when displaced. For instance, Jacobson et al. (1993) and later Couch & Placzek (2010) study the earnings losses of displaced workers of distressed firms in Pennsylvania and Connecticut, respectively. The studies find earnings losses in the period immediately after the job loss of more than 30%. The losses are persistently in a range of 15-25% in later years following the displacement. Cortes & Gallipoli (2018) estimate mobility costs across occupations for the U.S. Dix-Carneiro (2014) estimates a structural dynamic equilibrium model of the Brazilian labor market under the assumption of job switching costs between sectors and imperfectly transferable human capital. Costs to transition between sectors are immense in the Brazilian case. Related work for Denmark has been done by Ashournia (2018) who also finds adjustment costs in the range of 10%-15% lower wages after transition. For Germany, we cannot confirm strong adjustment costs. This is presumably due to a strong and clear vocational training system through which workers acquire human capital that is widely transferable between industries. In their influential study on occupational mobility in the U.S., Moscarini & Thomsson (2007), similarly to the present paper, highlight the importance of the measurement of workers' activities, i.e., occupations. For the U.S., about one third of job-to-job switches involve no change in occupation. In addition, a large proportion of all occupation switches occurs without changing employers. We find similar results for the German labor market while arguing that, indeed, workers' occupations are crucial in determining their return to labor.

A recent study for Germany considers job losses over the business cycle (Schmieder et al. 2020).[11] The authors find persistent effects of job displacements during recessions. More recently, Gathmann et al. (2020) consider spatial spillovers of massive layoffs of more than 500 employees at very large, "systemic" firms. Another study on spillovers of employment responses to international trade shocks has been carried out by Helm (2020). Spatial clusters of industries lead to particular spillover effects. For instance, regions inhabited by high-tech industry clusters are the primary beneficiaries of increasing export opportunities.

The current paper is also related to the literature on assortative matching between employers and employees, and segregation of workers with different productivity levels

[11] See also Davis & von Wachter (2011) for a study on the U.S. with similar results.

across employers, e.g., Card et al. (2013) and Song et al. (2019). These papers consider the contribution of assortative matching between high-performing workers and extremely productive firms. We do not explicitly consider the effects of structural change on pay inequality in this paper[12], but our results suggest that mass layoffs triggered by structural change can contribute to pay inequality if only high-performing workers are able to keep their occupation and lower-performing workers have to switch their occupation. This paper is hence also related to recent studies on the declining demand for specific occupations, e.g., Edin et al. (2019).

Finally, this paper adds to the literature on the employment effects of increasing globalization and trade integration. We provide evidence that aggregate effects are less severe than has been previously reported (e.g., Autor et al. (2013) or Dauth et al. (2014)). We also add to the literature on occupational effects of trade; see Ebenstein et al. (2011), Ebenstein et al. (2015), Utar (2018), Traiberman (2019), Helm (2020) or Bloom et al. (2019). All these studies argue for the use of occupations when assessing effects of international trade on labor markets. However, while these studies identify strong negative consequences for workers in particularly heavily affected occupations, we find in the aggregate that total regional employment in manufacturing occupations is not hit by trade since the service sector functions as an alternative employment option for those workers. Ebenstein et al. (2015) argue, as does the present paper, that workers are forced out of the manufacturing into the service sector. They find strong wage penalties for workers forced out of the manufacturing sector and into the service sector by import competition and offshoring opportunities for the U.S. Dauth, Findeisen & Südekum (2021) provide a similar analysis for Germany. For Germany, export opportunities outweigh the negative effects of import competition or offshoring of labor intensive tasks. The authors identify two equally important channels through which workers profit from increasing exports, be it (i) on the job or by (ii) switching employers to firms that benefit more from international trade than the previous firm within the same industry. The second channel mainly benefits high-skilled workers identified through two-way fixed effects (see Abowd et al. (1999)).

The remainder of the paper is organized as follows. In Section 3.2, we introduce the data. Thereafter, in Section 3.3, we compare the two measurements of structural change based on the sector of the establishment (concept (I)) and the occupation of the workers (concept (O)) and present new stylized facts on structural change and the decline of manufacturing employment in Germany. We present a short application highlighting differential results of the effect of trade integration on manufacturing employment. Section 3.4 shows that workers increasingly make use of the employment option in the service sector while carrying out manufacturing occupations. This holds for all occupations. We provide first evidence on the pay differences between the sectors. In Section 3.5, we assess the individual consequences for workers with manufacturing occupations when forced to

[12]However, we can highly recommend Boddin & Kroeger (2021*b*) for a take on this matter.

switch to the service sector. In particular, we evaluate the impact of the service sector on workers' outcomes in its function as an alternative employment option. Section 3.6 concludes.

3.2 Data

For this paper, we rely on detailed datasets based on social security records provided by the Institute for Employment Research (IAB) of the German Federal Employment Office. The first is the Establishment History Panel (in German: Betriebs-Historik Panel (BHP)), a detailed establishment-level dataset. The second and third datasets are the detailed longitudinal linked employer-employee dataset (LIAB) and the sample of integrated employment biographies (SIAB), respectivley.[13]

These data are based on official administrative data and employers are required by law to submit reports for all employees subject to social security contributions to the responsible social security institutions at least once a year. This ensures that the data are highly reliable and not prone to misreporting.[14]

The BHP is a detailed representative 50% sample of all establishments in Germany ranging from 1975 to 2017 (for the 1975-1991 period, it includes only establishments in West Germany) with at least one employee subject to social insurance contributions.[15] It contains rich information on the labor structure of the establishment such as the labor composition in terms of the occupational mix (12 different occupation categories according to Blossfeld (1987)), the education of the employees (employment by skill categories), the number of female and male workers, the share of foreign workers, the age structure, etc. Additionally, the dataset provides information on the wage structure and the industry of the establishment. The data cover between 640,000 and 1,500,000 establishments yearly and constitute an unbalanced panel, as establishments may drop out of or enter the sample.

The LIAB and the SIAB combine the establishment data extracted from the BHP and employee data on individuals' employment biographies. The matched employer-employee data are a 2% representative sample of all employees and their employers who

[13]For further information on the data, see Heining et al. (2016) concerning the LIAB, Antoni et al. (2019) on the SIAB and Schmucker et al. (2018) concerning the BHP.

[14]The procedure is based on the integrated notification procedures for health, pension and unemployment insurance (DEÜV; formerly DEVO / DÜVO; see for further details: Bender et al. (1996), p. 4ff.; Wermter & Cramer (1988)). http://doku.iab.de/fdz/reporte/2019/DR_06-19.pdf

[15]In Germany, employers are required by law to provide information on the social insurance contributions of their employers. The legal basis for this is Section 28a Social Security Code IV (SGB IV). To enable establishments to participate in the automated social insurance registration process, they need an establishment number. The definition of establishments follows exact specifications. A holding is a regionally and economically separate unit in which at least one person subject to social security or marginal employment is employed. Regional assignment is based on the municipalities in Germany (more than 11,000 in 2017). That is, a firm with branches in different municipalities consists of different establishments with different establishment numbers.

For the analysis in this paper, we rely on the long-term data for West Germany. The figures and results all hold when we include East Germany for the respective time period.

have been subject to social security contributions at one point in time or were notified to the Federal Employment Agency over the 1975 to 2017 period. The dataset contains individual worker data on labor market variables such as occupations, hierarchy levels, time on the job, time at the employer, daily wages, and other variables influencing human capital such as schooling, university degrees, family status, etc.

The data cover the period between 1975 and 2017 and include between 1,006,028 and 1,533,327 persons and between 244,170 and 399,785 establishments per year.[16] The LIAB yields further information on a much broader set of firm-level information on production, exports, worker training, etc.

For our purpose, one feature of the BHP as well as the SIAB/LIAB is of central importance: The information about the occupation of the worker in addition to the industry classification of the establishment in order to assess structural change by defining it as a shift in occupations and in order to compare this measurement to the commonly used establishment-based classifications.

The BHP contains information on the aggregate numbers of workers' occupations by establishment code in the classification of Blossfeld (1987). The Blossfeld categories are constructed such that educational and task requirements are very homogeneous within and very heterogeneous across Blossfeld categories. In total, there are twelve occupational groups which can be divided into two main fields, i.e., manufacturing and services. Services occupations include the subcategory administrative services.[17] Each of the fields is subdivided further according to the skill requirement of the occupation (low, medium, and high skill). See Table 3.6 for a more detailed description of the occupational groups as well as examples. The Blossfeld categories constitute aggregations over finer occupation definitions. This aggregation is carried out by the Federal Employment Agency once employers report information on their employees which includes the occupation of the worker at 5-digit level on a mandatory basis (see below).

The SIAB/LIAB data contain both the total number of workers by Blossfeld categories for the workers' establishment and the worker's occupation at 5-digit level according to the "Classification of Occupations" (in German: "Klassifikation der Berufe", KldB) (Federal Employment Agency 2011).[18] This is reported by the employer to the Federal Employment Agency on a mandatory basis.[19] The classification structure can be related and matched to ISCO-8 of the ILO[20], is hierarchical, and distinguishes 1,286

[16] See Section B.1.1 in the Appendix for more information on the data cleaning. Naturally, the number of establishments is lower compared to the BHP as it is limited by the 2% IEB sample. The number of observations is larger in later years.

[17] Administration services, for instance, include occupations such as bookkeepers which are support staff for business operations or management occupations.

[18] This classification is also used in Spitz-Oener (2006) or Goldschmidt & Schmieder (2017)

[19] The fact that reporting is mandatory (and at the annual level) has crucial advantages; e.g., Moscarini & Thomsson (2007) highlight the difficulties when working with the U.S. Current Population Survey in which occupations are self reported by workers.

[20] The ISCO and hence the KldB are constructed such that "the basis of any classification of occupations should be the trade, profession or type of work performed by an individual, irrespective of the branch of economic activity to which he or she is attached or of his or her status in employment." Source:

occupations at the 5-digit aggregation level.[21] Similar to the Blossfeld classification, the KldB is based on tasks but also on the hierarchy and delegating power within the establishment.[22]

We employ both the KldB and the Blossfeld categories for our analysis. The first classification is more detailed than the Blossfeld classification. However, the Blossfeld classification allows us to identify the total number of workers per category belonging to each establishment.[23] For comparison, we transfer the SIAB/LIAB's KldB occupational categories into Blossfeld categories using a crosswalk provided by the IAB.

Both the SIAB/LIAB and the BHP data contain information on the establishment's industry classification that would commonly serve to identify services and manufacturing employment. The industry classification of the establishments is determined by the Federal Statistical Office and available in the revision of 1993 ("Klassifikation der Wirtschaftszweige 1993", WZ93).[24] The WZ industry classification is a slightly adjusted version of the European NACE industry classification and of hierarchical structure.[25] The economic classification follows the economic focus of the establishment, which depends on the purpose of the establishment or economic activity of the majority of the employees. Accordingly, establishments with activities in various areas are also economically assigned to a single category only. This implies that all workers of this establishment are labeled as either service or manufacturing workers, regardless of their actual occupation, if the industry of the establishment is used as the basis for determining service or manufacturing employment.

This procedure is not purely a German phenomenon, but common international practice and the basis for determining the industry classification in the vast majority of datasets. For instance, in the data description for ILOSTAT's identifier of employment by economic activity, one of the main sources for labor statistics, the ILO describes the concept for categorizing the industry of a worker: *"Having detailed statistics on employment by economic activity allows for the calculation of the share of manufacturing in total employment* [...] *The classification by economic activity refers to the main activity of the establishment in which a person worked during the reference period. The branch of economic activity of a person does not depend on the specific duties or functions of*

http://www.ilo.org/public/english/bureau/stat/isco/intro2.htm

[21] For an example of this scheme, see Table 3.7 in the Appendix.

[22] The occupational categorization is stored in the first three digits, the fourth digit of the classification captures the hierarchical aspect, and the fifth digit of the classification describes the skill intensity of the respective occupation. Accordingly, at the disaggregate level, the classification of workers might differ, if hierarchy and skill intensity differ, even if the occupations are identical.

[23] Since SIAB/LIAB data are based on a 2% sample, the data do not necessarily cover all workers for a specific establishment. Contrary, using BHP we know aggregate employer information at the establishment level, but not worker-level information.

[24] The industry classification is also available in a newer revision for later years. To ensure the uniformity of the data, however, we use WZ93.

[25] Overall, there are five levels of aggregation including sections (digit 1), divisions (digit 2), groups (digit 3), classes (digit 4), and subclasses (digit 5). The distinction between service and manufacturing categories is generally based on the sectional level.

the person's job, but on the characteristics of the economic unit in which this person works.", International Labor Organisation ILO (2018).[26] Both the European NACE classification and the International Standard Industrial Classification (ISIC) follow the same procedure. SIAB/LIAB and BHP contain information on both the worker's industry classification based on the establishment's classification and the occupation of the worker, allowing the comparison between both measurements and a reevaluation of structural change.

One concern for this paper may be changing industry classification of establishments. For instance, Bernard et al. (2017) report for Denmark that such switchers account for about half of the overall decline in manufacturing employment for the period of 1994-2007. Contrary to Bernard et al. (2017), we find switchers to have much less of an impact on structural change in Germany, presumably as we focus on establishments (i.e., individual plants) rather than firms (i.e., whole firms including all plants of any industry). We find that switchers affect less than 0.1% of the workers and establishments. Additionally, the number of establishments (and the number of affected workers) that switch from manufacturing to services is approximately identical to the number of establishments that switch from services to manufacturing. Our focus is not on switchers, but on the occupational reorganisation at the establishment level.[27]

3.3 Structural Change revisited

In this section, we contrast the measurement of manufacturing and service employment based on the industry of the establishment (i.e., concept (I)) with the measurement based on the workers' occupations (i.e., concept (O)).[28] We show that the two measurements differ substantially, which entails serious risks of misclassification and misinterpretation, for example when discussing structural change and its consequences. The use of the occupation-based measurement offers new insights into structural change and the definition of services and manufacturing employment. In the following descriptive analysis, we will focus on West Germany to make use of the long-term data starting in 1975. Data for East Germany are available from 1991 onwards.[29]

[26] See https://www.ilo.org/ilostat-files/Documents/description_ECO_EN.pdf, page 1.

[27] As switchers are not the primary focus of the present paper, we refer the interested reader to Section B.3 in the Appendix where we show that industry switching and re-classification are not affecting the patterns we present. In fact, merely .2% of observed establishments per year switch sector classes and the switches from service to manufacturing are in equal ranges as vice versa.

[28] For our analysis, we only consider establishments that are classified as service or manufacturing. This excludes the primary sector and construction as well as energy and water supply.

[29] The findings do not qualitatively differ when we focus on East Germany only or on West and East Germany combined. Analyzing both is only possible from 1991 onwards. Results are available upon request.

3.3.1 Establishment vs. Occupation-based Measurements of Service & Manufacturing Employment

Figure 3.1 displays the shares of service and manufacturing employment from 1975 to 2017 in West Germany based on the industry classification of the establishment ((I) – dashed line) and based on the occupation of the worker ((O) – solid line). Both measurements indicate a significant decrease in the manufacturing employment share over the period of 43 years. The first measurement shows that employment in the manufacturing sector decreased from 45% in 1975 to only 25.8% in 2017 (from 7.1 million workers to 4.86 million), while the second measurement shows a decrease in the share of workers in manufacturing occupations from 44.2% to 31.1% in the same period (from 6.97 million workers to 5.38 million). Note that the latter measurement takes into account manufacturing occupations in both the manufacturing and service sector.

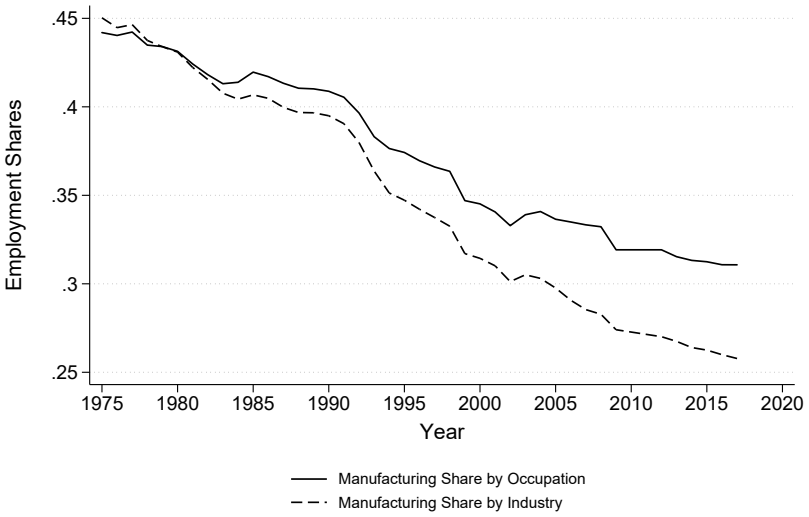
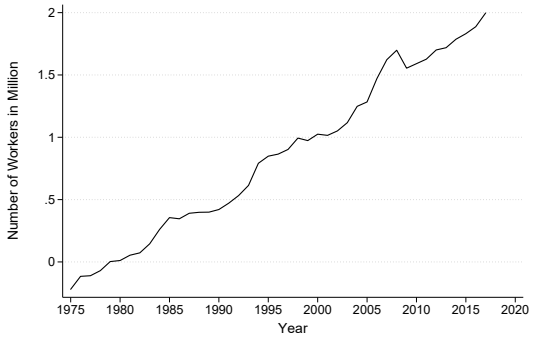


Figure 3.1: Manufacturing employment shares according to establishment- and occupation-based accounting methods
The graph depicts the shares in total employment for West Germany either by employment classified according to the industry classification of the establishment or according to the individual's occupation. Datasource: BHP.

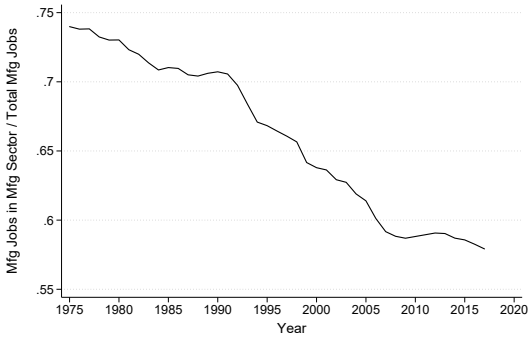
Although the general trend is similar for both measurements, the magnitude differs considerably. First, we see that structural change is more pronounced when measured by concept (I), i.e., based on the establishment's industry. With this measurement, the share of manufacturing employment decreased by 19.2 percentage points from 1975 to 2017. Based on the occupations of the workers (concept (O)), the share of manufacturing employment decreased by 13.1 percentage points over the same period. The discrepancy between the two measurements generally increases over time and reaches a maximum of 5.3 percentage points in 2017, the last year of observation. The discrepancy between both measurements is increasing over time as manufacturing workers find more and more jobs in the service sector. On average, the share of employment in the manufacturing sector

falls by 0.5 percentage points per year whereas the share of workers in manufacturing occupations falls only by 0.36 percentage points. Notice that the share of workers in the manufacturing sector in 1975 was .8 percentage points higher than the share of workers with manufacturing occupations. From 1980 onward, the latter share was higher and the diverging trend started to increase in speed.

Figure 3.2, Panel (a) translates this discrepancy into absolute numbers and shows the annual number by which establishment-based definitions would underestimate the number of manufacturing workers. From 1975 to 2017, the number of workers holding manufacturing occupations was on average 833,000 higher than the number of workers in manufacturing establishments. The highest discrepancy between both measurements corresponds to a difference of about 2 million workers in 2017. As before, the discrepancy between both measurements is explained by manufacturing workers who are increasingly employed in the service sector. The figure of -220,000, in the first year of observation, implies that in 1975, there were still more workers in the manufacturing sector than workers with manufacturing occupations. Figure 3.2, Panel (b) depicts the share of manufacturing jobs in the manufacturing sector in all manufacturing jobs in Germany. While almost 74% of workers with manufacturing occupations were employed in the manufacturing sector in 1975, this number had fallen to around 58% by 2017.



(a) Surplus of manufacturing workers when occupation rather than industry of the establishment is used to distinguish between services and manufacturing



(b) Number of manufacturing workers in manufacturing industries relative to total number of manufacturing workers

Figure 3.2: Trend of manufacturing occupations toward the service sector
West Germany. Datasource: BHP, Federal Statistical Office Germany.

Overall, we find that the measurements deliver very different results when determining manufacturing employment. The findings show that the use of the conventional industry-based measurement carries the risk of overestimating the structural change. The number of existing manufacturing workers is clearly underestimated, while the decline in manufacturing employment is overestimated. Of course, this has important implications for numerous applications, for example for the assessment of structural change and its causes or for the preparation or assessment of labor market policies and reforms (e.g.,

when determining whether retraining through labor market programs is necessary). Additionally, this also carries the risk of misjudging the potential extent of structural change that the economy could still be exposed to.

Keep in mind that we compare the occupation-based measurement with the measurement based on the *establishments'* industry classification. When using establishments, it is already ensured that establishments belonging to the same firm can have different locations or branches depending on their economic focus (e.g., production location, headquarters, office for customer services, etc.) and are thus treated independently. It is very likely that the misspecification when using firms as the basis for the division of manufacturing and service employment is much higher than when using establishments.

We rule out the possibility of our descriptive findings being attributable to technical factors. We are able to show in detail that (i) establishments entering or leaving the sample, (ii) establishments changing industries, and (iii) workers changing occupations cannot explain the difference in the measurements. Instead, our results are almost entirely explained by changes in the occupational structure of the establishments. The results are shown in Appendix Section B.3.

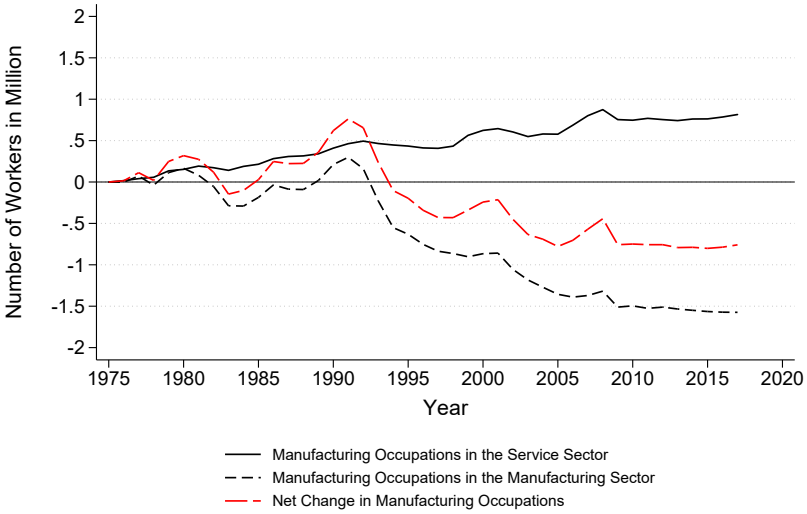


Figure 3.3: Total number of manufacturing jobs in the service and manufacturing sector (normalized to 1975=0), and the net change in manufacturing jobs across both sectors
West Germany. Datasource: BHP.

Figure 3.3 helps to gain a deeper understanding of why the proportion of manufacturing workers who are employed in the manufacturing sector decreases over time (cf. Figure 3.2, Panel (b)). The dashed, black line and the solid, black line show the total decrease and increase in manufacturing jobs compared to 1975 in the manufacturing sector and in the service sector, respectively. The long-dashed, red line shows the net change in manufacturing occupations. Compared to 1975, the number of manufacturing jobs in the manufacturing sector decreased by approximately 1.6 million jobs from 5.2 million

to 3.6 million.

During the same time period, the number of manufacturing jobs in the service sector rose from 1.8 to 2.7 million. Accordingly, the net loss in manufacturing jobs totals about 760,000 jobs. This figure is much lower compared to the commonly mentioned numbers relating to the decline in manufacturing employment. The reason for this is that the reappearance of manufacturing jobs in the service sector offers an outside employment option for manufacturing workers in the manufacturing sector and greatly reduces the decline in total manufacturing employment. Overall, about 52% of the manufacturing jobs lost in the manufacturing sector between 1975 and 2017 are offset by new manufacturing jobs in the service sector.

3.3.2 Occupational vs. Industry Employment – an empirical application

The discrepancies between the two measurement concepts raise concerns about our understanding of structural change and its severity, which is built upon previous studies that rely on concept (I), i.e., classification of manufacturing employment based on the industry class of the firm. For a large number of research and policy questions, however, it is of importance to know what the consequences of certain shocks are for individual workers, including their transition in response to the shock.

Trade exposure is commonly discussed as one such shock and potential driver of shrinking manufacturing employment (e.g., Autor et al. (2013), Caliendo et al. (2019), Dauth et al. (2014), or Pierce & Schott (2016)), making it a well suited topic to evaluate whether the distinction between occupation and industry-based (manufacturing) employment also implies different empirical findings. To do so, we estimate the impact of import and export exposure from China and Eastern Europe on the employment of workers in manufacturing occupations in Germany and compare the findings with the impact of exposure to international trade on workers employed in manufacturing industries as found by Dauth et al. (2014) (cf. Autor et al. (2013) for the U.S. case). We follow precisely their identification strategy, i.e., we use Bartik-type instruments of regional trade exposures that identify effects based on the cross-regional variation in the industry structure and use trade flows to other advanced economies as instruments for trade between Germany and Eastern Europe, respectively China. The estimating equation is

$$\Delta Manu_{rt} = \alpha + \beta_1 \Delta Exp_{rt}^{East} + \beta_2 \Delta Imp_{rt}^{East} + \Gamma' X_{rt} + \sigma_r + \kappa_t + u_{rt}, \tag{3.1}$$

$\Delta Manu_{rt}$ is computed as either the ten-year change in the share of all workers employed at establishments with a manufacturing industry class (concept (I); analyzed by Dauth et al. (2014)) in a region r's total working age population; or the share of all workers with a manufacturing occupation irrespective of the employer in the total working age population within region r (concept (O); proposed in this paper). ΔImp_{rt}^{East} and

ΔExp_{rt}^{East} are the changes in regional import and export exposure to China and Eastern Europe, respectively, and X_{rt} is a vector of regional control variables. The regional trade exposures are constructed as shift-share instruments according to

$$\Delta(TradeExposure)_{rt}^{East} = \sum_{j} \Delta(TradeFlow)_{jt}^{East} \frac{E_{rjt}}{E_{jt}} \frac{1}{E_{rt}},$$

where j denotes industry and $E_{(\cdot)}$ is the employment in either region r, industry j, or industry j's employment in region r. Trade flows between Germany and "the East" are estimated in a first stage with corresponding trade flows of other advanced countries with "the East" as instruments to mitigate endogeneity issues such as German supply or demand shocks driving both employment changes and changes in international trade. We follow Dauth et al. (2014) and stack long differences from 1988 to 1998 and from 1998 to 2008. The first difference includes West Germany only, the second difference includes reunified Germany.[30]

First, we replicate the baseline specification of Dauth et al. (2014) (see Panel (A) of Table 3.1). $\Delta Manu_{it}$ is the ten-year change in total employment in manufacturing industries as the share of the labor force in a region r, i.e., manufacturing employment is defined according to concept (I). The results – naturally identical to the findings of Dauth et al. (2014) – indicate job losses in manufacturing industries as a result of increased import exposure and job gains in manufacturing industries as a result of increased export exposure in a region. The preferred specification in column (5) contains a set of local labor-market controls and region-time fixed effects. The estimated coefficients of this specification "imply that a ten-year change of \$1,000 per worker in import exposure reduces manufacturing employment relative to working age population by 0.19 percentage points, whereas export exposure increases this share by 0.4 percentage points", Dauth et al. (2014), p. 1656.

Second, we change the concept of measuring manufacturing employment to concept (O). We consider all workers with manufacturing occupations as manufacturing employment and $\Delta Manu_{it}$ accordingly is computed as the ten-year change of the share of workers with manufacturing occupations in a region r's total labor force. Results are displayed in panel (B) of Table 3.1. We can rely on the Bartik instruments to measure the effects of trade exposure in this definition since also total regional employment is differently affected by an increase in trade exposure depending on the industry structure (i.e., the underlying regional distribution of firms). By estimating whether total employment in manufacturing occupations within regions is differently affected by changes in trade exposure, we take job opportunities outside the previous employers into account. More precisely, we incorporate the possibility of workers finding a new job at a different

[30]For a detailed description of the identification strategy, the data, the estimations and a more detailed description of the six different specifications, see Dauth et al. (2014). Panel (A) of Table 3.1 is identical to Table 1 of Dauth et al. (2014), page 1653, and is replicated using the files and data provided in their supplementary material.

employer in the same region – potentially belonging to the service sector – if the previous employer is negatively hit by import competition.

This approach is actually more closely related to the original reasoning behind the applicability of the shift-share design as proposed in Autor et al. (2013). Regions are treated as secluded labor markets without in- and outflow of workers and hence increasing exposure to imports or exports will have effects on labor demand and supply within that region dependent on the industry structure (and demand). If a regional labor market is shocked, there will be general equilibrium adjustments in wages which affect labor demand in all industries not only those directly competing with imports or exporting.

The specifications and control variables remain unchanged in comparison to Panel (A) of Table 3.1. The employment effects of the increase in export exposure are in a similar range as before (if not lower in the more reliable specifications of columns 3-5 when including fixed effects) and the estimates of controls are broadly comparable. The effect of import exposure on manufacturing employment measured as the total number of workers holding manufacturing occupations is, however, different from the effects on employment in manufacturing industries. We can no longer identify a significant effect of import exposure on manufacturing employment (using the occupation-based measurement). This finding is in line with the previously presented observation that a large proportion of workers with manufacturing jobs who disappear from the manufacturing sector reappear in the service sector, where the number of workers with manufacturing occupations is increasing. Contrary to the importing side, where outside job opportunities seem to mitigate the negative effects of import exposure, the exporting side shows almost identical effects, as both the goods producing industries and also the goods producing occupations seems the be equally positively effected by foreign demand. Previous studies that evaluate the effect of trade on manufacturing generally do not consider these workers with manufacturing occupations employed in service industries.

Our result also matches recent findings of Bloom et al. (2019) and Caliendo et al. (2019) who, based on a dynamic general equilibrium model of discrete job choice, show that a large fraction of workers in the U.S. relocate to construction and service industries when facing the "China shock". Their model, though, is not able to capture occupation choice. We provide evidence that previous occupations matter with respect to relocation and that the occupational composition of sectors is less different than widely perceived. By considering manufacturing employment according to workers' occupations, our approach also connects to recent findings that, in particular, workers in specific occupations are negatively affected by import shocks (Ebenstein et al. (2011), Ebenstein et al. (2015), Utar (2018), Traiberman (2019), or Helm (2020)). Our findings, however, take a slightly opposing stand in that occupational tenure is a main component of what determines human capital and thus wages are set irrespective of the employer's industry; see, e.g., Kambourov & Manovskii (2009). More importantly, on average, occupations that are negatively affected by import shocks in manufacturing industries are also in demand

in service industries (cf. section 3.4.1) and the growth of this sector offsets the initial negative effects of international trade on import competing industries.

This empirical application has important implications, as it calls for a rethink of the way we measure structural change and classify employment in general. At present, the distinction between occupation and industry-based measurements of manufacturing oftentimes is not clear and, as we show, empirical effects and implications are different. Consequently, it is important to distinguish between the effects on employment in manufacturing industries and employment of workers holding manufacturing occupations, for instance when evaluating the effect of trade on manufacturing. The fact that import exposure leads to shrinking employment in the manufacturing sector does not imply declining employment in manufacturing occupations as well. Differentiating between the two is crucial, as the implications, for instance in terms of policy advice, e.g., concerning labor market reforms or policies, will differ.

Table 3.1: Industry vs. occupational measurement

	(1) IV	(2) IV	(3) IV	(4) IV	(5) IV	(6) OLS
Panel A: Manufacturing by Industry						
Δ import exposure	0.035	-0.028	-0.149**	-0.158**	-0.190***	-0.075
	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)	(0.05)
Δ export exposure	0.332***	0.444***	0.409**	0.425**	0.399*	0.442***
	(0.12)	(0.12)	(0.18)	(0.21)	(0.21)	(0.12)
manuf. of tradable goods	-0.108***	-0.083***	-0.073***			
	(0.01)	(0.02)	(0.02)			
high skilled		0.011	-0.046	-0.042	-0.039	-0.047
		(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
foreigners		-0.197***	-0.159***	-0.159***	-0.162***	-0.161***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
women		-0.057***	-0.062***	-0.061***	-0.060***	-0.060***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
routine occupations		-0.039	-0.025	-0.021	-0.014	-0.023
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
manuf.				-0.073***	-0.068***	-0.083***
of other tradable goods				(0.02)	(0.02)	(0.02)
manuf. of cars				-0.081**	-0.074**	-0.092***
				(0.03)	(0.03)	(0.03)
Panel B: Manufacturing by Occupation						
Δ import exposure	0.243***	0.179**	-0.004	0.010	-0.015	0.053
	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.10)
Δ export exposure	0.467***	0.538***	0.281**	0.258**	0.239**	0.251***
	(0.07)	(0.07)	(0.11)	(0.11)	(0.10)	(0.06)
manuf. of tradable goods	-0.086***	-0.063***	-0.020			
	(0.01)	(0.01)	(0.02)			
high skilled		-0.127***	-0.067	-0.072*	-0.070*	-0.074*
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
foreigners		-0.063*	-0.092**	-0.093**	-0.096***	-0.095**
		(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
women		-0.040***	-0.035***	-0.036***	-0.034***	-0.035***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
routine occupations		-0.131***	-0.060**	-0.066***	-0.061**	-0.066**
		(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
manuf.				-0.020	-0.015	-0.023
of other tradable goods				(0.02)	(0.02)	(0.02)
manuf. of cars				-0.009	-0.004	-0.012
				(0.03)	(0.03)	(0.03)
Time dummies	-	-	yes	yes	-	-
Region dummies	-	-	yes	yes	-	-
Region x time dummies	-	-	-	-	yes	yes

Notes: Standard errors are clustered at the level of 50 labor market regions. $N = 739$ (326 regions in first and 413 regions in second period – Periods are ten year changes between 1988-1998 and 1998-2008). Panel A shows effects on total employment in manufacturing industries, Panel B shows the effects on employment in manufacturing occupations irrespective of the industry the workers are employed in.

3.4 The service sector as an alternative employment option

We have presented new stylized facts that stress the importance of focusing on workers' occupations when assessing certain labor market developments, reactions, and policies. While the manufacturing sector and, in particular, the number of manufacturing jobs in the manufacturing sector has been shrinking over the past 43 years, an increasing number of manufacturing jobs have emerged in the service sector. In combination with the reestimation of the impact of trade exposure on employment in local labor markets, this development indicates that the service sector plays a mitigating role for workers with manufacturing occupations that are affected by the shrinking manufacturing sector. A sizeable share of lost manufacturing jobs in the manufacturing sector has been absorbed by growing employment in the service sector. In the period from 1975 to 2017, the number of manufacturing jobs in the manufacturing sector has decreased by about 1.6 million. During the same time period, the number of manufacturing jobs in the service sector has grown by more than 800,000. Thus, the net decline in manufacturing jobs in the German economy is just about half of the extent to which jobs in the manufacturing sector are lost.

In this section, we first document the distribution of workers with manufacturing occupations across the manufacturing and service sectors in more detail. We will show that the service sector is not an alternative employment option for a mere handful of occupations, but rather a sizeable share of manufacturing jobs can be found in the service sector across almost all occupations.

Second, we provide evidence that workers switch between the manufacturing and service sector in significant numbers. Accordingly, the service sector does indeed present an outside employment option for manufacturing workers who are already employed in the manufacturing sector (and, e.g., not only for workers who enter the job market for the first time). A considerable proportion of the new manufacturing jobs in the service sector consists of sector switchers who were employed in the manufacturing sector before. We show that workers who are laid off when their employer in the manufacturing sector faces an exogenous negative shock are (in part) able to find a new job in the service sector. Overall, about a third of laid-off workers do not find a new job in a manufacturing occupation in the manufacturing sector. Roughly 80% of these unsuccessful workers switch to the service sector. Surprisingly, 50% even find a new job in their original occupation and this fraction is increasing over time. For the latter workers, the sector switch implies only minimal additional losses as such workers will lose less of their accumulated human capital than workers who have to switch both employer and occupation or workers who fall into (long-term) unemployment.

Third, we will provide preliminary evidence of the impact of such a switch between the sectors on workers' wages. Clearly, tasks performed in the manufacturing sector may differ slightly from tasks performed in the service sector. However, it seems reasonable

to assume that tasks remain rather similar and that comparatively little human capital is lost if only the sector but not the occupation changes.[31] Hence, the presence and the increasing number of manufacturing jobs in the service sector offer a plausible channel through which negative consequences of structural shocks such as trade, automation or routine-biased technical change on manufacturing workers will be dampened.

3.4.1 Distribution of Occupations Across Sectors

Table 3.2 shows the distribution of 2-digit occupations across the two sectors, manufacturing and services, for the years 1975 and 2017 in columns (1)-(4). A sizeable proportion of workers are present in establishments where the service or manufacturing affiliation of the establishment does not correspond to the service or manufacturing occupation of the worker. For the manufacturing occupations, which are of special interest for us (see lines 1 to 19 of Table 3.2), a share of between 3.7% (ceramic workers) and 46.6% (nutrition occupations) of all workers with these occupations can be found in the service sector in 1975 (cf. column 2). In 2017, this share has increased for all manufacturing occupations and ranges between 12.9% (ceramics workers) and 69.6% (nutrition occupations). The ranking of the shares according to which the occupations are present in the service sector almost remains constant over time.

In column (5), we show the shift of the distribution towards the service sector. For almost all occupations, the service sector employs a significantly higher share in 2017 than in 1975. This is due to two reasons: (i) the total number of workers in the manufacturing sector is shrinking, including the number of workers with manufacturing occupations and (ii) the number of jobs in the service sector is growing, including the number of manufacturing jobs for a large share of 2-digit occupations; see column (7).[32]

We also observe that almost all manufacturing occupations experience a decline in total numbers from 1975 to 2017, see column (6). This decline reflects the overall structural change, e.g., through technical change such as robotization and computerization but also changing organization of production through outsourcing and offshoring, and the split into global value chains across the globe. Notable exceptions to this decline are electricians and machinists and related occupations. The figures grow by a third for electricians and almost triple (an increase of 190%) for machinists. The increase in these occupations is very much in line with the increasing use and application of electrical machinery and the emergence of computerization and robotization in high-tech industries

[31] Anecdotally, think of a mechatronic technician working at a car manufacturer. Among other things, she has to lay wiring harnesses. When now displaced and re-employed at an auto repair workshop, she will no longer lay the wiring harnesses but repair them. In this example, the affected worker will perform very similar tasks and, more importantly, the previous knowledge is equally valuable in the new job. This is in line, for instance, with Kambourov & Manovskii (2009). By contrast, Neal (1995) stresses the importance of industry specific human capital. However, the underlying data are limited and the author cannot control for occupational changes of workers.

[32] A negative value in column (7) in combination with a positive value in column (5) would indicate that the number of workers in a given occupation decreases in the service sector, but the decrease in jobs in that occupation is even higher in the manufacturing sector.

for which Germany is well known.

Table 3.2 thus once again stresses that structural change occurs for (almost) all manufacturing jobs and that it is a broad phenomenon covering a diverse set of industries and a comprehensive set of occupations. The change in distributions also illustrates that the service sector is increasingly offering jobs for manufacturing occupations. This is the case for all manufacturing occupations in significant shares. Accordingly, the figures support the statement that the service sector is an alternative employment option for almost all manufacturing occupations.

Table 3.2: Occupations' distribution across sectors

Occupation	(1) 1975 Manufacturing	(2) 1975 Service	(3) 2017 Manufacturing	(4) 2017 Service	(5) 1975 - 2017 Δ to Service	(6) 1975 - 2017 Total %-Δ	(7) 1975 - 2017 Service sector %-Δ
Miners, oil quarriers	80.4%	19.6%	34.0%	66.0%	46.5 p.p.	-80.8%	-35.2%
Stone preparers, building material makers	94.5%	5.5%	80.9%	19.1%	13.6 p.p.	-42.0%	101.6%
Ceramics workers, glass makers	96.3%	3.7%	87.1%	12.9%	9.2 p.p.	-58.7%	42.6%
Chemical workers, plastics processors	92.4%	7.6%	79.2%	20.8%	13.2 p.p.	-20.8%	117.8%
Paper makers, printers	92.9%	7.1%	79.6%	20.4%	13.4 p.p.	-52.7%	36.7%
Wood preparers, wood products makers and related occupations	93.4%	6.6%	79.8%	20.3%	13.7 p.p.	-49.3%	55.8%
Metal producers	95.6%	4.4%	81.3%	18.7%	14.4 p.p.	-28.8%	204.7%
Toolmakers, smiths, mechanics	69.2%	30.8%	60.8%	39.2%	8.3 p.p.	-25.0%	-4.7%
Electricians	60.0%	40.0%	57.1%	42.9%	2.9 p.p.	33.3%	43.1%
Assemblers and metal workers (no further specification)	94.4%	5.6%	77.1%	22.9%	17.3 p.p.	-31.4%	182.5%
Textile processors	87.2%	12.8%	67.0%	33.0%	20.2 p.p.	-88.2%	-69.6%
Leather makers, leather and skin-processing occupations	86.5%	13.5%	72.1%	27.9%	14.4 p.p.	-87.3%	-73.8%
Nutrition occupations	53.4%	46.6%	30.4%	69.6%	23.0 p.p.	21.6%	81.6%
Construction workers	37.9%	62.1%	28.3%	71.7%	9.7 p.p.	-59.7%	-53.4%
Room equippers, upholsterers	58.0%	42.0%	45.6%	54.4%	12.4 p.p.	-36.7%	-18.1%
Carpenters, model makers	76.4%	23.6%	68.2%	31.8%	8.2 p.p.	-32.6%	-9.2%
Painters, lacquerers and related occupations	66.1%	33.9%	39.6%	60.4%	26.5 p.p.	-17.1%	47.6%
Goods examiners, despatchers	80.2%	19.8%	80.7%	19.3%	-0.5 p.p.	-76.2%	-76.8%
Machinists and related occupations	66.6%	33.4%	78.6%	21.4%	-12.0 p.p.	190.1%	85.8%
Technicians, technical specialists	67.4%	32.6%	56.0%	44.0%	11.4 p.p.	26.9%	71.2%
Engineers, chemists, physicists, mathematicians	59.1%	40.9%	51.1%	48.9%	8.0 p.p.	183.9%	239.7%
Wholesale and retail trade	19.7%	80.3%	17.8%	82.2%	1.9 p.p.	55.0%	58.7%
Services agents and related occupations	4.3%	95.7%	8.0%	92.0%	-3.7 p.p.	99.1%	91.4%
Transport occupations	31.6%	68.4%	18.9%	81.1%	12.7 p.p.	43.2%	69.8%
Administrative occupations, office occupations	33.2%	66.8%	20.4%	79.6%	12.9 p.p.	46.3%	74.5%
Security occupations	20.2%	79.8%	7.9%	92.1%	12.3 p.p.	118.2%	151.8%
Publicists, translators, artists	27.1%	72.9%	19.8%	80.2%	7.3 p.p.	104.5%	125.1%
Health service professions	1.1%	98.9%	0.5%	99.5%	0.6 p.p.	206.3%	208.2%
Social, education-related occupations, humanities specialists, scientists	4.7%	95.3%	3.0%	97.0%	1.7 p.p.	491.8%	502.5%
Housekeeping, cleaning, guest attendance occupations	12.4%	87.6%	3.1%	96.9%	9.3 p.p.	26.4%	39.8%

Notes: The table shows the distribution of 2-digit occupations across the two sectors, manufacturing and service, for 1975 and 2017 as well as the change toward the service sector from 1975 to 2017, and the change within the service sector. Δ stands for "change", %-Δ for "percentage change". Data: SIAB 7517, 1975-2017.

3.4.2 Flows of Manufacturing Workers Across Sectors

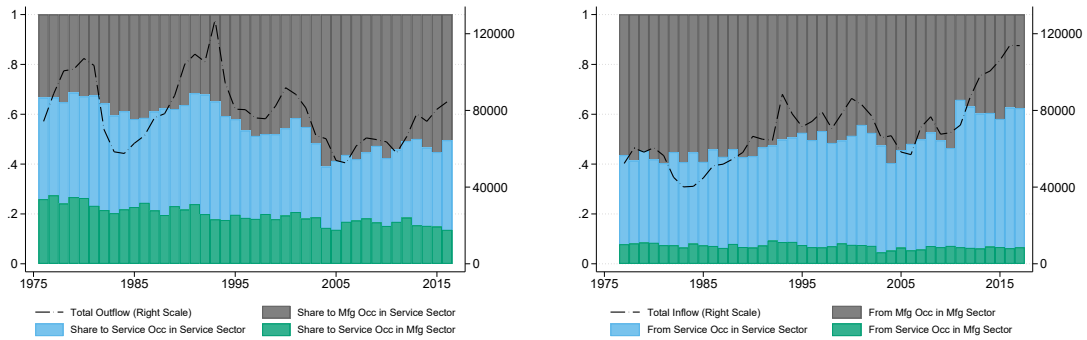
To reinforce our claim that the service sector presents an alternative employment option for manufacturing workers, it is important not only to show that a large number of manufacturing workers can be found in the service sector and that this number is increasing over time (cf. Section 3.3.1), but also that workers do indeed actively switch between the manufacturing and the service sector. The descriptive statistics in this section show that this is the case. Workers who originally hold manufacturing occupations increasingly switch from the manufacturing to the service sector and account for a large share of newly created manufacturing jobs in the service sector. This indicates that the barriers to a job switch across sectors are sufficiently low and rules out the notion that occupations in the service and manufacturing sector require different sets of skills.

Figure 3.4 shows the total outflow of workers with manufacturing occupations from the manufacturing sector (including shares by destination) in Panel (a) and the total inflow of workers with manufacturing occupations into the service sector (including shares by origin) in Panel (b). Neither figure includes workers who are out of employment. Starting with Panel (a), we observe fluctuating outflows out of manufacturing occupations in the manufacturing sector around a stable annual mean of approximately 79,700. The bars show the shares of alternative occupation-sector combinations into which the workers move. Over time, an increasing share of workers moves to manufacturing jobs in the service sector. In 1975, at the beginning of the sample period, only about 32% of workers leaving the manufacturing sector find a new job with a manufacturing occupation in the service sector. At the end of the period, in 2017, this share has increased to almost 50%. We observe a maximum of 60% in 2004. Simultaneously, the total share of workers switching to a service occupation is decreasing. In particular, the share moving to service jobs in the manufacturing sector declines from a value of 25% in 1975 to 15% in 2017.

Panel (b) depicts the inflow into manufacturing jobs in the service sector. The total inflow into manufacturing jobs in the service sector is increasing over time. The yearly increase in the second half of the 1970s is between 60,000 and 65,000 jobs. In the late 2010s, this number has reached a value of 115,000 per year after several years with strong growth. The differentiation by origin shows that the share of workers switching from a service job in the service sector to a manufacturing job in the service sector is increasing over time and hence covers a large part of the newly created jobs. The share increases from about 42% in 1975 to about 60% in 2017. In addition, the share of workers moving from manufacturing occupations in the manufacturing sector into manufacturing occupations in the service sector is sizeable. The share is close to 60% throughout the 1970s and 1980s and about 50% in the following years. In the years after 2010 the share falls to 40%. Note that the absolute number of switchers into manufacturing occupations in the service sector is increasing over time. The decreasing share therein of workers moving from manufacturing occupations in the manufacturing sector is explained by an even larger increase in the numbers of workers moving from service occupations in the

service sector.[33]

In summary, the descriptives show that there are significant flows of workers between the sectors. Increasingly, workers with manufacturing occupations who were originally employed in the manufacturing sector switch to establishments in the service sector while retaining their manufacturing occupation. Likewise, we increasingly observe inflows into manufacturing occupations in the service sector. A sizeable fraction of these inflows comes from workers who previously held manufacturing jobs in the manufacturing sector. The trends once again confirm our claim that the service sector functions as an alternative employment option for workers with manufacturing occupations. Switches into the sector occur frequently and increasingly. Through its growth, the service sector is able to dampen the decline of jobs for workers with manufacturing occupations in the manufacturing sector.



(a) Outflow of manufacturing occupations in the manufacturing sector

(b) Inflow into manufacturing occupations in the service sector

Figure 3.4: Total flows of manufacturing occupations out of the manufacturing sector and into the service sector by other occupation-sector pairs.
Datasource: SIAB.

3.4.3 Differences across the manufacturing and service sectors

Before going into more detail in evaluating the effects of the service sector on individual workers affected by structural shocks in Section 3.5, we first provide evidence of wage differences between the two sectors. We presume that a switch from the manufacturing sector to the service sector is associated with a wage penalty as the data show that the (unconditional) wage level is on average 30 euros lower in the service sector (corresponding to a difference of 28%). We follow Dube & Kaplan (2010) and estimate Equation 3.2

[33]Note that the shares reported in Figure 3.4 , Panels (a) and (b) are conditional on the fact that the underlying workers change jobs and are observed in the data in both years around the job switch. Also, the shares reported in Panel (a) consider as a denominator only workers who do not switch between two manufacturing jobs in the manufacturing sector. The numbers do not coincide with the figures presented in the previous section, since here we only consider persons who switched between the two sectors, manufacturing and service, whereas in the previous section, the figures included workers newly entering the labor force as well as workers moving out of the labor force, e.g., through retirement.

as a first indicator.

$$\ln(\text{wage})_{i(j)t} = \alpha_i + \gamma \text{Service}_{i(j)t} + X'_{it}\beta + \epsilon_{it}, \tag{3.2}$$

where $\text{wage}_{i(j)t}$ is the wage of person i employed at establishment j at year t. $\text{Service}_{i(j)t}$ is a dummy indicating that establishment j at which person i is employed belongs to the service sector. We are interested in the sign and size of coefficient γ, which measures the wage premium (or penalty for that matter) of the service sector over the manufacturing sector for workers who switch between the two sectors. The inclusion of person fixed effects (α_i) implies that the coefficient γ is identified through workers who at least once changed employers between the two sectors, manufacturing and services. X_{it} includes time-variant personal characteristics such as age, age squared, and education indicators.

Since the identification of the wage penalty relies on workers who switch in either direction, i.e., from the manufacturing to the service sector or vice versa, while holding a manufacturing occupation, this empirical strategy cannot differentiate between voluntary and forced switches. But the strategy makes it possible to draw general conclusions about the pay differences between the two sectors. We estimate Equation 3.2 to retrieve the average effect of working in the service sector for all workers with manufacturing occupations.[34] For all estimations and all outcomes, we focus on the main employment spell only, i.e., the highest paying spell the person has on the cutoff date of June 30 of a given year (unless stated otherwise).

Table 3.3 reports results on the average wage penalty for working in the service sector across all workers with manufacturing occupations. Working in the service sector is on average associated with a 29% lower wage compared to working in the manufacturing sector. In addition, we further differentiated by 47 2-digit occupation classes. Table 3.9 in the Appendix shows the results. For 42 out of these we find a (statistically significant) negative wage premium, i.e., a wage penalty, for working in the service sector. These range from -51% to -4%. By contrast, for only 2 out of 47 occupations, we find a (statistically significant) positive wage premium for working in the service sector, 3.25% for metalworkers and 7.6% for meat and fish processors. The remaining occupations do not show statistically significant effects.

In summary, the results indicate that workers with manufacturing occupations in the service sector will have to accept wage cuts compared to their remuneration in the manufacturing sector. Since this approach is not able to differentiate between voluntary

[34] In the following analyses, we focus on 2-digit occupations and switches between these. We rely on a relatively high aggregation level, because occupation classes at the 2-digit level are sufficiently homogeneous to argue that workers can switch easily switch occupations within these classes without requiring retraining or losing human capital. Gathmann & Schönberg (2010) advocate this procedure. They argue that human capital, interpreted as the knowledge of task combinations and how to perform them, is easily transferable between occupations. Our focus on 2-digit occupations takes more specific tasks into account than Gathmann & Schönberg (2010), including knowledge on how to operate specific machines or tools, which is not considered in the task surveys underlying typical studies on the matter.

and involuntary job changes, the effects may be biased downwards. If a person changes jobs voluntarily, we can assume that the new job is more desirable, which most often will also be reflected by a higher wage. In this specification, it is also possible that switches from the service to the manufacturing sector are the dominant force, for instance if they are combined with promotions.[35]

Table 3.3: Wage penalty of working in the service sector for workers with manufacturing occupation

	(1) coefficient	(2) std. error
Service (γ)	-.286***	(.0012)
Age	.198***	(.0002)
Age^2	-.002***	(.0000)
Years of schooling	.005***	(.0001)
College	.374***	(.0029)
Number of observations	11,062,219	
Number of groups	878,814	
R^2 (within)	0.6959	
R^2 (between)	0.2076	

Notes: The table reports the estimation results of Equation (3.2). The inclusion of worker fixed effects leads to identification of coefficient γ through workers who at least once switched employers between the manufacturing and the service sector but did not switch their occupation. Standard errors are clustered at the worker level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Datasource: LIAB, 1975-2017.

3.5 Displacements through mass layoffs and structural change

The previous sections showed (i) that we overstate structural change when employment measurements are based on the industry classification of the firm instead of on the occupations of the workers, and (ii) that the service sector is able to absorb a large fraction of lost jobs for workers with manufacturing occupations. However, what remains to be shown in detail are the consequences for workers when they switch employment to the service sector.

To assess the effects of switching employment between the sectors on workers' outcomes, we want to resort to events where workers presumably are forced to leave their job for exogenous reasons (most likely triggered by structural change). In particular, we focus on mass-layoffs in manufacturing establishments that affect workers with manufacturing occupations. Since there are many potential drivers of structural change, we utilize events where an establishment shrinks by a significant fraction from one year to the next (i.e., mass layoffs, cf. Schmieder et al. (2020) and Gathmann et al. (2020)). We identify mass layoffs according to the regulations in the German Employment Protection

[35]We do find large, so far unexplained wage differences for the same occupations between the sectors. One reason not addressed in this paper could be outsourcing activities of manufacturing firms to service firms. Such activities have been shown to go in parallel with depressed wages at the new employers, see e.g., Goldschmidt & Schmieder (2017) or Bilal & Lhuillier (2021).

Act.[36]

We use such mass layoffs because the methodology in Section 3.4.3 is not able to differentiate between voluntary and involuntary job changes and the data do not allow us to determine the reasons why establishments shrink. Nonetheless, it will mainly be exogenous reasons such as severe demand, competition or cost shocks that will force establishments to lose a sizeable portion of their overall employment over a short time. Any potentially endogenous (mis)management is still exogenous to the individual workers we consider and caused solely by actions of the firm's management. We only consider workers who were already working at the establishment at least two years prior to the layoff event. In addition, German labor regulations are very strict, which makes layoffs more difficult the longer a person is employed in a firm – independent of the workers' productivity. Both factors make the layoff event itself even less endogenous for the worker. In that sense, our results represent a lower bound for the costs of switching sectors as voluntary switches (due to better job opportunities) are most likely not covered. See Jacobson et al. (1993) for a first study utilizing mass layoffs and arguing for exogeneity; likewise see Schmieder et al. (2020) for further reasoning behind the use of mass layoffs in the German context.

First, we report numbers on such layoffs and flows of the affected workers into new, alternative employment by occupation and sector. Thereafter, we follow workers into their new jobs and evaluate the impact of the job switch on employment outcomes. To do so, we match laid-off workers with workers who are not laid off but employed in the same occupation-industry combination in the year before the layoff. Then, we estimate average treatment effects of being laid off on the laid-off workers (average treatment effect on the treated, ATT; cf. Goldschmidt & Schmieder (2017) and Schmieder et al. (2020)).

3.5.1 The incidence of mass layoffs

Figure 3.5 plots the observed total annual number of manufacturing establishments with mass-layoffs (dashed-dotted line, right scale), the total annual number of laid-off workers therein (blue bars, left scale), and the total annual number of laid-off workers with manufacturing occupations therein (grey bars, left scale).[37] The number of layoff

[36] Under the Act, an employer is obliged to notify the employment agency of any event that terminates a significant proportion of its jobs between two reporting years. In particular, for establishments with more than 20 and less than 60 employees, an event is defined as firing at least 5 employees. For establishments with 60 to 500 employees, an event is defined as shrinkage by at least 10% or more than 25 employees. An event for establishments with more than 500 employees is defined as shrinkage by 30 or more employees from one year to the next. Most papers studying layoffs rely on larger shares for the reduction in employment to define mass-layoffs. However, we argue that our layoff definition covers more relevant layoffs since structural change is a slow process. In the following, whenever we mention 'layoffs' we refer to this concept of 'mass-layoffs'.

[37] Note that the underlying data are from the SIAB dataset, a matched employer-employee dataset that does not necessarily provide us with worker-level information for all laid-off workers. The data, however, always contains aggregated employment data for a given establishment such that layoff events are identified according to the total number of full-time workers. This explains why the number of laid-off workers is only approximately two times higher than the number of layoff events at manufacturing

events in the manufacturing sector is roughly stable across the years affecting around 2% of all establishments in a given year. The number peaks in the early 1990s due to restructuring after German reunification. The numbers of laid-off workers are similarly stable, with the exception of peaks after reunification and more recently after the global financial crisis. In recent years, the numbers have declined, but we still observe around 7,500 laid-off workers annually. The fraction of laid-off workers with manufacturing occupations therein is equally stable at a level of 50 to 60%.

A share of 70% of the laid-off manufacturing workers manages to find new employment in a manufacturing occupation in the manufacturing sector. However, 30% do not find new employment in their initial or a similar occupation in the manufacturing sector. For these, Figure 3.6 shows the shares of workers who find new employment in a manufacturing occupation in the service sector, a service occupation in the manufacturing sector, or a service occupation in the service sector. The share of workers finding new employment in a manufacturing occupation in the service sector grows continuously over the years, starting with a share of around 40% in the second half of the 1970s and clearly dominating with a share of more than 60% in 2017. Some 17-25% only change their occupation to a service occupation and remain in the manufacturing sector. Likewise, 25-35% change both occupation and sector so that they are re-employed in a service occupation in the service sector after being hit by a layoff. Both of the latter shares decrease over time.

In summary, mass layoffs occur frequently, while their incidence increases during crises and restructuring after large structural shocks, such as reunification. A significant proportion of workers with manufacturing occupations usually does not find new employment in a job where the occupation and industry of the employer are the same as before. Importantly, the service sector functions as a safety net for a sizeable share of these workers, and increasingly so during recent years. More than 60% of laid-off workers who have to switch either occupation or sector only switch to the service sector but keep their occupation. This proves to be important for future employment trajectories as we will show next.

3.5.2 Effects of a sector switch – exogeneity through layoffs

We identify workers affected by a mass layoff event. Similarly to Goldschmidt & Schmieder (2017) and Schmieder et al. (2020), we then compare the affected workers with a control group, which consists of workers with similar characteristics who held the same occupation in the same industry in the year prior to the layoff event but were not affected by mass layoffs (and also did not change employers for other reasons). The set of treated persons is restricted to workers who are employed at an establishment that experiences a mass layoff and who hold a manufacturing occupation in the year of the layoff. We exclude workers who stay at an establishment where a layoff is observed.

establishments.

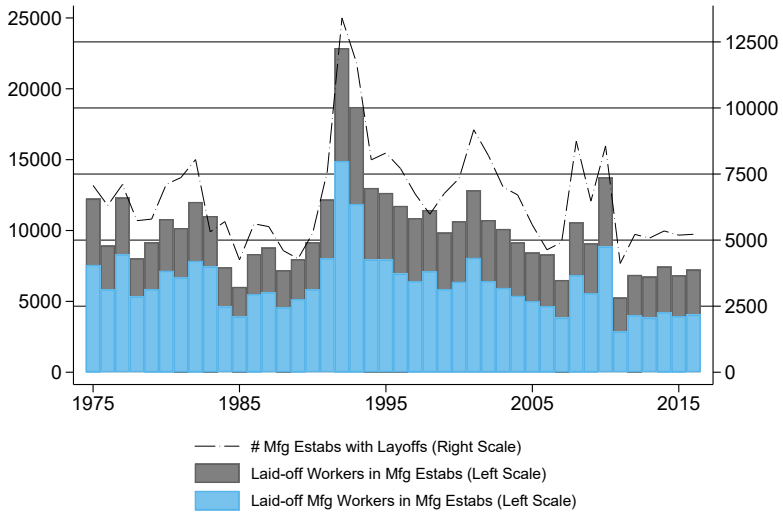


Figure 3.5: Layoffs and laid-off workers in the manufacturing sector

The figure shows the yearly number of layoff events observed in the dataset (right scale) and the number of laid-off workers in total and with a manufacturing occupation in the year of the layoff (left scale). Datasource: SIAB 7517.

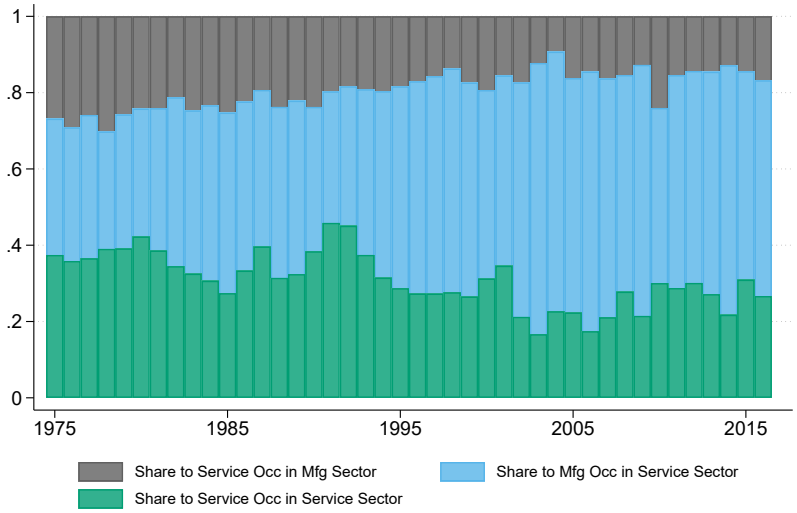


Figure 3.6: Laid-off manufacturing workers of manufacturing establishments and next year's occupation-sector combination

The figure shows, for laid-off workers with manufacturing occupations in the manufacturing sector, their occupation-sector combination in the year following the layoff if they leave the sector or switch to a service occupation. On average, this is the case for 30% of all laid-off workers with production occupations in the manufacturing sector. Datasource: SIAB 7517.

3.5.2.1 Effects within the group of laid-off workers

Before turning to the more robust estimations with a matched control group, we first present results from a simple event study design. We estimate the following regression on four different outcome variables for persons i at establishment j in year t. The logarithmic

wage in the workers main job, the accumulated yearly income, i.e., daily wages multiplied by days worked and summed across all jobs the worker has, the days in employment per year, and the number of different employers, as proxy for job volatility:

$$y_{ijt} = \sum_{\iota=1}^{4} \sum_{\kappa=-5}^{10} \gamma_{\kappa\iota} \mathbb{1}\{t = t^* + \kappa\} \times \mathbb{1}\{i = \mathcal{M}_\iota\} + \alpha_i + \chi_j + \theta_t + X'_{it}\xi + \epsilon_{it}, \tag{3.3}$$

where t^* indicates the year the layoff occurs. α_i are person fixed effects, χ_j establishment fixed effects, and θ_t year fixed effects, X_{it} is a third-order age polynomial. $\mathcal{M}_\iota$ indicates the ιth element in the set of movements, i.e., the potentially new employment type of laid-off manufacturing workers,

$$\mathcal{M} = \left\{ \begin{array}{l} \text{manufacturing occupation at manufacturing establishment,} \\ \text{manufacturing occupation at service establishment,} \\ \text{service occupation at manufacturing establishment,} \\ \text{service occupation at service establishment} \end{array} \right\}.$$

By nature of this exercise, the sample is restricted to laid-off workers that held manufacturing occupations previous to the layoff only and, hence, identification of the effect stems from different treatment years or so-called staggered adoption of treatment. The regression thus compares workers' outcomes relative to the point in time when the layoff occured. By normalizing this point in time across workers, we are able to identify the effects of the layoff without relying on matching assumptions.[38]

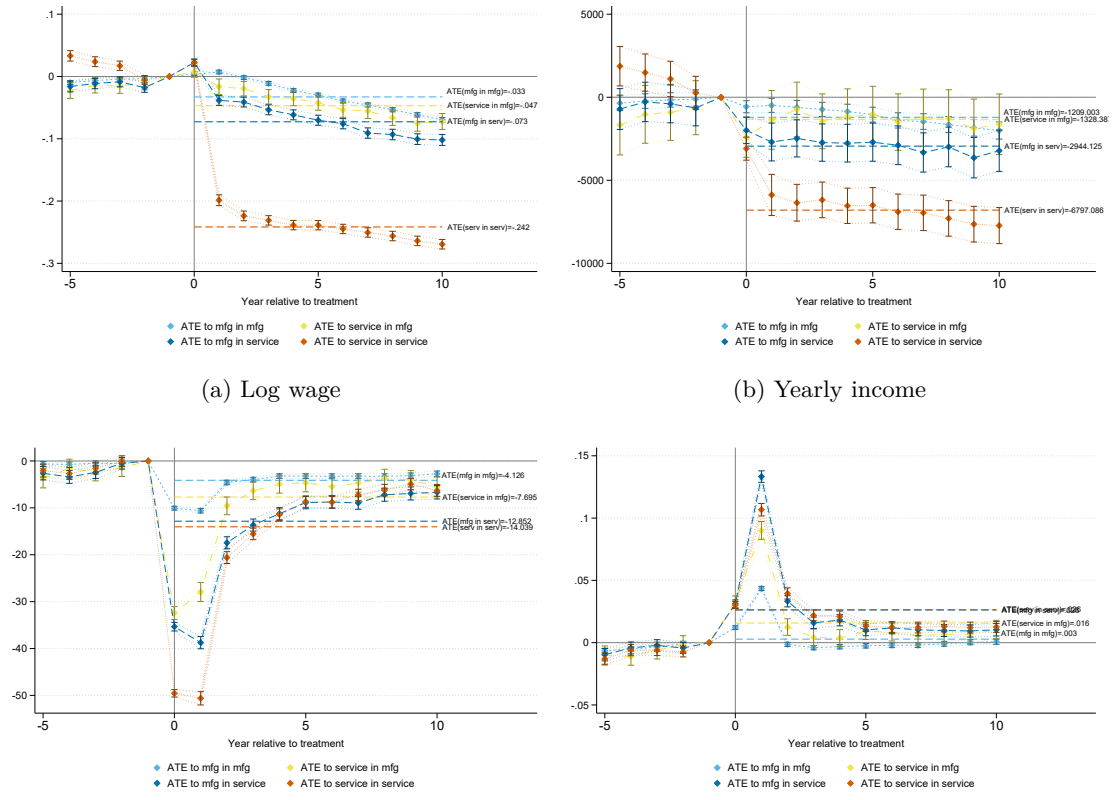
Figure 3.7, panels (a)-(d) show the results for the four possible transitions $\mathcal{M}_\iota$ after a layoff (excluding unemployment) for the four outcomes. Outcome paths are negative and similar (parallel) for all four transitions but differ strongly in effect size. Workers that transition from a manufacturing occupation in the manufacturing sector to a service occupation in the service sector experience the strongest negative effect. The average treatment effect on wages is at a 24% decline in daily wages (panel (a)). Likewise, the accumulated annual income for these workers falls by almost 6,800 euro (panel (b)) – about 14% of the average yearly household income or about 1.62 times a household's gross monthly wage. These workers are also the ones who experience the longest unemployment periods (panel (c)).

Workers that switch to a manufacturing occupation in the service sector experience the second strongest effects. However, the effects on pecuniary outcomes are considerably smaller than for the previously discussed group (service occupation in service industries). In fact, for wages and accumulated income the effects are statistically different but in very similar ranges as those of laid off workers who find a new job in the manufacturing

[38]This design is able to identify causal estimates as discussed in a series of recent papers (Athey & Imbens (2021), Borusyak et al. (2021), and Sun & Abraham (2020)). We follow best-practice when estimating event-studies with unbalanced panels and bin the end points and do not report them (Goodman-Bacon 2021).

sector, irrespective of their new occupation.

The outcomes of future job search and job stability (panels (c) and (d)) complement the previous results. Workers who switch their jobs retaining their manufacturing occupation within the manufacturing sector show the smallest effects on days in employment. On average, they are approximately employed 10 days less in each of the two years following the layoff (as compared to a situation in which the worker is not affected by a layoff). Workers who either switch sectors or switch their occupation experience significantly larger effects. Workers switching to a service occupation in the manufacturing sector and workers switching to a manufacturing occupation in the service sector experience similar effects; on average they are approximately employed 30 to 40 days less in each of the two years after the layoff. Workers who take up a service occupation in the service sector show about 50 days less in employment. From the third year after the layoff, the treatment effects on the days in employment decrease remarkably for all kinds of switchers. The picture for the number of employers shows the same pattern.



(a) Log wage

(b) Yearly income

(c) Days employed

(d) Number of employers

Figure 3.7: Regression results of coefficient γ_k from Equation (3.3)

The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event. Horizontal lines show the average treatment effect for the 10 years post layoff. The sample is restricted to only laid-off workers. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

3.5.2.2 Treatment effects of a layoff – difference-in-difference design

The event study without control group is illustrative to assess the effect of becoming laid off. However, it does not directly allow us to infer treatment effects on the treated. For more detailed and more accurate estimates of the treatment effect, we construct a control group from workers that do not become laid-off but show the same propensity to becoming laid-off within narrowly defined occupation-industry cells per year.

More specifically, we build the control group from the set of workers who, in the year of the layoff, hold the same 3-digit occupation and are employed in the same 2-digit industry as the laid-off workers, but whose employer is not affected by a mass layoff in that year (and ever before). We compute the propensity score of being laid off in the following year with a probit regression using one and two-period lagged wages, tenure length, and the size of the establishment as covariates. Workers are matched according to the nearest neighbor principle and each potential control worker can function as control only once.[39]

Table 3.4 reports basic characteristics of the treatment and control groups in the years immediately before and after the layoff event. The characteristics are remarkably similar for treated and matched control workers – even for characteristics on which we do not condition in the matching procedure.

It is illustrative to consider the trajectories of both, the treatment group (moving to the service sector after layoff) and the control group (matched workers in the same initial occupation and industry remaining at their employer in the manufacturing sector), after a layoff. Figure 3.8, panels (a) and (b) show log daily wages and days in employment relative to the layoff event for laid-off and control workers. Before the layoff event, treatment and control group workers exhibit almost identical wage developments, indicating a well-functioning matching procedure. The same is true for the number of days worked before the mass layoff.

Once workers are laid off, they have to endure a cut in daily wages at their new employer. However, in subsequent years their wages appear to grow faster and by the end of our observation window ten years after the layoff, wages of laid-off and non-laid-off workers are identical again. A similar picture emerges for days in employment. Dismissed workers spent an average of 50 days less in employment, but the values for days in employment converge relative to the ones for the control group as well.

We repeat the exercise for a balanced panel in which we only include workers who we observe for the full 16-year window around the point in time the layoff occurred. In Figure 3.8, panels (c) and (d), we plot unconditional means of log wages and days in active employment for the laid-off workers and their matched, non-laid-off counterparts relative to the treatment time for the balanced panel. Compared to the unbalanced panel, we observe a smaller dip in wages and days employed that both recover almost

[39] See for instance Davis & von Wachter (2011), Schmieder et al. (2020) or Goldschmidt & Schmieder (2017) for similar matching approaches and their application to layoffs.

Table 3.4: Worker characteristics in years $t^* - 1$ and $t^* + 1$ relative to layoff event

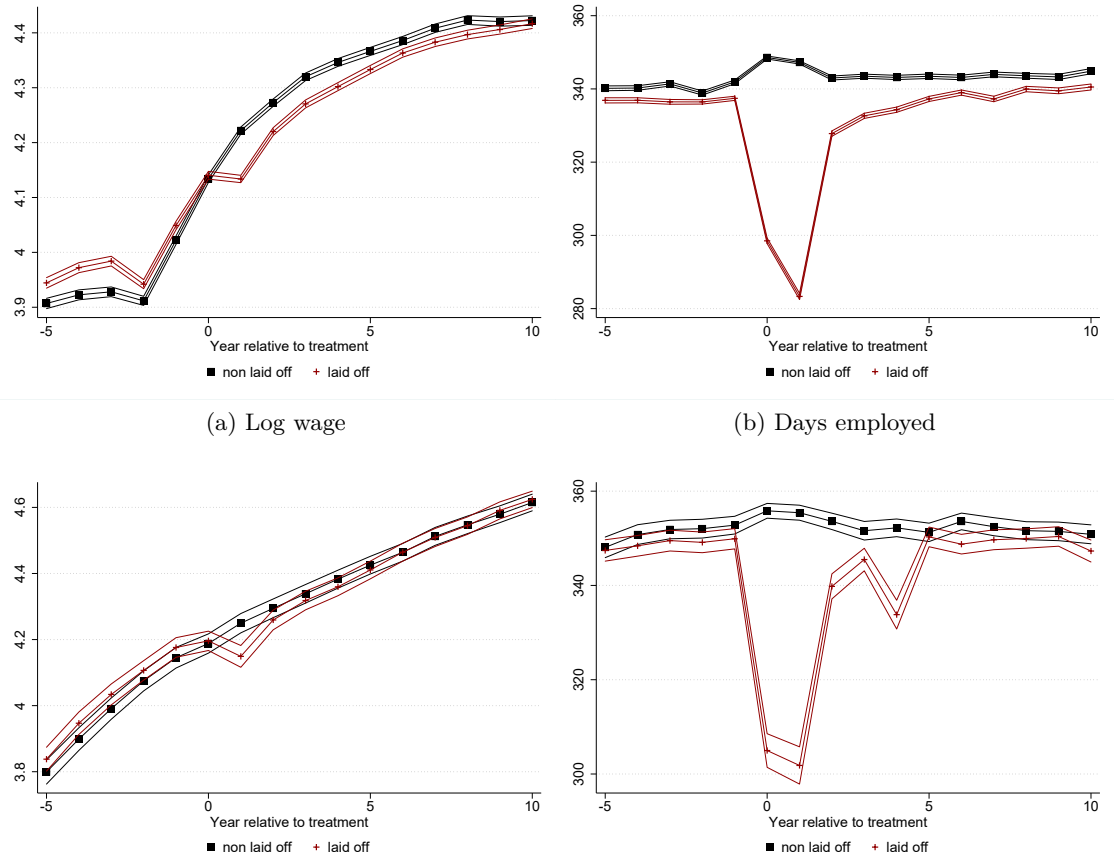
	(1) Full Sample	(2) Laid-off Workers $t^* - 1$	(3) Non-laid-off Workers	(4) Full Sample	(5) Laid-off Workers $t^* + 1$	(6) Non-laid-off Workers
Panel A: Demographics						
Year of birth	1967.1	1967.4	1966.9	1967.1	1967.4	1966.9
	[11.9]	[11.7]	[12.0]	[11.9]	[11.7]	[12.0]
Age	34.9	34.7	35.1	35.9	35.7	36.1
	[10.9]	[10.7]	[11.1]	[10.9]	[10.7]	[11.1]
Sex (0 male, 1 female)	0.2	0.2	0.2	0.2	0.2	0.2
	[0.4]	[0.4]	[0.4]	[0.4]	[0.4]	[0.4]
Years of formal education	10.5	10.4	10.5	10.6	10.5	10.6
	[2.7]	[2.7]	[2.7]	[2.7]	[2.7]	[2.7]
Panel B: Earnings Variables						
Daily wage	69.9	70.0	69.8	74.4	74.4	74.5
	[54.8]	[51.9]	[57.6]	[53.7]	[53.7]	[53.7]
Log wage	4.0	4.0	4.0	4.1	4.1	4.1
	[0.7]	[0.7]	[0.7]	[0.7]	[0.7]	[0.7]
Yearly income of worker	25,123.3	25,041.7	25,203.9	26,202.7	25,407.6	26,987.9
	[19,821.8]	[18,812.1]	[20,770.9]	[19,315.3]	[18,977.6]	[19,611.9]
Lifetime income	228,055	231,120	225,027	253,842	255,611	252,095
	[253.576]	[256.806]	[250,314]	[267,095]	[269,730]	[264,461]
Panel C: Firm Characteristics						
Employment in year	991.6	1,036.8	947.0	967.6	998.3	937.2
	[3,445.4]	[3,641.8]	[3,239.3]	[3,319.2]	[3,528.8]	[3,098.1]
Number of observations	50023	24855	25168	50023	24855	25168

Notes: Average characteristics of individuals, Non-laid-off Workers refers to the matched control group, Full Sample includes both treatment and control group. We report the characteristics in the year before the layoff event occurs. Standard deviations in brackets. Yearly income of worker refers to days worked × daily wage (for all employment spells of a person). Lifetime income is computed as accumulated, deflated income for all years the person is observed.

immediately in year two or three after the layoff.

These unconditional average trajectories of employment outcomes strengthen the conjecture that structural change may not affect workers as strongly as previously perceived. Not only does the service sector offer an alternative employment option for dismissed manufacturing workers, but also the accompanying remuneration cuts are neither severe nor long-lasting. Note though, that these figures neither differentiate between the occupation nor the sector of the new job.

Still, there are potentially confounding factors underlying the trends observed. Since layoff events occur every year, we therefore apply an event study methodology and estimate Equations (3.4) and (3.5) on the full employment histories of the set of laid-off workers and their non-laid-off matched counterparts. We estimate the equations individually for each treatment of $\mathcal{M}$; in Appendix Section B.4.1 we repeat this for the full set



(a) Log wage

(b) Days employed

(c) Log wage – balanced panel

(d) Days employed – balanced panel

Figure 3.8: Workers' outcomes of laid-off and non-laid-off persons relative to layoff time
The figure shows employment outcomes for laid-off and control group workers relative to the mass layoff event. For panels (c) and (d), the sample is restricted to worker pairs (treated and control) who we observe for the full 16-year window around the layoff event. The layoff occurs between June 30 year 0 and June 30 year 1. The matching between laid-off workers and the potential control group takes place in year 0 before the layoff occurs. Datasource: LIAB, 1975-2017.

$\mathcal{M}$ of laid-off workers and their matched counterparts.

$$y_{ijt} = \gamma_\iota \mathbb{1}\{i = \mathcal{M}_\iota\} \times \mathbb{1}\{t \geq t^*\} + \beta_{t^*} \mathbb{1}\{t \geq t^*\} + \alpha_i + \chi_j + \theta_t + X'_{it}\xi + \epsilon_{it}, \tag{3.4}$$

$$\begin{aligned} y_{ijt} = &\sum_{\kappa=-5}^{10} \gamma_{\kappa\iota} \mathbb{1}\{i = \mathcal{M}_\iota\} \times \mathbb{1}\{t = t^* + \kappa\} + \sum_{\kappa=-5}^{10} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} \\ &+ \alpha_i + \chi_j + \theta_t + X'_{it}\xi + \epsilon_{it}, \end{aligned} \tag{3.5}$$

The estimation includes person (α_i), establishment (χ_j), and year (θ_t) fixed effects. $\mathbb{1}\{i = \mathcal{M}_\iota\}$ indicates that worker i is treated according to the ιth element out of the set

of movements, i.e., potential new employment type, of laid-off manufacturing workers in a mass layoff,

$$\mathcal{M} = \left\{ \begin{array}{l} \text{manufacturing occupation at manufacturing establishment,} \\ \text{manufacturing occupation at service establishment,} \\ \text{service occupation at manufacturing establishment,} \\ \text{service occupation at service establishment} \end{array} \right\}.$$

We bin the end points and do not report them. t^* is the year in which a layoff occurs. Note that for the difference-in-difference approach with matching $\mathbb{1}\{t \geq t^*\}$ and $\mathbb{1}\{t = t^* + \kappa\}$ vary also for the matched control-group workers. This methodology results in a difference-in-difference type estimator combined with propensity score matching (c.f., Davis & von Wachter (2011) and Goodman-Bacon (2021)).

The approach allows us to identify the differences between workers' outcomes for workers who lost their job, presumably due to structural change, and for workers in the control group who were not affected by mass layoffs, hence the ATT. The coefficients γ_ι and $\gamma_{\kappa\iota}$ thus measure the difference in the dependent variable on average and for each year κ before and after the layoff occurred between the treatment and control group. The event study allows for the inclusion of other time-varying confounders, X_{it}, age, age^2, and age^3.

Table 3.5 contains the results for the static difference-in-difference estimation (3.4) and Figures 3.9 and 3.10 (as well as 3.11, 3.12 in the Appendix) for the dynamic difference-in-difference estimation (3.5).

We contrast relative employment trajectories across the four transition types after being laid off for the four outcomes introduced above. Column (1) of Table 3.5 and Figure 3.11 show that effects on future wages depend heavily on the future occupation-sector combination the worker manages to obtain. Workers who find new employment in a manufacturing occupation in the manufacturing sector even experience an increase in future wages of on average 0.7%. All other transitions show negative treatment effects, but these vary greatly depending on the transition. Workers who find a new job in an manufacturing occupation in the service sector show a less strong wage cut as compared to workers who find new employment in a service occupation in the manufacturing sector. Nevertheless, the treatment effects of these two transition types are in a similar range and divert strongly from the large effect on wages for workers taking up a service occupation in the service sector following the layoff. Workers switching to a manufacturing occupation in the service sector lose about 2.8% in wage levels, workers with a new job with service occupation in manufacturing industries lose 3.8%, whereas those workers transitioning to a service occupation in services experience a wage cut of about 12%.

Similar figures emerge for accumulated income (column (3) of Table 3.5 and Figure 3.12). It increases by about 500 euros for workers transitioning to a manufacturing occupation in manufacturing industries. It falls for the other transition types, again

with similar ranges for new manufacturing occupations in services and for new service occupation in manufacturing (even though the former is not statistically significant from zero) – we observe a decline of 490 euros and 520 euros, respectively. Again, workers transitioning to service occupations in the service sector are hit hardest by the layoff. They lose about 3,000 euros in accumulated income.

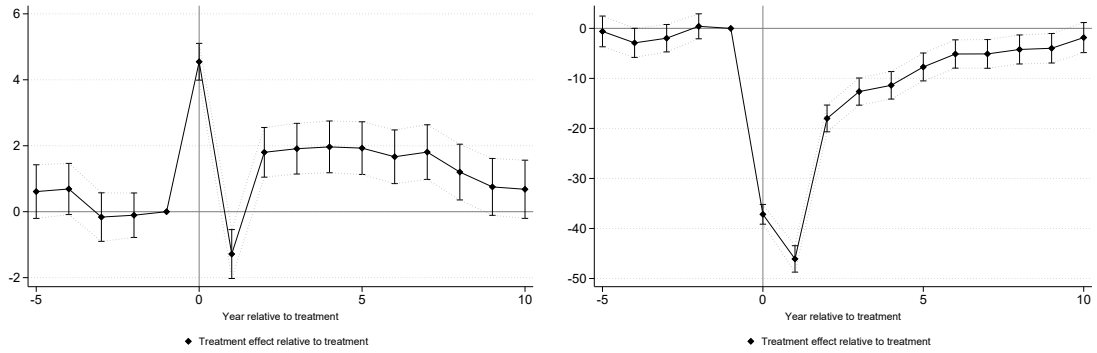
For the remaining indicators, we refer to the dynamic estimation because treatment effects are showing dynamic paths. Results are presented in Figures 3.9 and 3.10. Figure 3.9 shows results on the days in employment, hence indicating search periods after becoming laid off. As before, workers who find new employment in manufacturing occupations in manufacturing show the shortest search periods, even with a slight increase in days employed per year (panel (a)). Workers transitioning to a new employer in the manufacturing sector but switching occupation type have also rather short search periods (panel (c)). Workers with new employment in a manufacturing occupation in the service sector search for longer but for the benefit of retaining a manufacturing occupation, presumably retaining much human capital (panel (b)). Longest search periods are shown by workers transitioning to a service occupation in services. Presumably, these workers searched for new jobs with similar features as their old jobs but were unable to find such an opening and after a search period they settled on an apparently less attractive job with new occupation at a very different employer, i.e., in the service sector.

In comparison to the evidence from Section 3.4.3, this exercise highlights that the unconditional wage differences and wage differences observed when including individually triggered job to job transitions are driven by other factors than wage differences across occupations between the sectors.

Table 3.5: Results: Difference-in-difference with matching – sample restricted to one treatment only

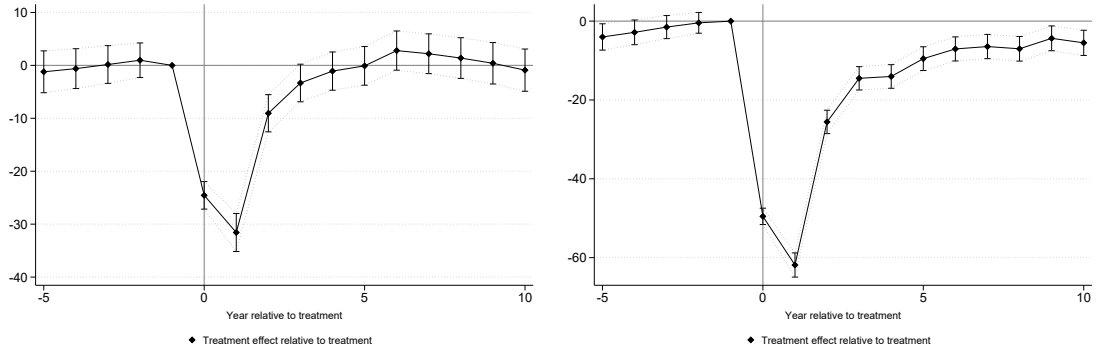
	(1) log(wage)	(2) Number of employers	(3) Yearly income	(4) Number of days worked
Panel A: Switch to manufacturing occupation in manufacturing sector				
γ	0.00679***	0.02671***	522.58***	-0.07638***
	(0.00095)	(0.00055)	(52.87)	(0.15292)
N	3,213,428	3,225,057	3,225,057	3,225,057
R^2	0.48	0.17	0.18	0.02
Panel B: Switch to service occupation in manufacturing sector				
γ	-0.03798***	0.02829***	-521.23	-0.31213
	(0.00532)	(0.00273)	(319.46)	(0.78041)
N	133,587	134,072	134,072	134,072
R^2	0.41	0.13	0.15	0.02
Panel C: Switch to manufacturing occupation in service sector				
γ	-0.02770***	0.04501***	-488.06**	-1.8055***
	(0.00431)	(0.00241)	(246.75)	(0.69276)
N	252,269	253,103	253,103	253,103
R^2	0.47	0.09	0.17	0.02
Panel D: Switch to service occupation in service sector				
γ	-0.12065***	0.03651***	-3022.05***	1.31361*
	(0.00484)	(0.00240)	(202.00)	(0.74917)
N	248,344	249,469	249,469	249,469
R^2	0.35	0.07	0.14	0.02

Notes: The table reports regression results of the the difference-in-difference terms γ of Equation (3.4). Standard errors are clustered at the individual level. Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.



(a) Manufacturing occ. in manufacturing sector

(b) Manufacturing occ. in service sector

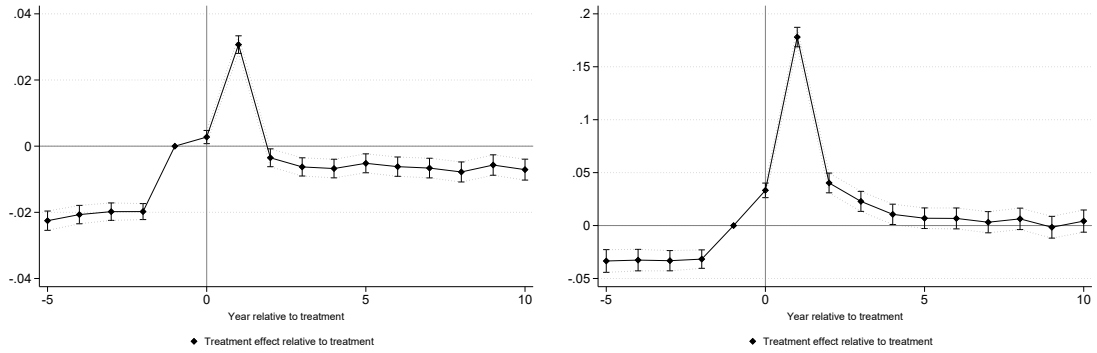


(c) Service occ. in manufacturing sector

(d) Service occ. in service sector

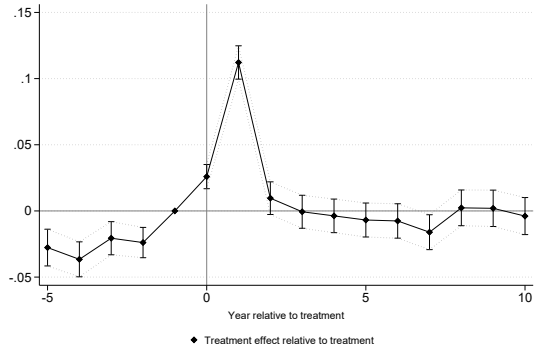
Figure 3.9: Difference in difference estimation with matching by treatment – days in employment

The figure plots coefficients $\gamma_{\kappa\iota}$ relative to the mass layoff event by treatment. Each regression is run only on the sample of treated workers within the respective transition group and their matches. Horizontal lines show the average treatment effect for the 10 years post layoff. The matching between laid-off workers and the potential control group takes place in year 0 before the layoff occurs. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

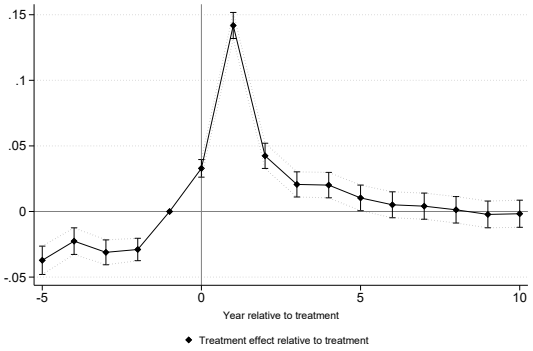


(a) Manufacturing occ. in manufacturing sector

(b) Manufacturing occ. in service sector



(c) Service occ. in manufacturing sector



(d) Service occ. in service sector

Figure 3.10: Difference in difference estimation with matching by treatment – number of employers

The figure plots coefficients $\gamma_{\kappa\iota}$ relative to the mass layoff event by treatment. Each regression is run only on the sample of treated workers within the respective transition group and their matches. Horizontal lines show the average treatment effect for the 10 years post layoff. The matching between laid-off workers and the potential control group takes place in year 0 before the layoff occurs. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

Discussion: Sector or occupation – what is behind the strong effects on employment outcomes?

Our analysis complements related contemporary research on the impact of displacements on workers biographies. Relying on similar methodologies several papers study job transitions after mass layoffs. For instance, Davis & von Wachter (2011) show that transitions are more difficult and accompanied by larger earnings losses in recessions, Dauth, Findeisen & Südekum (2021) discuss adjustments in light of increasing globalization and labor competition from low wage countries, Blien et al. (2020) differentiate by routine intensity. Here, however, we neither take a stance on the cause for the mass-layoff nor on the general economic environment (except controlling for year effects). The contribution rather shows that occupation specific human capital is important in determining job prospects. But also the sector of employment is important since the service sector in general pays lower wages irrespective of the occupation.

In fact, we can compare average treatment effects across the different new occupation-sector employment types after becoming laid-off. From Table 3.5 it becomes clear that both the occupation and the sector in which workers are employed matter for their outcomes. However, when we compare the treatment effects across new employment types where only one characteristic changes with respect to the job prior to the layoff, i.e., effects reported in Panels B and C, we observe that to change industries but to retain a manufacturing occupation hurts workers less in terms of pecuniary outcomes than to change occupations but to remain in the manufacturing sector. Accordingly, we show that a sector switch leads to lower losses than an occupation switch, however, the difference in the treatment effects is small.[40]

In summary, the exercises in this section show that workers with manufacturing occupations do indeed find new employment in the service sector when displaced in an exogenous layoff event. A sizeable proportion of these manages to retain their initial occupation, which is beneficial for future employment trajectories. We can thus conclude that while there is structural change at the aggregate level, i.e., declining total employment in manufacturing industries, workers directly affected by this trend are not necessarily hit as hard as commonly perceived. They can rely on an increasing number of employment options in the service sector that require similar knowledge and skills as their previous jobs in the manufacturing sector. Switching to these outside employment options is associated with only moderate wage penalties.

3.6 Conclusion

In light of increasing concerns about rapidly shrinking manufacturing employment, this paper seeks to raise awareness of the limitations of commonly used employment

[40]The result that the occupation is more important for workers' outcomes than the industry, or in our context, sector, after a displacement confirms what previous studies for different contexts already indicated, e.g., Moscarini & Thomsson (2007).

measurements based on the industry classification of the firm or establishment. We use the occupation of the worker as a measurement for structural change instead and straighten out some relevant facts.

We show that structural change in Germany is significantly lower if the measurement is based on the occupation of the workers. While total employment in the manufacturing sector is shrinking, about 52% of manufacturing jobs that were lost in manufacturing industries between 1975 and 2017 are replaced by new manufacturing jobs in service industries. In 2017, the number of workers with manufacturing occupations in manufacturing industries is only about 1.3 times greater than the number of workers with manufacturing jobs in service industries, whereas this factor was 3 in 1975.

Numbers derived from measuring employment types according to the industry classification of the establishment can deviate enormously from the numbers based on the actual occupation of the workers. Both service and, in particular, manufacturing occupations are found in large numbers in establishments of the opposite category. The implications are critical for empirical research such as assessing the impact of shocks on the labor market, especially on types of employment such as manufacturing. This is evident when we assess the effect of international trade, especially import competition, on employment in manufacturing occupations. In this application, import exposure has no effect on employment in manufacturing occupations. Combined with the negative effect of import exposure on total employment in manufacturing industries, (Dauth et al. 2014), this implies that service industries are able to mitigate these effects by hiring substantial shares of the affected workers.

In line with this claim, we document that 40 to 60% of new manufacturing jobs in the service sector are filled by workers that were previously holding a manufacturing occupation in the manufacturing sector. We then assess the labor market consequences at the worker-level by exploiting mass layoff events in the manufacturing sector. A sizeable proportion of affected workers switches to the service sector while retaining their initial manufacturing occupation. For these workers, labor market consequences are fairly moderate overall. On average, they experience a decline in yearly income of approximately 490 euros.

The exercise highlights that the service sector offers an alternative employment option for dismissed manufacturing workers. Not only do we document that workers with manufacturing occupations switch from the manufacturing to the service sector in large numbers, we also show that the accompanying remuneration cuts are moderate and decreasing over time. Our exercise also shows that a clear separation between service and manufacturing based on the industry affiliation is becoming more and more difficult, in particular, when the focus lies on consequences for individual employees. Instead, the boundaries between the two categories are blurring, as the service sector is increasingly employing workers with manufacturing occupations, and vice versa, workers with service occupations are increasingly finding jobs in manufacturing industries.

Our findings call for a rethink of the way we measure structural change and classify employment in general. Of course, our findings also have important implications for numerous policy applications beyond the evaluation of structural change and its causes, e.g., when considering the preparation or evaluation of labor market policies and reforms.

This paper opens up an important area for future research. For instance, it would be crucial to check whether, apart from trade exposure covered in this paper, the influence of other drivers of structural change, such as digitalization or robotization, have similar differentiated effects on workers with manufacturing occupations and on total employment in the manufacturing sector.

The present paper stresses that structural change and particularly declining employment in the manufacturing sector needs to be assessed in a differentiated manner. Due to the overall growth of the service sector and the manufacturing occupations needed in the service sector, this sector provides a valuable alternative employment option for workers with manufacturing occupations. By focusing on mass layoffs, our exercise captures primarily involuntary switches. Workers that switch from the manufacturing to the service sector voluntarily due to better job opportunities are not covered. In that sense, it seems plausible to assume that our results represent an upper bound for the costs of switching sectors; the real average economic costs are likely to be lower.

Income losses and other labor market outcomes are similar for workers that, after being displaced, retain a manufacturing occupation irrespective of finding a new job in the manufacturing or the service sector. Accordingly, human capital seems to be firm-specific rather than industry-specific as the wage cut accompanying a switch in employment after a layoff is independent of the sector of the new employer. Industry-specific human capital thus appears to have little impact on workers' remuneration if they have to change employers.

B Appendix

B.1 Additional Data Description

B.1.1 Processing of the employer-employee data

The reporting requirements of the Federal Employment Agency were altered during the observation period, which influences data precision. In 1999 marginal part-time workers were integrated into the notification procedure. This led to an increase in covered establishments, because the threshold for reporting was lowered to one part-time worker per establishment, and additionally overall worker numbers increased per establishment. We report in this section how we adjust the data to cope with this break in the reporting procedure.

In the data, the selection of the population of establishments in the BHP and the LIAB might be biased twofold: First, from 1992 onwards establishments in East Germany are included. We simply exclude them in our analysis for West Germany. Second, in 1999 marginal part-time workers were integrated into the notification procedure. On the one hand, this leads to a rise in the number of establishments covered in the dataset. Before, only establishments with at least one full-time employee subject to social security were reported, whereas from 1999 onwards one part time employee is a sufficient condition to be subject to reporting. We adjust for this bias by dropping these additional establishments. On the other hand, the inclusion of marginal part-time workers affects employment figures for establishments already subject to reporting (with at least one full-time employee). After the change in the reporting procedure, establishment-level employment figures now include both part-time and full-time workers. The BHP does not allow any adjustment for this bias. For every establishment, the total number of full and part-time workers is provided, but for other employment data such as the Blossfeld occupational categories, there is no distinction between the two categories. Nevertheless, to create a consistent and unbiased dataset despite changes in the reporting procedure, we make use of the individual worker-level data provided by the LIAB. For every worker, the data contain the full or part-time status as well as the classification of jobs under the German occupational classification scheme issued in 1988 (KldB88). Using a crosswalk between the KldB88 and the Blossfeld occupational categories provided by Stops (2016), we reclassify the data. Aggregating the data to the national level, we obtain information about the distribution of part-time workers across Blossfeld occupational categories. This information allows us to clean the BHP by subtracting part-time workers from the sample and also by adjusting for the reporting procedure bias within reporting establishments.

B.1.2 Occupational categories

Table 3.6: Occupational classification of Blossfeld (1987)

Name of Occupational Group	Description of the Occupational Group	Examples
Manufacturing		
Agricultural occupations (agr)	Occupations with predominantly agricultural orientation	Farmers, agricultural workers, gardeners, fishermen
Unskilled manual occupations (emb)	All manual occupations with at least 60 percent unskilled workers in 1970	Miners, rock breakers, paper makers, wood industry occupations, printing occupations, road and rail-road construction workers
Medium-skilled manual occupations (qmb)	All manual occupations with at most 40 percent unskilled workers in 1970	Glassblowers, bookbinders, typesetters, locksmiths, precision instrument makers, electrical mechanics, coopers, brewers
Technicians (tec)	All technically trained specialists	Machinery technicians, electrical technicians, construction technicians, mining technicians
Engineers (ing)	Highly trained specialists who solve technical and natural science problems	Construction engineers, electrical engineers, production designers, chemical engineers, physicists, mathematicians
Service		
Unskilled services (edi)	All unskilled personal services	Cleaners, security guards
Medium-skilled services (qdi)	Essentially order and security occupations as well as skilled service occupations	Locomotive engineers, registrars
Semiprofessions (semi)	Service positions which are characterized by professional specialization	Interpreters, educators
Professions (prof)	All liberal professions and service positions which require a university degree	Statisticians, economists, social scientists
Service (administration)		
Unskilled commercial and administrational occupations (evb)	Relatively unskilled office and commercial occupations	Postal occupations, office hands, typists
Medium-skilled commercial and administrational occupations (qvb)	Occupations with medium and higher administrative and distributive functions	Credit and financial assistants, foreign trade assistants, data processing operators, bookkeepers, goods traffic assistants
Managers (man)	Occupations which control factors of production as well as functionaries of organizations	Managers, business administrators, deputies, CEOs

Table 3.7: Exemplary occupational hierarchy according to KldB2010 scheme

KldB2010 4-digit	
43	Informatics-, information- and communication technology occupations
431	Informatics
432	IT system analysis, IT consultancy and IT distribution
4321	Occupations in IT system analysis
4322	Occupations in IT consultancy
43223	Occupations in IT consultancy - complex specialists
43224	Occupations in IT consultancy - highly complex specialists
4323	Occupations in IT distribution
4329	Executive personnel – IT system analysis , IT consultancy and IT distribution

B.2 Additional results

Table 3.8 displays the average distribution of manufacturing and service occupations within sectors and within the economy as a whole. The table highlights where the conventional wisdom comes from that somewhat bluntly equates industry classification of employers with workers' occupations. It shows the share of workers with manufacturing and service occupations within the manufacturing and the service sector (columns headed "within sector") and the share of the occupation-sector pair in the total economy (columns headed "in total") as simple average over all years – therefor not taking into account the time trends emphasized in the main part of the paper. Indeed, the average within-sector distribution shows that the majority of workers in manufacturing industries hold manufacturing occupations (71%) and the majority of workers in service industries hold service occupations (81%) but the table also shows that the distribution of in particular manufacturing occupations in the total economy is more equal. Only about two thirds ($\frac{25\%}{37\%}$) of workers that hold manufacturing occupations are employed in the manufacturing sector and in the main part of the paper we show that this share exhibits a clear, almost linear, decreasing trend over the last 43 years. The table thus makes clear once again that simply equating sector classifications with worker traits, i.e., occupations and tasks performed or more generally human capital, is not sensible for a variety of applications and research and policy questions.

Table 3.8: Occupation shares within sectors and in total economy – average across 1975-2017

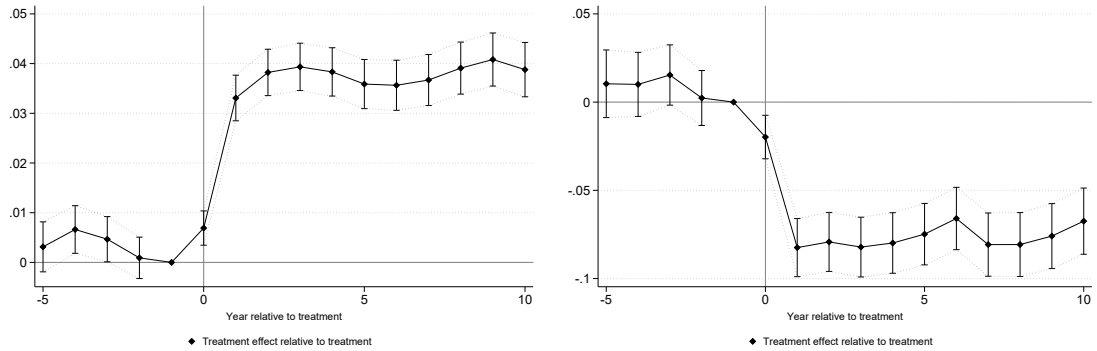
	Manufacturing sector		Service sector		Economy
	within sector	in total	within sector	in total	
manufacturing occupations	70.98%	25.02%	18.97%	12.28%	37.3%
service occupations	29.02%	10.23%	81.03%	52.48%	62.7%

Notes: The table shows the average distribution of occupation types within sectors and within the total economy over time. Data: BHP

Table 3.9: Wage penalty of working in the service sector for occupation-hierarchy groups of manufacturing occupations

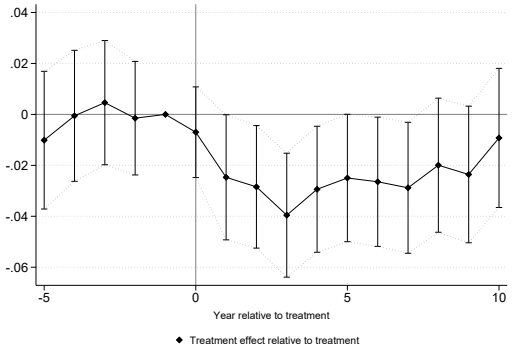
Occupation	(1) Coefficient	(2) Std. error	(3) Number of observations	(4) R^2 (within)
Stone workers	-0.0495	(0.057)	17841	0.5
Building materials manufacturer	-0.111***	(0.000)	24633	0.463
Ceramist	-0.339***	(0.000)	27726	0.623
Glassmaker	-0.167***	(0.000)	51344	0.672
Chemical workers	-0.0548***	(0.000)	285378	0.642
Plastics processor	-0.216***	(0.000)	159024	0.54
Paper manufacturers and processors	-0.00807	(0.388)	66244	0.6
Printer	-0.0702***	(0.000)	78127	0.629
Wood processor and manufacturer	-0.259***	(0.000)	75559	0.497
Metal producers	-0.0260***	(0.001)	229277	0.782
Moulders, molding casters	-0.514***	(0.000)	86152	0.621
Metal deformers (non-cutting)	-0.393***	(0.000)	168890	0.509
Metal deformers (cutting)	-0.392***	(0.000)	320768	0.690
Metal surface processing, coating and coating	-0.222***	(0.000)	65591	0.654
Metal connectors	-0.320***	(0.000)	115895	0.568
Smiths	-0.127***	(0.000)	39464	0.609
Sheet metal workers, installers	-0.204***	(0.000)	372160	0.660
Locksmiths	-0.228***	(0.388)	1020913	0.706
Mechanics	-0.424***	(0.000)	710124	0.752
Toolmakers	-0.276***	(0.000)	216824	0.772
Metalworkers	0.0325**	(0.004)	40470	0.525
Electricians	-0.153***	(0.000)	836053	0.732
Assemblers and metal professions	-0.394***	(0.000)	534752	0.574
Spinning professions	-0.352***	(0.000)	24677	0.649
Textile manufacturers	-0.0895***	(0.000)	29440	0.592
Textile processors	-0.0482***	(0.000)	62509	0.461
Textile finishers	-0.00943	(0.643)	16848	0.541
Leather manufacturers, leather and fur processors	-0.0673***	(0.000)	25548	0.513
Bakery, confectionery manufacturers	-0.0385***	(0.000)	92356	0.615
Meat, fish processors	0.0761***	(0.000)	108267	0.585
Food processors	-0.204***	(0.000)	292126	0.472
Beverage and luxury goods manufacturers	-0.0845**	(0.003)	15646	0.610
Other nutritional professions	-0.0909***	(0.000)	131942	0.524
Bricklayer, concrete workers	-0.199***	(0.000)	230537	0.536
Carpenters, roofers, scaffolders	-0.189***	(0.000)	99707	0.475
Road and civil engineering occupations	-0.0936***	(0.000)	114007	0.537
Construction workers	-0.0912***	(0.000)	123112	0.321
Building outfitters	-0.210***	(0.000)	73389	0.445
Interior decorators, upholsterers	-0.0466***	(0.000)	50357	0.547
Carpenter, model makers	-0.0959***	(0.000)	195730	0.62
Painter, painter and allied professions	-0.306***	(0.000)	262979	0.614
Inspectors, dispatchers	-0.179***	(0.000)	393549	0.619
Auxiliary workers without detailed job description	-0.493***	(0.000)	554851	0.479
Machinists and related professions	-0.259***	(0.000)	428841	0.57
Engineers	-0.130***	(0.000)	887904	0.546
Technicians	-0.108***	(0.000)	945273	0.617
Technical specialists	-0.0357***	(0.000)	299636	0.716

Notes: The table reports the estimation results of coefficient γ of Equation (3.2) for 2-digit occupations. Standard errors clustered at worker level and reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Datasource: LIAB, 1975-2017.

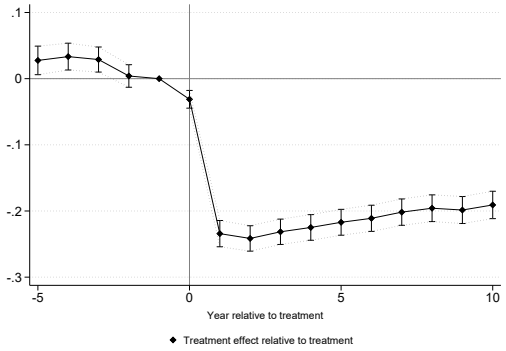


(a) Manufacturing occ. in manufacturing sector

(b) Manufacturing occ. in service sector



(c) Service occ. in manufacturing sector



(d) Service occ. in service sector

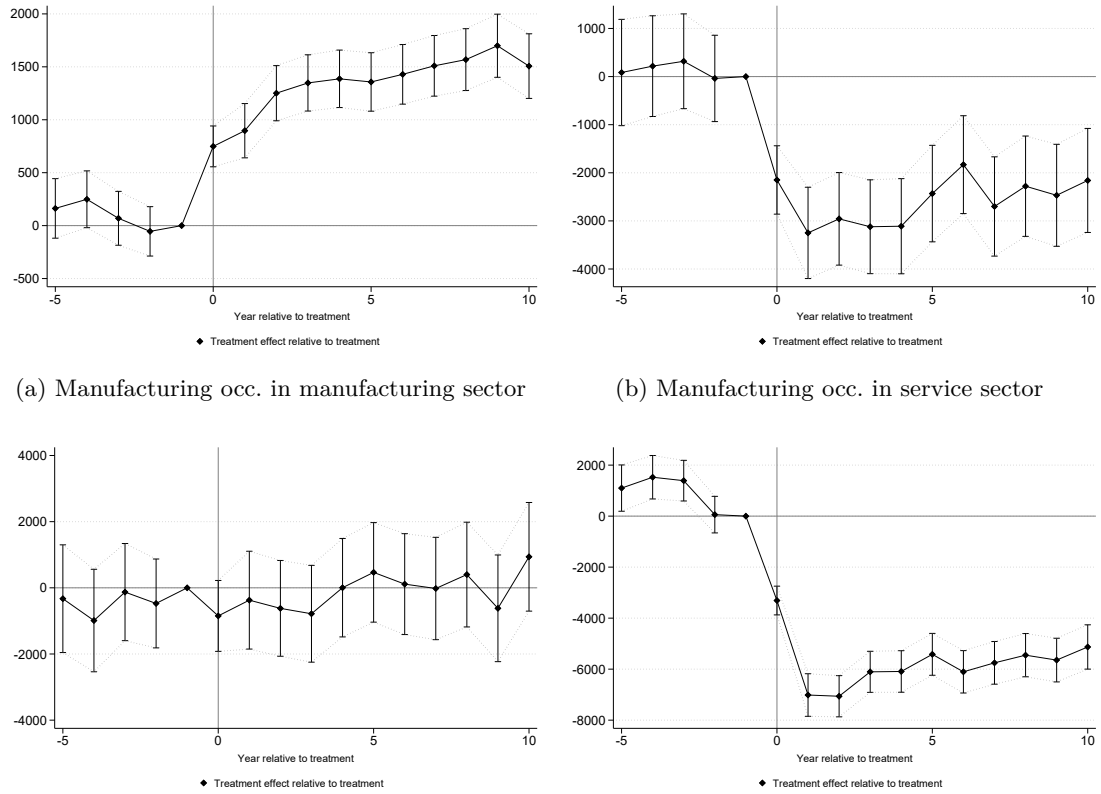
Figure 3.11: Difference in difference estimation with matching by treatment – log(wage)
The figure plots coefficients $\gamma_{\kappa\iota}$ relative to the mass layoff event by treatment. Each regression is run only on the sample of treated workers within the respective transition group and their matches. Horizontal lines show the average treatment effect for the 10 years post layoff. The matching between laid-off workers and the potential control group takes place in year 0 before the layoff occurs. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

B.3 Entering, Exiting, and Switching Establishments

In this section, we test if our findings are driven by purely technical reasons such as changes in the sample composition, i.e., by establishments entering or exiting the sample, or by establishments switching industries. We find that our results are almost completely explained by changes over time in the occupational structure of the establishments. The impact of occupation and workplace switchers and also the impact of technical reasons such as the reclassification of establishments are largely negligible. The same holds true for the impact of establishments entering or exiting the sample.

B.3.1 Entering and Exiting Establishments

First, we check if our findings are driven by changes in the sample composition or by adjustments of the occupational structure within establishments, i.e., by the extensive or intensive margin of employment. Both, establishment entries and exits, could



(a) Manufacturing occ. in manufacturing sector

(b) Manufacturing occ. in service sector

(c) Service occ. in manufacturing sector

(d) Service occ. in service sector

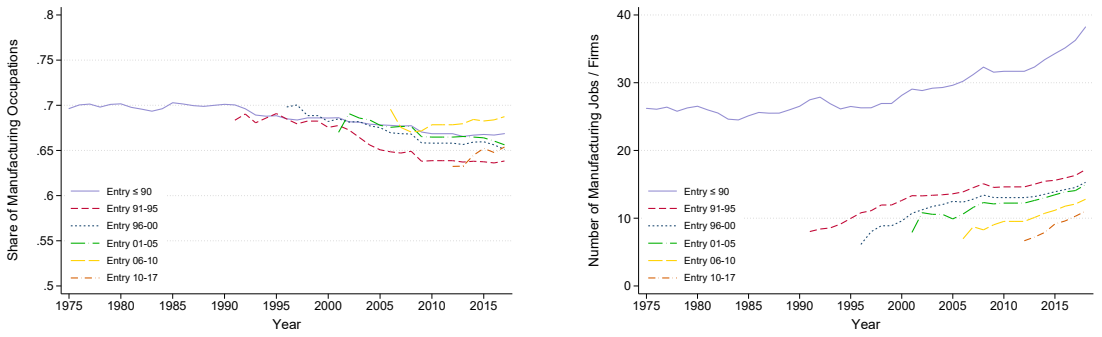
Figure 3.12: Difference in difference estimation with matching by treatment – yearly accumulated income

The figure plots coefficients $\gamma_{\kappa\iota}$ relative to the mass layoff event by treatment. Each regression is run only on the sample of treated workers within the respective transition group and their matches. Horizontal lines show the average treatment effect for the 10 years post layoff. The matching between laid-off workers and the potential control group takes place in year 0 before the layoff occurs. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

potentially drive the results if the service shares of entering or exiting establishments differed significantly from that of "old establishments" that were already in the sample in the previous years. It may be that new establishments cumulatively have a greater impact on our results over the years. It is possible that establishments that entered the market later will develop differently from those that have been in the market for a long time. We thus compare the average occupational employment structure of newly entered establishments with that of old establishments. Again, the outcome tells us whether our findings are driven by adjustments within establishments or through different occupational structures in newly entered establishments. We show the average share of manufacturing occupations in manufacturing industries (3.13) and service industries (3.14), respectively, for five periods in which the establishments first entered the market. The base period covers all establishments that first entered before 1991. The other periods cover five years each (1991-1995, 1996-2000, 2001-2005, 2006-2010). The data

make apparent that the results are not driven by changes in the sample composition, i.e., by new establishments with a much lower manufacturing share entering the sample. Instead, our results are evidently driven by adjustments within existing establishments. Figure 3.13 shows that the initial average manufacturing share of establishments that were first part of our sample before 1991 was considerably higher than the initial average share of all following periods. However, the average share of manufacturing occupations for these establishments is continuously decreasing such that the average manufacturing share of the original establishments is in similar ranges as the average initial manufacturing share of new establishments. Interestingly, the general trend is identical for all establishments independent from the period in which they first entered. The average share of manufacturing occupations is always highest after entering the market and then shrinks continuously over time. The data confirms that increasing servitization is triggered by changes in the occupational structure at the establishment level. Interestingly, for the service sector the average initial manufacturing share is very similar for all firms entering the sample in any of the five periods with exception of the first period. This if at all counters increasing servitization in the aggregate if entering establishments have lower service shares than incumbents. After entering the sample, the general trend of decreasing average shares of manufacturing occupations is identical for all establishments independent from the period in which they first entered. The picture is similar when we consider establishments that leave the sample.

This section confirms that our results are hardly driven by the extensive margin. Rather, technical or other developments affect all establishments and the labor composition is adjusted over time.



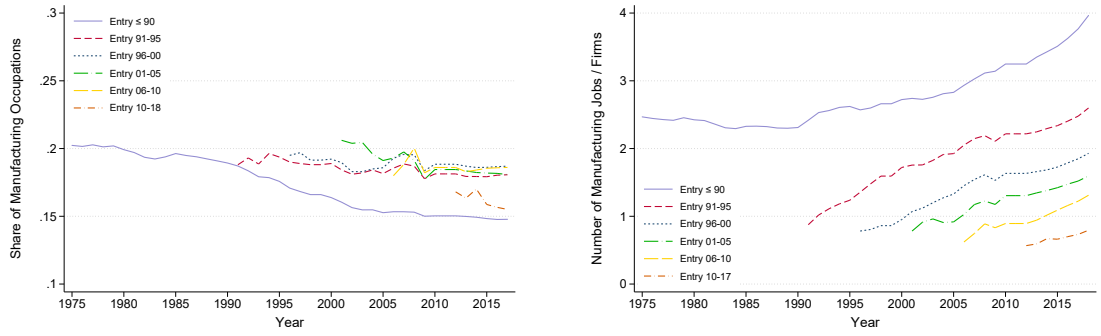
(a) Share mfg occupations

(b) Avg. number of mfg occupations

Figure 3.13: Establishment entrants' labor force composition: Manufacturing sector
Datasource: BHP

B.3.2 Reclassification - Switching Establishments and Workers

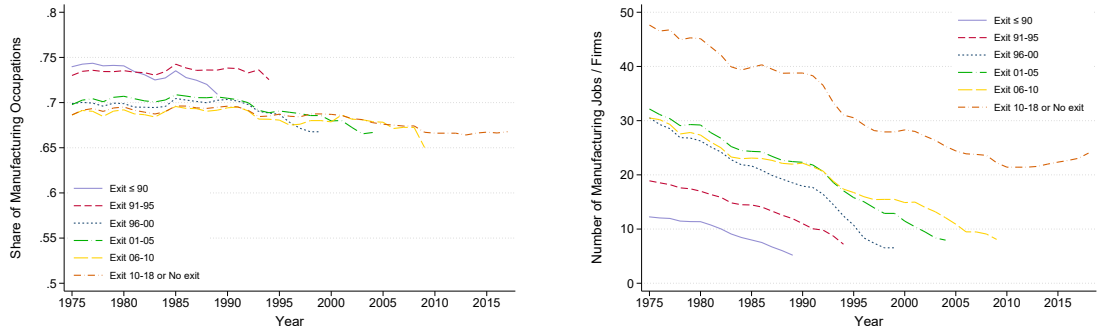
As previously mentioned, the industry classification of establishments follows the economic focus of the establishment, which depends on the purpose of the establishment



(a) Share mfg occupations

(b) Avg. number of mfg occupations

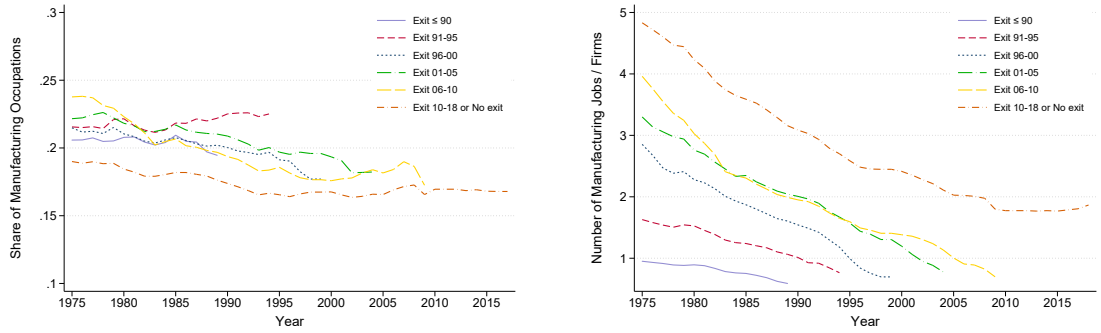
Figure 3.14: Establishment entrants' labor force composition: Service sector
Datasource: BHP



(a) Share mfg occupations

(b) Avg. number of mfg occupations

Figure 3.15: Establishment exiters' labor force composition: Manufacturing sector
Datasource: BHP



(a) Share mfg occupations

(b) Avg. number of mfg occupations

Figure 3.16: Establishment exiters' labor force composition: Service sector
Datasource: BHP

or economic activity of the majority of the employees. Accordingly, the classification may

change over time, if the focus of the establishment shifts.[41] Bernard et al. (2017) report for Denmark on average a share of 1.6% of manufacturing firms switching to service industries and a share of 1.1% of service firms switching to manufacturing. They find that switchers have a significant impact on industry employment: During the 2002 to 2007 period, 10% of the manufacturing firms switched industries from manufacturing to services which accounted for a substantial 42% of job losses in manufacturing.

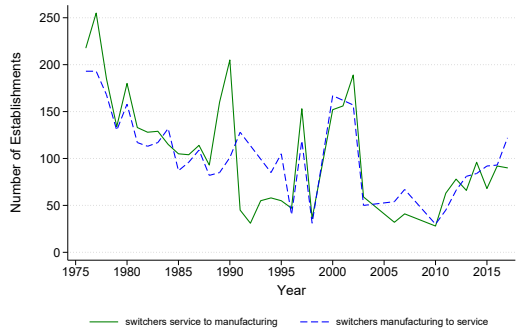
In our analysis, we cannot confirm those findings for Germany. Both the number of establishments switching the sector as well as the number of affected workers is negligible.[42] Figure 3.17a shows the number of establishments that switch from manufacturing to services (blue line) and from services to manufacturing (green line) for the 1975 to 2017 period based on BHP data. The number of switchers in both directions follows a very similar development over time. During the 40 years of observation, an average yearly number of 178 establishments switches industries, which accounts for less than 0.0002% of the total number of establishments. The picture looks very similar for the number of workers of the switching establishments (Figure 3.17b). Again, the number of workers whose establishment switches from services to manufacturing is very similar to that of the workers whose establishment switches from manufacturing to services. On average, a yearly share of 0.0003% of the population of workers is affected by switchers. Contrary to Bernard et al. (2017), the switchers do not account for manufacturing job losses. In fact, the switcher balance is even positive for manufacturing, with manufacturing employment increasing by a (negligible) net amount of 4,395 workers over the 40 years of observation. Switchers also play no role in increasing servitization.

Figure 3.18 breaks down the number of workers of switching establishments by service and manufacturing occupations. Again, the number of both workers holding service occupations and workers holding manufacturing occupations whose establishments switch from services to manufacturing and vice versa is about the same. Thus on average, a yearly net amount of around 262 workers with manufacturing occupations move from services to manufacturing industries, and a yearly net amount of 152 workers with service occupations move from manufacturing to service industries as a result of establishments switching their industries. In this respect, switchers generally have an influence that counteracts the servitization of establishments in manufacturing. However, the switcher effects are so small that they can be neglected.

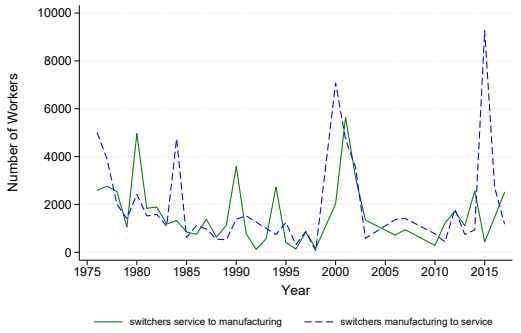
A likely reason for the differences in the importance of switchers between our paper and that of Bernard et al. (2017) is that we look at establishments while Bernard et al. (2017) focus on firms. On the one hand, of course, there is a greater likelihood that the

[41] One such example is IBM corporation. Starting as a traditional hardware manufacturer, IBM increasingly focused on the provision of customer services from the 1990s onwards (see Ahamed et al. (2013)). In 1990, IBM's service segment only accounted for approximately 16% in total revenues, whereas it reached a share of 63% in 2017 (Spohrer 2017). Eventually, IBM was reclassified to a service firm after a particular threshold was met.

[42] We also look at the impact from employees changing occupations while staying with the same employer, but cannot find newsworthy effects.

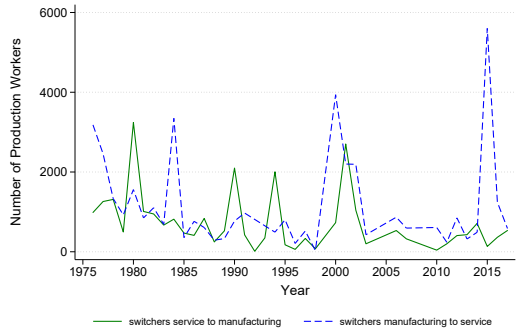


(a) Number of establishments switching sector classification

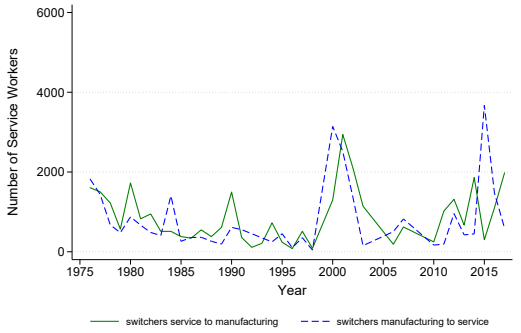


(b) Number of workers in sector switching establishments

Figure 3.17: Establishments switching sector classification and workers therein
Datasource: BHP 1975-2017



(a) Workers with manufacturing occupations



(b) Workers with service occupations

Figure 3.18: Workers in classification switchers by type
Datasource: BHP 1975-2017

industry will change at the firm level than at the establishment level. On the other hand, it is especially the large firms that would have to be subject to a change in the industry classification to gain a significant impact on our measurements. However, it is precisely the large firms, which often consist of different establishments that are subdivided according to economic focus. These firms would thus not show an industry switch at the establishment level, but only at the firm level. Again, this discussion highlights that the misspecification in the use of firms as a basis for the division of manufacturing and service employment is most likely much higher as compared to the use of establishments.

B.4 Robustness

B.4.1 Dynamic event study by individual treatment

$$y_{ijt} = \sum_{\kappa=-5}^{10} \sum_{\iota=1}^{4} \gamma_{\kappa\iota} \mathbb{1}\{t = t^* + \kappa\} \times \mathbb{1}\{i = \mathcal{M}_\iota\} + \sum_{\kappa=-5}^{10} \beta_\kappa \mathbb{1}\{t = t^* + \kappa\} + \alpha_i + \chi_j + \theta_t + X'_{it}\xi + \epsilon_{it}, \tag{3.6}$$

The estimation includes person (α_i), establishment (χ_j), and year (θ_t) fixed effects, as well as time varying person characteristics (X'_{it}). $\mathcal{M}_\iota$ indicates the ιth element out of the set of movements, i.e., potential new employment type, of laid-off manufacturing workers in a mass layoff,

$$\mathcal{M} = \left\{ \begin{array}{l} \text{manufacturing occupation at manufacturing establishment,} \\ \text{manufacturing occupation at service establishment,} \\ \text{service occupation at manufacturing establishment,} \\ \text{service occupation at service establishment} \end{array} \right\}.$$

We bin the end points and do not report them. t^* is the year in which a layoff occurs. Note that for the difference-in-difference approach with matching $\mathbb{1}\{t = t^* + \kappa\}$ varies also for the matched control-group workers.

Figure 3.19 shows the difference-in-difference effects, $\gamma_{\kappa\iota}$, of a layoff on various worker level outcome variables for all four transition paths, i.e., elements of $\mathcal{M}$. Overall, pre-trends are zero or negligible, reinforcing our claim of well-functioning matching and a clear identification of the difference-in-difference effect. We only observe minor non-zero pre-trends for log wages and yearly accumulated income. This might be due to two reasons. First, firms may face structural change over longer time horizons which does not immediately lead to adjustments in employee numbers but which leads to adjustments in worker compensation. Since we match on characteristics one year before the layoff event, pre-trends have a positive sign and are declining even before the layoff event. This may lead to an underestimation of the treatment effect. The second reason why we observe non-zero pre-trends is purely technical. The estimates are for an unbalanced panel of workers and matches. Hence, we repeat the exercise for a balanced panel of treatment and control group pairs.

Panel (a) of Figure 3.19 yields results on the logarithmized wage. As before in the pure event study, workers who switch to a service job in the service sector experience the cut in wages. Over the next 10 years, their wage declines on average by about 20% as compared to their matched control group. With respect to the narrative of this paper, the effect on workers switching to a manufacturing job in services is of interest. We do find a significant drop in wages which slowly converges over the next 10 years but never reaches the level of the control group workers. However, the cut in wages is far less strong as for the workers switching to a service occupation. Rather, manufacturing

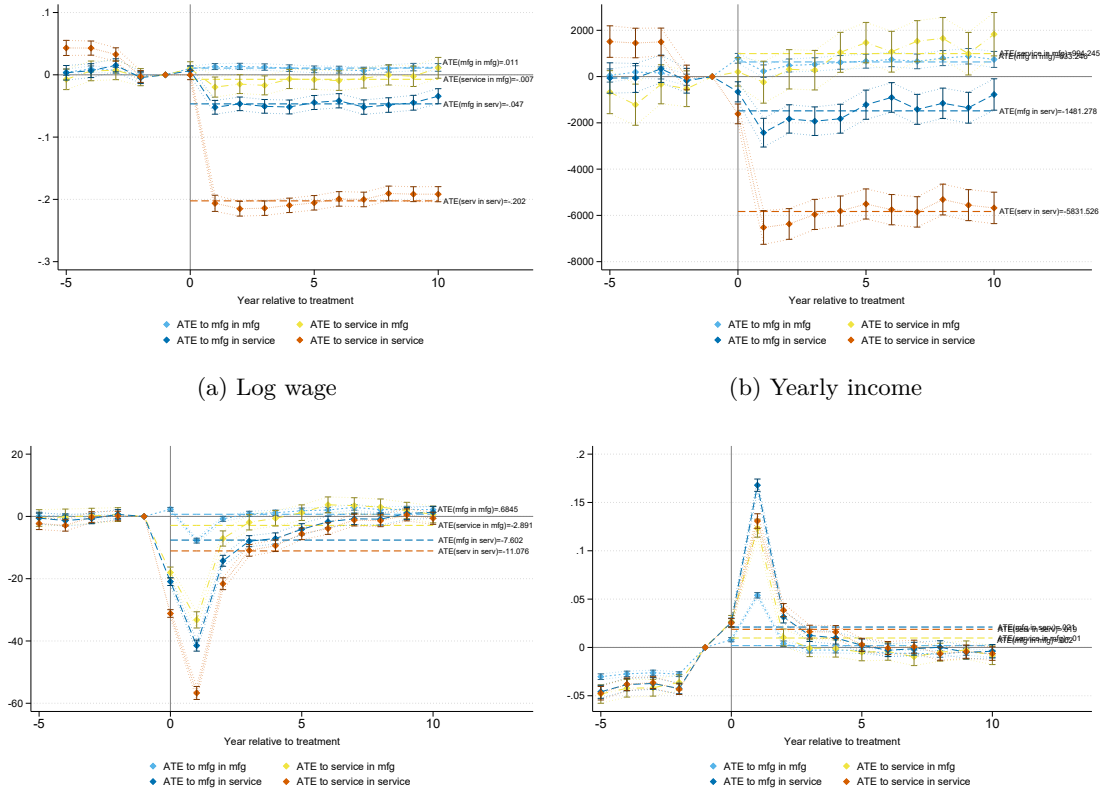
workers who switched to the service sector earn about 5% less than their non-laid-off counterparts immediately after the layoff. The average loss in wages is 4.7% over the ten-year period.

Workers remaining in the manufacturing sector do not experience economically significant changes in their wage. In fact, workers who manage to find a new job with manufacturing occupation in the manufacturing sector earn stably about 1% more than the matched counterpart. Quite possibly, these workers are more productive and manage to obtain a new job at an establishment that benefits from structural change (or manages to cope better with the negative shocks).

A similar pattern emerges for yearly income (Panel (b)) which, apart from the main employment spell, also takes secondary and tertiary jobs into account. For workers finding new employment in a manufacturing occupation in the service sector, the yearly income of a laid-off worker initially is by about 2,500 euros lower than that of the non-laid-off counterpart. Subsequently, yearly income recovers but remains around 1,000 euros lower. In total, affected workers lose about 14,800 euros during the ten-year period. Far harder hit are workers that have to switch to a service job in the service sector. They lose about 58,000 euros in income throughout the following ten years post layoff.

Panel (c) shows treatment effects for the days in employment per year. The number of days in employment per year drops after layoff for all treatment types (to different extend); however, it recovers quickly – with about even rate for all treatment types – and reaches the same level as that of the control group in the second to seventh year after treatment (dependent on treatment type). Whereas workers that switch to a service job in the manufacturing sector after the layoff do not experience strong effects on pecuniary outcomes we do observe that these workers seemingly take longer to find new and stable employment.

Similarly, the number of different employers experiences a peak in the two years following the layoff, hinting at more unstable employment spells after being laid off, but the effect phases out and four to five years after the layoff, no significant differences between laid-off and non-laid-off workers remain. (Panel (d) shows the effect on the number of different employers based on the main spell.)



(a) Log wage

(b) Yearly income

(c) Days employed

(d) Number of employers

Figure 3.19: Regression results of coefficient γ_k from Equation (3.6)

The figure plots coefficients $\gamma_{\kappa\iota}$ and 95% confidence intervals relative to the mass layoff event. Horizontal lines show the average treatment effect for the 10 years post layoff. The sample is restricted to only laid-off workers. The layoff occurs between June 30 year 0 and June 30 year 1. Datasource: SIAB, 1975-2017.

4 Servitization, Inequality, and Wages

Summary: This paper studies the effect of servitization, i.e., within-establishment changes in the labor force composition towards higher shares of workers with service occupations, on within-establishment wage inequality. We identify servitization as being a main driver of increasing within-establishment wage inequality. Servitization accounts for roughly 7% of the observed increase in the within-establishment wage inequality in manufacturing industries between 1994 and 2017. Higher servitization of an establishment's labor force is associated with, on average, a lower wage level for otherwise equal workers across the majority of occupations. The wage decrease is particularly pronounced for workers in low-skilled manufacturing occupations and workers at the lower end of the wage distribution. These heterogeneous wage effects explain the increase in within-establishment wage inequality.[1]

[1]This chapter is co-authored work with Dominik Boddin and in press at *Labour Economics* under https://doi.org/10.1016/j.labeco.2021.102011. We thank Laura Bickel, Johannes Bröcker, Davin Chor, Emmanuel Milet, Horst Raff, and Georg Schaur as well as the editors, Maia Guell and Claudia Olivetti, and two anonymous referees for their valuable comments and suggestions. We further thank participants at seminars at the EALE/SOLE/AASLE conference 2020, the Workshop on Labour Economics 2019 in Trier, Kiel University, the ETSG in Warsaw, the KCG Workshop 2018, and the Aarhus-Kiel Workshop 2018.

4.1 Introduction

In this paper, we examine the effect of servitization on within-establishment wage inequality. We define servitization as the increase in the share of workers with service occupations in total employment within establishments. For our analysis, we use disaggregated German matched employer-employee data covering the years from 1994 to 2017. The time period is not only marked by pronounced shifts in the labor composition at the establishment level toward workers in service occupations. We also observe distinct wage growth and dispersion of wages across different occupation-skill groups and an economy-wide increase in wage inequality by approximately 12% during the period of observation.

We find that establishment-level servitization explains about 7% of the observed establishment-level increase in wage inequality in the manufacturing sector during the 1994 to 2017 period of observation. The current paper is, to the best of our knowledge, the first to identify establishment-level servitization as an additional cause of increasing wage inequality. Increasing wage inequality is the result of underlying heterogeneous wage responses by occupation groups as the occupational composition of establishments changes towards a higher share of service occupations. While servitization causes a lower wage level for otherwise identical workers in almost all occupations, the wage decrease is particularly pronounced for low-skilled manufacturing workers and workers at the lower end of the wage distribution. For instance, wages for low-skilled workers with manufacturing occupations fall on average by 11% as the result of an increase in the establishment's service share by one standard deviation. Wages of workers in high-skilled manufacturing occupations decrease by merely 3%. Generally, the effects are more pronounced in the manufacturing sector than in the service sector.

Our paper is motivated by three stylized facts: (i) Structural change at the sectoral level has been identified as one of the main drivers of wage inequality. Blum (2008) reports that changes in the sectoral composition account for approximately 60% of the relative increase in the wages of skilled workers between 1970 and 1996. (ii) Recent research has shown that structural change is not only a sectoral phenomenon but also occurs at the firm (and even establishment) level.[2] In Germany, the share of service workers in the manufacturing sector increased by approximately 28% during the 1994 to 2017 period. In 2017, nearly 36% of the workers in the manufacturing sector held service occupations (Boddin & Kroeger 2021*a*). (iii) As we show in the current paper, the lion's share of wage inequality occurs within rather than across establishments. We show with a variance decomposition that 79% of residual wage variance occurs within establishments. It is thus natural to ask whether servitization drives establishment-level wage inequality.

This paper contributes to the growing literature on wage inequality and its underly-

[2]For instance Bernard et al. (2017), Ding et al. (2019) or Boddin & Kroeger (2021*a*).

ing causes in industrialized economies and in Germany in particular (cf. Dustmann et al. (2009) and Card et al. (2013) for seminal contributions). These studies report an increase in the wage dispersion which can partly be explained by changes in the labor composition within firms and assortative matching processes between workers and firms. Other potential causes of increasing wage inequality at the aggregate level include increasing trade and offshoring opportunities as well as automation.[3] Goldschmidt & Schmieder (2017), for instance, document that outsourcing contributes to about 9% of the increase in overall wage inequality for Germany since the 1980s.

Recently, within-firm inequality has gained increasing attention. For the United States for instance, Song et al. (2019) attribute a third of the increase in income inequality between 1978-2013 to within-firm developments. For Korea, Kim & Konings (2019) show that a substantial share of wage inequality originates from within-establishment differences. Larger firms and those owned by international business groups exhibit higher inequality than smaller firms. For the UK, Mueller et al. (2017*a*) and Mueller et al. (2017*b*) find that within-firm wage inequality increases in firm size, mainly because larger firms pay higher wages for employees at higher skill or hierarchy levels. For Germany, Antonczyk et al. (2010), Felbermayr et al. (2018), and Baumgarten et al. (2020) show that a large part of wage inequality stems from within establishments, a finding we confirm and build on here.

So far, there are few studies that consider drivers of within-firm wage inequality even though it has been shown to have significant economic implications on workers' performance and firms' outcomes. Barth et al. (2012) show how performance pay may lead to within-firm wage inequality. Heyman (2005) studies how within-firm wage dispersion affects white collar workers' wages. He finds that higher within-firm wage dispersion is associated with higher pay for workers in white collar occupations. Within-firm wage inequality that is not clearly associated with productivity differences across workers has adverse effects on firms' output (Breza et al. 2018).

As one potential driver of within-firm wage inequality, Smeets & Warzynski (2008) assess wage inequality between hierarchy levels within firms. Friedrich (2020) shows that recent trade shocks affected hierarchy structures within firms and hence the labor composition. This is associated with an increase in within-firm wage inequality. For Norway, Barth et al. (2020) show that the implementation of industrial robots raises within-firm wage inequality through higher wages for high-skilled workers relative to low-skilled workers. We add to this literature by establishing the firm's labor composition as an important source of within-firm wage inequality, thereby connecting research on wage inequality to recent studies on structural change.[4]

[3]See for trade Autor et al. (2013), Baumgarten (2013), Klein et al. (2013), and Pierce & Schott (2016); for offshoring Grossman & Rossi-Hansberg (2008) and Becker et al. (2013), and for automation Acemoglu & Restrepo (2020) and Dauth, Findeisen, Südekum & Wössner (2021).

[4]E.g., Goos & Manning (2007), Boddin & Henze (2015), Crozet & Milet (2017), Fort et al. (2018), Caliendo et al. (2019), Duernecker & Herrendorf (2019), and Boddin & Kroeger (2021*b*).

The remainder of the paper is organized as follows. In Section 4.2, we introduce the data. We then present stylized facts on wage inequality and wages in Germany in Section 4.3. Section 4.4 introduces our empirical strategy and documents the effects of servitization on establishment-level wage inequality and, subsequently, on wages of occupation groups. Section 4.5 concludes. An Appendix contains additional material.

4.2 Data

For this paper, we use the LIAB, a linked employer-employee data set, provided by the Institute for Employment Research (IAB) of the German Federal Employment Office (see Heining et al. (2016)). The data set combines establishment data extracted from the Establishment History Panel (in German: Betriebs-Historik Panel (BHP)) with individual worker data from the Integrated Employment Biographies (in German: Integrierte Erwerbsbiographien (IEB)).[5] The employee data of the IEB is a 2% representative sample of all employees who have been subject to social security contributions at one point in time or were notified to the Federal Employment Agency during the 1994 to 2017 period.[6]

This data set is based on official administrative records, and employers are required by law to submit reports for all employees subject to social security contributions to the associated social security institutions at least once a year. This ensures that the data are highly reliable and not prone to misreporting.[7] The data set contains individual worker data on labor market variables such as daily wages, occupations, hierarchy levels, time in the job, time at the employer, and other variables influencing human capital such as schooling, university degrees, family status, etc. The data include between 700,000 and 1,400,000 persons per year.[8]

For our purpose, two features of the LIAB data are of central importance: Knowledge of the occupation of the worker in order to compute servitization and information on the workers' wages to estimate the servitization effect on within-establishment wage

[5] In addition, we use the BHP, also provided by the IAB, for our descriptive analysis of servitization. We describe this data in detail in Section C.2.1 in the Appendix.

[6] In Germany, employers are required by law to provide information for the social insurance contributions of their employees. The legal basis for this is §28a Social Code IV (SGB IV). To enable companies to participate in the automated social insurance registration process, they need an establishment number. The required delimitation of establishments follows exact specifications. An establishment is a regionally and economically separate unit in which at least one person subject to social security or marginal employment is employed. The regional assignment is based on the municipalities in Germany (more than 11,000 in 2017). That is, a company with branches in different municipalities consists of different establishments with different establishment numbers.

[7] The procedure is based on the integrated notification procedures for health, pension and unemployment insurance (DEÜV; formerly DEVO / DÜVO; for further details, see: Bender et al. (1996), p. 4ff.; Wermter & Cramer (1988)). http://doku.iab.de/fdz/reporte/2019/DR_06-19.pdf See Section C.1.1 in the Appendix for a description of how data are adjusted for reporting changes.

[8] For our analysis we start with the year 1994 in line with IAB's recommendation due to concerns that the data in prior years may be biased by reunification effects.

Naturally, the number of establishments is lower compared to the BHP as it is limited by the 2% IEB sample. The number of observations is larger for later years.

inequality and wages.

The LIAB contains both the total number of workers by Blossfeld (1987) categories for the workers' establishment and the workers' occupation at the 5-digit level according to the "Classification of Occupations 2010" (in German: "Klassifikation der Berufe", KldB) (Federal Employment Agency 2011). The Blossfeld categories are constructed such that educational and task requirements are very homogeneous within and very heterogeneous across Blossfeld categories. There are a total of twelve occupational groups which can be divided into two main fields, i.e., manufacturing and service occupations. Service occupations, i.e., those occupations that do not directly involve the production of physical goods, include the administrative service subcategory.[9] Each of the fields is subdivided further according to the skill requirement of the occupation (low-, medium-, and high-skill).[10] The KldB classification structure can be related and matched to ISCO-8 of the ILO, is hierarchical, and distinguishes between 1,286 occupations at the 5-digit aggregation level.[11] Similar to the Blossfeld classification, KldB is based on tasks but also on the hierarchy and delegating power within the establishment.[12] We transform LIAB's KldB occupational categories into Blossfeld categories using a crosswalk provided by Stops (2016).

The establishment level data include information on the establishments' industry classification (in revision of WZ93 based on NACE). Accordingly, in addition to the distinction between manufacturing and service occupations, we also distinguish between service and manufacturing industries.[13] Thus, we can assess (occupational) service and manufacturing employment within the service and manufacturing sectors.

In our analysis, we only include full-time employees. According to social security reporting regulations, employers must report the employees' gross wages liable to contribution. Gross wages above the income threshold are capped in the data.[14] This applies to approximately 10% of the wages. To circumvent this problem, we impute individual wages following the strategy of Card et al. (2013); see Section C.1.2 in the Appendix for a short description. For all analyses we restrict the data to Western Germany only. Doing so excludes potential biases resulting from the differences in wage levels between Eastern and Western Germany and the (potential) convergence process of the former GDR.[15]

[9] Administrative services, for instance, contain management occupations.

[10] See Table 4.5 in the Appendix for a more detailed description of the occupational groups as well as examples.

[11] For an example of this scheme see Table 4.6 in the Appendix.

[12] The occupational categorization is stored in the first three digits, the fourth digit of the classification captures the hierarchical aspect, and the fifth digit of the classification describes the skill intensity of the respective occupation. Accordingly, at the disaggregated level, the classification of workers might differ, if hierarchy and skill intensity differ, even if the occupations are identical.

[13] Note: Throughout the paper we use the terms industry and sector interchangeably.

[14] In Germany, there is an assessment ceiling which caps the amount up to which the salary or pension of a legally insured person is subject to social security contributions.

[15] Nevertheless, as a robustness check we also run all regressions for Germany as a whole, i.e., Western and Eastern Germany combined. Results are qualitatively and quantitatively in similar ranges and are available upon request.

That implies that we only refer to Western Germany whenever we mention "Germany" in this paper.

4.3 Stylized Facts

Wage Inequality

To motivate our focus on within-establishment wage inequality, we first perform a simple variance decomposition of residual log daily wages to document the fact that a sizable fraction of wage inequality originates from within-establishment differences. This is in line with a variety of recent papers that show that a substantial share of wage dispersion occurs within narrowly defined economic units as opposed to between those units (e.g., Becker et al. (2019) or Baumgarten et al. (2020)). The variance of wages is a widely employed measure of inequality (e.g., Card et al. (2013) or Song et al. (2019)) and allows by its additive separability to be decomposed into within and between components (Shorrocks 1980).

Table 4.1 shows the decomposition of wage inequality along three dimensions, industry, occupation, and establishment, into within and between components. The within-group part of each dimension explains a sizable share of wage inequality. In the context of this paper the establishment dimension is of greatest relevance. Here, about 79% of wage dispersion is observed within establishments. Between establishment dispersion only explains the remaining 21% of total wage inequality. We obtain the wage residuals from a Mincerian wage regression controlling for standard worker characteristics as well as year, industry, and region fixed effects.

Panel 4.1a of Figure 4.1 plots the yearly average standard deviation of log daily wages in Germany and Panel 4.1c its growth relative to 1994.[16] We show economy-wide wage inequality in total as well as separately for the manufacturing sector and the service sector. We define economy-wide wage inequality as the standard deviation over log wages of all employees in the economy. During the 1994 to 2017 period, economy-wide wage inequality increased by approximately 11.7%.[17]

The figure also shows that wage inequality in the years following the financial crisis declined after a steady increase until 2008, both within the service and the manufacturing

[16]For this exercise, we only cover establishments with an average worker coverage of more than 90% of full-time employees in the data. For certain establishments, only a fraction of the total number of workers may be covered. The reason lies in how the data set is constructed. For a representative set of establishments daily administrative employment histories are added. These workers are followed over time such that in an additional step establishment information is also added for those workers who at some point in time switch to another establishment that was not part of the initial representative sample. Naturally, the worker coverage in these "newly added" establishments will oftentimes be low and the establishment specific standard deviation of log wages may be biased. Accordingly, we restrict our sample to establishments with high coverage in order to be able to compute meaningful values for within-establishment wage inequality.

[17]Figures are well in line with previous studies on wage inequality in Germany (see for instance Dustmann et al. (2009) and Card et al. (2013)).

Table 4.1: Decomposition of residual log daily wage inequality

Dimension	Contribution in % within group	between group
Industry	86.62	13.38
Occupation	80.01	19.99
Establishment	78.84	21.16

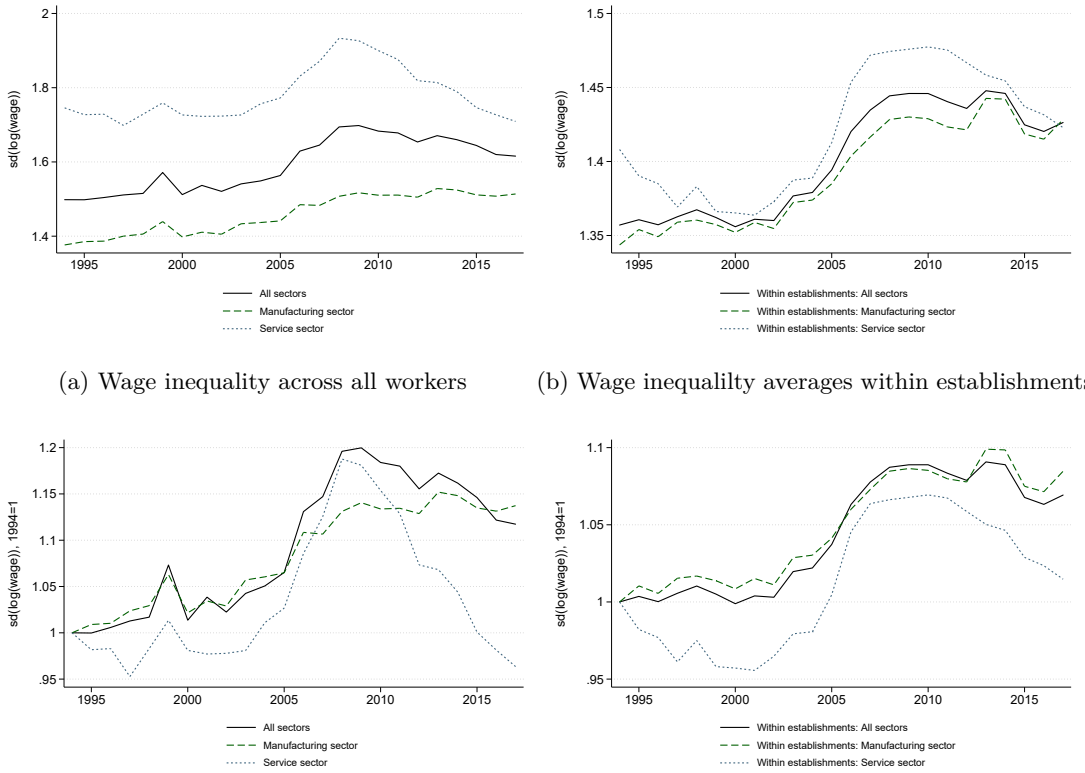
Notes: Data: LIAB – variance decomposition of contributing factors to exponentiated residual log daily wage inequality. Only workers at establishments with more than ten full-time employees are included. We do not include establishments that switch industries during our period of observation. Residual wages are obtained from a Mincerian wage regression controlling for age, age^2, years of schooling, graduate degree or vocational degree dummies, tenure, as well as year, region, and industry fixed effects ($R^2 = 0.53$). The first row's residual wages are obtained from a similar regression excluding industry fixed effects ($R^2 = 0.50$).

sector. A possible explanation for this may be that during the financial crisis low-wage workers have been laid off or high-paid workers have experienced wage cuts. The graph also shows that wage inequality development differs between service and manufacturing industries. In 1994, wage inequality in the service sector was about 26.8% higher than in the manufacturing sector. In 2017, the magnitude of this difference declined, and wage inequality in the service sector was just 13% higher than in the manufacturing sector. The reason for this is that the decrease in wage inequality following the Great Recession is largely caused by a decrease in wage inequality in the service sector. In 2017 wage inequality in the service sector is about 3.6% lower than at the beginning of the sample period. In the manufacturing sector, there has been no significant reversal of the increase in wage inequality.

Panel 4.1b of Figure 4.1 displays within-establishment wage inequality and Panel 4.1d its growth relative to 1994. We first compute the standard deviation of log wages per establishment and then take the average across all establishments. The described trend for economy-wide wage inequality coincides with those for within-establishment wage inequality. During the 1994 to 2017 period, within-establishment wage inequality increased by approximately 7%.

In summary, we find increasing wage inequality in Germany both in the overall economy and within establishments during the 1994-2017 observation period. The within-establishment component of wage inequality makes up a sizeable part of the residual variance in wages which is not explained by usual worker characteristics.

During the same time period, there has been a clear trend towards increasing servitization in Germany. Employment shares of workers in service occupations – especially in the manufacturing sector – grew rapidly during the 24 years of observation: From 1994 to 2017 the share of workers in service occupations in the manufacturing sector increased by 7.8 percentage points. In 2017, 35.87% of the workers in the manufacturing



(a) Wage inequality across all workers

(b) Wage inequalilty averages within establishments

(c) Wage inequality growth across all workers

(d) Wage inequalilty growth averages within establishments

Figure 4.1: Wage inequality trends for the economy and within-establishment wage inequality

Notes: Data: LIAB. Panel (a) reports the standard deviation of log real wages across all workers in the respective sector or the whole economy (solid line), Panel (c) its growth. Panel (b) reports averages of within-establishment standard deviations of wages (Panel (d) its growth). Censored wages are imputed according to the procedure of Card et al. (2013).

sector worked in service occupations. The trend in the service sector shows the same pattern: From 1994 to 2017 the share of workers in service occupations in the service sector increased from 80.90% to 83.15%. Conversely, in both sectors the share of workers in manufacturing occupations decreased by more than 10%. Section C.2.1 in the Appendix discusses and displays occupational shifts within the manufacturing sector and the service sector as well as within establishments.

The observed servitization implies a change of the marginal product of different types of labor (i.e., service and manufacturing occupations) and is likely to go hand in hand with heterogeneous changes in the remuneration of workers. This can be an explanation of the observed change of within-establishment wage inequality. Accordingly, in the following subsection we document the heterogenous development of wages by occupation categories before we empirically link servitization and wage inequality.

Wages

Figure 4.2 shows the development of average real daily wages for all full-time workers with manufacturing occupations and service occupations independent of the sector and by sector from 1994 to 2017.[18]

Panel 4.2a shows the growth rate of real daily wages and Panel 4.2b reports levels. The plot reveals a pronounced dispersion between the compensation for workers in manufacturing occupations and for workers in service occupations. Wages of workers in manufacturing occupations rise slightly until around 2004 and decrease slightly between 2004 and 2008, with more pronounced real wage growth arising afterwards. In total, wages of workers in manufacturing occupations grew by about 23.3% until 2017 compared to their 1994 level. By contrast, real wages of workers in service occupations are stagnant between 1994 and 2004 and decrease until 2008 to a level of about -8.4% below that of 1994. Positive growth subsequently commences, and in 2017 wages for workers in service occupations were about 12.1% above their 1994 level. The wage growth for workers in service occupations is thus much lower as compared to wage growth for workers in manufacturing occupations.[19]

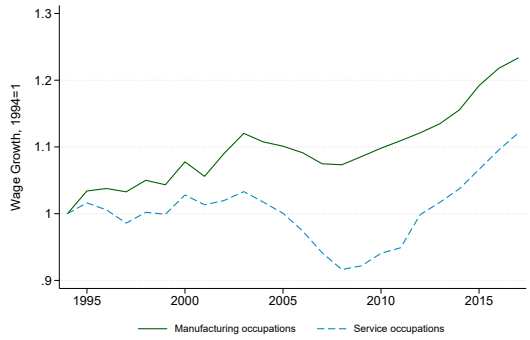
Accordingly, the spread between wages for workers in manufacturing occupations and wages for workers in service occupations widened. In 1994, the average daily wage for workers in manufacturing occupations (93.18 Euro) was 9.41 Euro higher than the average daily wage for workers in service occupations. By 2017, this spread had increased to a value of 23.12 Euro.

Panels 4.2c and 4.2d of Figure 4.2 break down the wage development further and show the wage growth for workers in service and manufacturing occupations in the manufacturing sector (Panel 4.2c) as well as for workers in service and manufacturing occupations in the service sector (Panel 4.2d). The figure is complemented by Figure 4.5 in the Appendix that displays the wages in levels.

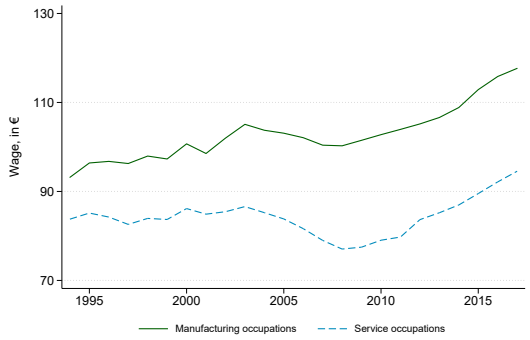
The first thing to notice is that the wage development differs not only across sectors but also across occupations within a sector. From 1994 to 2017, wages for workers in manufacturing occupations within the manufacturing sector increased by 24.4%, whereas wages for workers in service occupations within the manufacturing sector increased by 19.4%. In 1994, the average daily wage for a worker in a manufacturing occupation in the manufacturing sector was 100.50 Euro and thus about 3 Euro lower than the average daily wage for a worker employed in a service occupation in the manufacturing sector. In 2017, however, workers employed in manufacturing occupations in the manufacturing sector earned 2.67 Euro *more* than their counterparts working in service occupations

[18]Wages in this section are imputed according to the procedure of Card et al. (2013) and cover full-time workers only. Wages are in real Euro of 2015. Only establishments with at least ten employees are taken into account.

[19]The strong growth of real wages can to a large extent be attributed to the global financial crisis starting in 2008. The crisis restrained price inflation, but due to longer lasting collective bargaining agreements wage increases automatically resulted in a real wage increase.



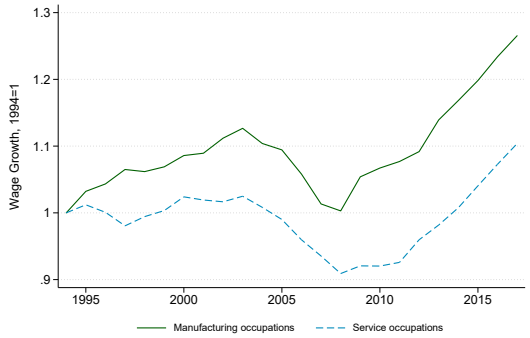
(a) Wage growth for occupation groups in all sectors



(b) Wage levels for occupation groups in all sectors



(c) Wage growth for occupation groups in the manufacturing sector



(d) Wage growth for occupation groups in the service sector

Figure 4.2: Wage Growth of Service and Manufacturing Occupations

Notes: Data: LIAB. Panel (a) reports wage growth for manufacturing and service occupations independent of the sector. Wages are normalized to 1 in 1994. Panel (b) reports daily wages in level (in Euro). Panel (c) and Panel (d) display wage growth for manufacturing and service occupations within manufacturing industries and service industries, respectively. Wages are normalized to 1 in 1994.

(128.23 Euro vs. 125.56 Euro in real euro of 2015).

While real wages for all workers grew almost linearly in the manufacturing sector, this is not the case in the service sector. Wages for workers in service occupations stagnated until 2004 and declined by 9.1% relative to their initial 1994 level until 2008. After the financial crisis growth commenced and real wages for workers with service occupations in the service sector increased by approximately 19.5% between 2008 and 2017, whereas the wage increase of workers employed in manufacturing occupations was approximately 26.2% during the same 2008-2017 period, almost linearly projecting the initial growth throughout the late 1990s and completely making up for the period of real wage decline between 2004 and 2008.

A second observation is that the average wage gap between manufacturing and service industries is immense (cf. Figure 4.5 in the Appendix). In 2017, the average daily wage for service occupations in the manufacturing sector was approximately 42% (or 37.56 Euro) higher than the daily wage for service occupations in the service sector. The

spread for manufacturing occupations looks very similar. Daily wages for manufacturing occupations in manufacturing are approximately 28.4% (or 28.33 Euro) higher than wages for manufacturing occupations in services.

Figure 4.2 indicates that the wage growth varies greatly not only between sectors but also between service and manufacturing occupations within sectors. The picture does not change if we look at wages in levels (cf., Figure 4.5 in the Appendix), nor is the reported occupation-specific wage dispersion within the service and manufacturing sectors driven by differences in skill intensity (cf., Appendix Section C.2.3).[20]

In summary, we can conclude that wage growth during the 1994 to 2017 period is mostly higher for workers in manufacturing than for workers in service occupations. The data confirm that remuneration in manufacturing industries is generally higher than in service industries. In addition, we also document pronounced variation in both wage growth and wage levels between manufacturing and service occupations within sectors. These observations support our hypothesis that servitization will impact wages and thus wage inequality.

4.4 The Effect of Servitization on Wage Inequality and Wages

In this section, we analyze the effect of servitization on within-establishment wage inequality and wages.

4.4.1 Servitization and Within-Establishment Wage Inequality

First, we assess the effect of servitization on wage inequality more closely. To do so, we make use of the panel structure of the data and estimate regression (4.1) using a fixed effects approach.[21]

$$\text{sd}(\log(wage))_{jt} = \alpha_j + \beta_1 \frac{\#\ service\ workers_{jt}}{\#\ employees_{jt}} + \mathbf{X}'_{jt}\boldsymbol{\gamma}_2 + \delta_t + \varepsilon_{jt} \tag{4.1}$$

We regress the standard deviation of logarithmic daily wages, $\text{sd}(\log(wage))_{jt}$, of all full-time employees at an establishment j in a given year t on the service share within that establishment, $\frac{\#\ service\ workers_{jt}}{\#\ employees_{jt}}$. The service share is computed as the share of workers employed in service occupations in all workers at establishment j.[22] $\mathbf{X}'_{jt}$ contains (time-varying) individual (establishment) confounders[23], α_j denotes establishment fixed effects,

[20] Additionally, unweighted wage averages within establishments reinforce the described observations, too (cf., Appendix Section C.2.4).

[21] We use the previously described imputed wages for all regressions. This approach is computationally and econometrically feasible when dealing with top censored data and a fixed effects structure. The semi-parametric model of Honoré (1992) is again not feasible due to large data and restricted computational power in connection with data access.

[22] We use the standard deviation of wages as a measure of inequality following previous work of, for instance, Dustmann et al. (2009), Card et al. (2013), or Friedrich (2020).

[23] For a full list of regressors see Appendix Section C.5, Table 4.10.

δ_t depicts year dummies, and ε_{ijt} denotes the error term.

The fixed effects structure is appropriate as it not only time demeans the data but also excludes any establishment-specific effects. In particular, it excludes firm productivity effects that have been found to relate to wage levels in contexts of assortative matching (Abowd et al. (1999) and Card et al. (2013)). With the fixed effects approach we can directly interpret the coefficient of the service share, β_1, as the effect of servitization on within-establishment wage inequality. Since time constant effects are excluded, the regression can be seen as a regression of changes. Hence, the results can be interpreted in a conservative fashion in that we identify the relationship between servitization and increasing wage inequality from changes over time while excluding different level effects between heterogeneous firms. Table 4.2 shows the results. We always present results for the whole economy (column (1)) as well as separately for the manufacturing (column (2)) and the service sector (column (3)). The specification always contains the full set of confounders including (time-varying) establishment explanatory variables. Generally, all our results are robust with respect to the selection of explanatory variables.

As hypothesized in the previous section, overall wage inequality increases with higher service shares. A ten-percentage-point higher service share within an establishment is associated with a .002 higher standard deviation of logarithmic wages. This corresponds to a roughly .5% higher standard deviation of log daily wages. For establishments in the manufacturing sector an increase in the service share by ten percentage points is associated with a .5 log points higher standard deviation of wages. Put into perspective, this finding implies that servitization accounts for 7% of the total increase in wage inequality in the manufacturing sector during the 1994 to 2017 period.[24] Hence, rising servitization contributes about as much to increasing wage inequality as outsourcing activities. Goldschmidt & Schmieder (2017) show that outsourcing of business service activities can explain up to 9% of the increase in German wage inequality between 1980 and 2010. We do not find significant effects on the standard deviation of logarithmic wages in the service sector, indicating that the positive effect for the whole economy is primarily driven by the manufacturing sector.[25]

[24]The service share in manufacturing increases by about 8 percentage points and the within-establishment wage inequality by about 6 log points. Hence, $\frac{.08 \times .051}{.06} \approx 7\%$.

[25]This is in line with the observation that servitization is much stronger in the manufacturing sector (cf. Figure 4.3 in the Appendix).

Table 4.2: Within-establishment wage inequality: sd(log(wage))

	(1) All sectors	(2) Manufacturing sector	(3) Service sector
Dependent variable	$\text{sd}(\log(\text{wage}))_{jt}$	$\text{sd}(\log(\text{wage}))_{jt}$	$\text{sd}(\log(\text{wage}))_{jt}$
Service share	0.018***	0.051***	0.009
	(0.005)	(0.013)	(0.006)
Additional confounders	Yes	Yes	Yes
Observations	1,027,954	260,688	679,475
Within R-squared	0.005	0.012	0.004
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Notes: Data: LIAB – estimating equation (4.1)
Only workers at establishments with more than ten full-time employees are included. We do not include establishments that switch industries during our period of observation. The explanatory variable *service share* is the (yearly) share of full-time employees with service occupations over all full-time employees in a given establishment based on the underlying BHP data. Accordingly, the service share is not subject to potential coverage issues. "All sectors" also include establishments in the primary sector, which explains the discrepancy between the sum of observations in *manufacturing* and *service sector* and observations in the *all sectors* sample.

4.4.2 Servitization and Wages

We now turn to the servitization effect on occupational groups to provide an explanation for the observed positive effect on within-establishment wage inequality. Naturally, servitization is likely to affect within-establishment wage inequality whenever (groups of) workers are differently affected by servitization. The reaction of (relative) wages across wage groups to the observed shifts in the occupational structure is not per se trivial. Relative labor demand has been decreasing for manufacturing occupations. If labor supply were constant, this would entail a decrease in wages for workers employed in manufacturing occupations. By contrast, assuming decreasing marginal productivity of labor, a decrease in manufacturing employment within an establishment would lead to an increase in wages for this type of labor if labor markets are competitive. Outsourcing and offshoring, occupation-specific technological progress or specialization of the production process could amplify the effect through an additional increase in the marginal product of labor of the remaining workers. A similar but reverse reasoning can be applied to service occupations. Hence, a priori it is not possible to predict the adjustment of wages.

We focus on two dimensions along which we distinguish between different worker groups: Occupation-skill groups and the workers' position in the wage distribution.

Occupation–skill groups

First, we look at occupation-skill groups. Establishments are heterogeneous in productivity which in part may be reflected by the employment structure. This means

that we expect wages of occupation-skill groups to vary across establishments. Wages across occupation-skill groups are heterogeneous since the contribution of different worker groups to an establishment's output and rent varies (labor productivity argument). Another reason for heterogeneous wages across worker groups may be the shortage of skilled labor in Germany (supply shortage and wage stickiness argument). Employers compete for labor groups that contribute strongly to the establishment's output and pay wages above marginal (revenue) products of labor to secure production. By contrast, types of labor of which there is no shortage will be paid according to marginal products, i.e., the competitive wage.

We estimate an augmented Mincer wage regression in which we interact the service share and occupation-skill groups according to equation (4.2).

$$\begin{aligned} log(wage)_{ijt} = \; & \alpha_i + \boldsymbol{\beta_1} \frac{\#\ service\ workers_{jt}}{\#\ employees_{jt}} \times \mathbb{1}\{occupation - skill\}_{it} \\ & + \boldsymbol{\beta_2} \mathbb{1}\{occupation - skill\}_{it} \\ & + \mathbf{X}'_{it}\boldsymbol{\gamma}_1 + \mathbf{X}'_{jt}\boldsymbol{\gamma}_2 + \delta_t + \varepsilon_{ijt} \end{aligned} \tag{4.2}$$

Regressors are similar to equation (4.1). $\frac{\#\ service\ workers_{jt}}{\#\ employees_{jt}}$ is the share of workers holding service occupations at establishment j. The interaction term $\mathbb{1}\{occupation - skill\}_{it}$ is a column vector containing dummies for the six skill-occupation groups equal to one if worker i's occupation falls into the respective group. Here, $\boldsymbol{\beta_1}$ is a row vector containing the coefficient of interest for each of the six occupation-skill groups.[26] $\mathbf{X}'_{it}$ ($\mathbf{X}'_{jt}$) contains (time-varying) individual (establishment) confounders[27], α_i are worker fixed effects, δ_t depicts year dummies, and ε_{ijt} denotes the error term.[28]

Again, we apply a fixed effects structure that not only time demeans the data but also excludes any person-specific effects. The same argument as before also applies to this augmented Mincer regression: By including worker fixed effects while at the same time excluding establishments switching sectors and workers switching sectors or occupations, the results are not biased by correlations between labor demand differences between different productivity levels of firms, assortative matching, and wage levels of workers (as documented by Card et al. (2013)).[29] Likewise, as before we can directly interpret the coefficients $\boldsymbol{\beta_1}$ as the effect of servitization on wages because level effects are excluded.

[26] We close the degrees of freedom by excluding the *service share* as not-interacted regressor, which allows to interpret the coefficients $\boldsymbol{\beta_1}$ independently.

[27] For a full list of regressors see again Appendix Section C.5, Table 4.10.

[28] We repeat all estimations using wages in levels instead of log wages as well as top censored wages. Using top censored wages will naturally result in biased estimates. However, the bias will tend towards zero, which allows us to interpret this procedure as a robustness test. Results are robust and significant in this regression. Results are not displayed in the paper, but available upon request.

[29] Indeed, a Hausman test rejects the null that individual effects are orthogonal, hence an RE specification would lead to inconsistent estimates. A Hausman-Taylor (or related) model could potentially lead to more efficient results, but is computationally not feasible. Due to the large number of observations, we are confident that our results do not lack precision. We cannot assume orthogonality between individual time-invariant characteristics and the error term.

Occupation-skill groups comprise the previously introduced six groups, i.e., low-skilled, medium-skilled, and high-skilled manufacturing and service occupations.

Table 4.3 shows the results of the coefficients of interest (i.e. $\boldsymbol{\beta_1}$). The effect of servitization on wages is negative for all six occupation groups when including all sectors. The same holds true for the manufacturing sector, with the exception of high-skilled manufacturing occupations, but not for the service sector. As expected, effects differ significantly in magnitude across worker groups.[30]

In the economy as a whole, we find that the group of low-skilled workers in manufacturing occupations experiences the strongest negative effect. The effect on workers in medium-skilled manufacturing occupations is only about half as large. A ten-percentage-point higher service share in their establishment decreases the wage on average by 3.3% for workers in low-skilled manufacturing occupations and by 1.7% for workers in medium-skilled manufacturing occupations. The effect on workers in high-skilled manufacturing occupations is eminently lower than for those in low- and medium-skilled occupations. This result is consistent with the changes in employment shares of the three groups in the aggregate economy, meaning that the occupation-skill groups with the largest employment losses also experience the largest wage losses as a result of servitization.

The effect of structural change on workers in service occupations shows a different picture. The effects on workers in low- and medium-skilled service occupations in the economy as a whole are negative, but the magnitude of the effect is less than half as large as for manufacturing occupations of equal skill level. Interestingly, workers in high-skilled service occupations are strongly affected within service occupations. Here we find that a ten-percentage-point increase in the service share decreases the average worker's wage in this skill-occupation group by 1.8%.

When repeating the regression of equation (4.2) for the manufacturing sector, results are similar to the effects for the economy as a whole. The effects on workers employed in manufacturing occupations within the manufacturing sector are pronouncedly different for the three occupation groups. The lower the skill level of the worker, the more strongly their wage is affected by servitization of the employing establishment – ranging from decreases in the daily wage of 3.2% for workers in low-skilled manufacturing occupations to a slight increase of 0.4% for workers in high-skilled manufacturing occupations per ten-percentage-point increase in the service share.

Workers in service occupations in the manufacturing sector are affected to the same extent as in the overall economy. In particular, workers in low-skilled service occupations are affected the strongest. A ten-percentage-point higher service share leads to a 1.6% decrease in low-skilled service wages. The effect on the high-skilled service workers in manufacturing is in a similar range, with a 1.1% wage decrease for a ten-percentage-point increase in the service share. The differences in the results may be attributed to the two

[30] As suggested by the results, the overall effect on the average worker is negative as well and the effects are more pronounced in the manufacturing than in the service sector. Appendix Section C.3 provides a discussion on the servitization effect on the average worker.

channels on wage development discussed earlier. The shifts in absolute and relative labor demand lead to changes in absolute and relative wages.

In the service sector results are notably different. Here, we find positive effects of servitization on workers' wages for some skill-occupation groups. For workers in low-skilled manufacturing occupations, a ten-percentage-point increase in the service share is associated with a .9% lower wage. Remarkably, the effect for workers employed in medium-skilled manufacturing occupations is positive. A ten-percentage-point increase in the service share results in a .3% higher wage. For service occupations, we also observe positive effects for workers employed in low- and medium-skilled occupations. For workers in high-skilled service occupations the effect is again negative (1% lower wage for a ten-percentage-point increase in the service share).[31]

Table 4.3: FE regressions: interaction with occupation-skill group

Dependent variable: log(wage)			
	(1)	(2)	(3)
	All sectors	Manufacturing sector	Service sector
low-skilled manu × service share	-0.332***	-0.323***	-0.088***
	(0.006)	(0.008)	(0.010)
medium-skilled manu × service share	-0.170***	-0.060***	0.034***
	(0.004)	(0.008)	(0.006)
high-skilled manu × service share	-0.092***	0.042***	-0.051***
	(0.005)	(0.011)	(0.009)
low-skilled service × service share	-0.128***	-0.156***	0.041***
	(0.003)	(0.010)	(0.006)
medium-skilled service × service share	-0.079***	-0.027***	0.023***
	(0.003)	(0.008)	(0.005)
high-skilled service × service share	-0.178***	-0.113***	-0.099***
	(0.004)	(0.011)	(0.008)
Observations	9,206,686	4,548,584	4,347,919
R-squared	0.35	0.23	0.40
Additional confounders	Yes	Yes	Yes
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Notes: Data: LIAB – estimating equation (4.2)
Only workers at establishments with more than ten full-time employees are included. We do not include establishments that switch industries during our period of observation. The explanatory variable *service share* is the (yearly) share of full-time employees with service occupations in all full-time employees in a given establishment based on the underlying BHP data. Accordingly, the service share is not subject to potential coverage issues. "All sectors" also include establishments in the primary sector, which explains the discrepancy between the sum of observations in *manufacturing* and *service sector* and observations in the *all sectors* sample. Occupation-skill groups are based on the Blossfeld specifications. We do not include *service share* as a separate regressor in equation (4.2); therefore, all interactions are directly interpretable.

[31] As a robustness check for the heterogenous effects across skill-occupation groups we reestimate equation (4.2) but, instead of the six occupational groups, we use the ten Blossfeld groups for the interaction term. Results are similar and discussed in more detail in the Appendix (Section C.4, Table 4.9).

Servitization and the Position in the Wage Distribution

We now check for heterogeneous effects across different income groups at the establishment. Even though correlated, grouping workers according to their income is not necessarily identical to the previous occupation-skill-level grouping (see Figure 4.7 in the Appendix). We can assume that a higher service share in establishments is a reflection of productivity changes across labor types and hence the offered wages. Thus, if due to structural change the productivity of already high-paid workers increases relative to low-paid workers, we would expect wages to increase for workers at the top of the within-establishment wage distribution relative to those at the bottom end of the wage distribution.

Econometrically, we perform a series of quantile regressions on the effect of servitization on wages in different percentiles in the wage distribution within establishments. We estimate our coefficient of interest β_1 for the 10th, 25th, 50th, 75th, and 90th percentiles of the wage distribution by solving the following expression:

$$\begin{aligned}\min_{\{\beta_1^q,\boldsymbol{\gamma}_1^q,\boldsymbol{\gamma}_2^q\}} \{q\mathbb{1}\{log(wage)_{ijt} \geq \beta_1^q \frac{\#\ service\ workers_{jt}}{\#\ employees_{jt}} + \mathbf{X}'_{it}\boldsymbol{\gamma}_1^q + \mathbf{X}'_{jt}\boldsymbol{\gamma}_2^q\} \\ +(1-q)\mathbb{1}\{log(wage)_{ijt} < \beta_1^q \frac{\#\ service\ workers_{jt}}{\#\ employees_{jt}} + \mathbf{X}'_{it}\boldsymbol{\gamma}_1^q + \mathbf{X}'_{jt}\boldsymbol{\gamma}_2^q\} \\ |log(wage)_{ijt} - \beta_1^q \frac{\#\ service\ workers_{jt}}{\#\ employees_{jt}} + \mathbf{X}'_{it}\boldsymbol{\gamma}_1^q + \mathbf{X}'_{jt}\boldsymbol{\gamma}_2^q\ |\}\end{aligned} \tag{4.3}$$

q denotes the percentile for which the expression is estimated. Accordingly, we retrieve five estimates for each of the elements of $\{\beta_1^q, \boldsymbol{\gamma}_1^q, \boldsymbol{\gamma}_2^q\}$.

As before, we estimate equation (4.3) for all establishments and for only the samples of establishments in the manufacturing or service sector, respectively. Again, establishments that switch their industry classification are excluded. The results are reported in Table 4.4, panels (A-C) reporting results for all sectors, the manufacturing sector, and the service sector.

In the economy as a whole, we observe that all workers experience declining wages from servitization. Effects differ slightly across groups. Workers with wages at the 10th percentile of the wage distribution are most strongly negatively affected by servitization. For those workers, an increase in the service share by ten percentage points is associated with a 1.4% lower wage. The effect becomes statistically smaller for workers at the 25th and 50th percentiles but is economically in similar ranges (wage reductions of -1.1% and -.97% respectively per ten-percentage-point increase in the service share). Nonetheless, these effects imply that the lower tail of the wage distribution becomes more dispersed when servitization is higher. Moving further up the wage distribution, the absolute effect becomes larger again; we therefore observe a decreasing dispersion of the wage distribution for the upper tail (wage effects of -1% at the 75th percentile and -1.2% at

the 90th percentile per ten-percentage-point increase in the service share).

Results are mainly driven by the manufacturing sector, for which we find an even stronger increase in the wage dispersion by servitization. Effects are negative and statistically significant at conventional levels throughout the wage distribution, but they show a ladder in effect size. Again, it is workers at the bottom end of the wage distribution who are hurt the most by servitization. Wages for workers at the 10th percentile of the wage distribution decline by 1% per ten-percentage-point increase in the service share. This effect size continuously diminishes for workers situated higher along the wage distribution and reaches merely a level of -.4% for workers at the 75th and 90th percentiles of the wage distribution. The fact that the effect size decreases in absolute magnitude from the lower to the upper end of the wage distribution will clearly result in a dispersion of wages. This estimation confirms that structural change at the establishment level results in higher wage inequality at the establishment, in particular for the manufacturing sector. In the service sector, workers in most positions of the wage distribution are not affected by servitization (contrary to occupation skill groups). The fact that we find stronger servitization effects for the manufacturing than for the service sector is in line with our previous findings that servitization causes within-establishment wage inequality to increase primarily in the manufacturing sector.

In total, the results indicate a divergence between wages as a result of increased servitization since the increase in wage dispersion at the lower tail of the wage distribution is stronger than the decline in the dispersion of wages at the upper tail. In particular, it is workers at the lower end of the wage distribution that lose out the most from servitization. Summarizing our findings for this approach, for both the economy overall and the manufacturing sector, effects of servitization are heterogeneous along the wage distribution and indicate an increasing dispersion of wages.

4.5 Conclusion

This paper connects servitization and within-establishment wage inequality. A sizable proportion of wage inequality in industrialized countries happens within establishments. For Germany, a variance decomposition shows that 79% of wage inequality occurs within establishments as opposed to between establishments. At the same time, labor demand is increasingly skewing towards service occupations, i.e., those occupations that do not directly involve the production of physical goods. The share of workers employed in such service occupations in manufacturing industries has increased by 28% during 1994-2017. In 2017, about 36% of all workers in manufacturing industries held service occupations.

We link both facts and show that servitization of an establishment increases the standard deviation of the logarithmic wage at the establishment level, primarily in the manufacturing sector. The increase in the service share explains about 7% of the observed increase in wage inequality in the manufacturing sector between 1994 and 2017 – a

Table 4.4: Quantile regression

	Dependent variable: log(wage)				
	q(0.10)	q(0.25)	q(0.50)	q(0.75)	q(0.90)
Panel A: All sectors					
Service share	-0.140***	-0.113***	-0.097***	-0.106***	-0.119***
	(-73.60)	(-139.85)	(-136.01)	(-87.08)	(-92.73)
N	9,809,173	9,809,173	9,809,173	9,809,173	9,809,173
Panel B: Manufacturing sectors					
Service share	-0.104***	-0.081***	-0.049***	-0.038***	-0.037***
	(-26.46)	(-72.96)	(-26.66)	(-24.88)	(-8.56)
N	4,994,144	4,994,144	4,994,144	4,994,144	4,994,144
Panel C: Service sector					
Service share	0.006	0.014***	0.009***	0.003	-0.011***
	(1.87)	(11.32)	(5.23)	(1.11)	(-4.48)
N	4,490,209	4,490,209	4,490,209	4,490,209	4,490,209
t statistics in parentheses					
* p < 0.05, ** p < 0.01, *** p < 0.001					

Notes: Data: LIAB – estimating equation (4.3)
Only workers at establishments with more than ten full-time employees are included. We do not include establishments that switch industries during our period of observation. The explanatory variable *service share* is the (yearly) share of full-time employees with service occupations over all full-time employees in a given establishment based on the underlying BHP data. Accordingly, the service share is not subject to potential coverage issues. "All sectors" also include establishments in the primary sector, which explains the discrepancy between the sum of observations in *manufacturing* and *service sector* and observations in the *all sectors* sample.

similar range to a recent finding on the contribution of outsourcing to rising overall wage inequality (Goldschmidt & Schmieder 2017).

Servitization is associated with lower wage levels for otherwise identical workers in almost all occupations. Effects for occupations in the manufacturing sector are, however, generally more pronounced than in the service sector. Importantly, effects are heterogenous across both occupation-skill groups and initial wage levels of workers: It is low-paid workers and workers in low-skilled occupations that are most adversely affected by servitization. Across all occupation-skill groups, it is low-skilled workers in manufacturing occupations that experience the strongest negative impact from servitization. A one-standard-deviation higher service share in a given establishment is associated with an 11% lower wage for this group.[32] Likewise, workers at the lowest end of the wage distribution show the strongest negative impact from servitization: For workers in the 10th wage percentile, an increase in the service share by ten percentage points is associated with a 1.4% lower wage.

Our analysis is, to the best of our knowledge, the first to identify shifts in the occupational composition as a cause of increasing within-establishment wage inequality. We have identified a new channel that amplifies wage inequality in Germany, especially in

[32]The standard deviation of the service share in establishments of all sectors averages to 0.32 , which means that the effect can be computed as $-.33 \times .32 = -.11$ (cf., Table 4.7).

the manufacturing sector. The findings have important implications for economic policy. Not only does the ongoing servitization trend imply an increasing gap between high- and low-wage workers, but it also shows that it is the workers already earning the least that suffer the most.

This finding must thus be seen in light of the ongoing discussion on the "working poor". This discussion goes hand in hand with that about old-age poverty because low wages throughout the individuals' working life imply a low pension level as well. Considering that the servitization trend can be expected to continue or even intensify in the future, this paper highlights the importance of the discussion on how to enable the low-paid workers to reach a certain standard of living. Accordingly, the findings should be considered for tax and transfer policies as well as labor market policies such as job market and retraining programs.

Further, servitization is associated with higher wages in service establishments and lower wages in manufacturing establishments. This could potentially reduce the differences in wage levels between both sectors. In the long run, servitization may align the manufacturing and the service sectors in terms of both employment structure and pay.

C Appendix

C.1 Additional Data Description

C.1.1 Processing of the Employer-Employee Data

The reporting requirements of the Federal Employment Agency were altered during the observation period, which influences data precision: (i) In 1992, the data were extended to cover the former East Germany. (ii) In 1999 marginal part-time workers were integrated into the notification procedure. This led to an increase in covered establishments, because the threshold for reporting was lowered to one part-time worker per establishment, and additionally overall worker numbers increased per establishment. (iii) In 2011 a further change in reporting of part- and full-time employees occured. We report briefly how we adjust the data to cope with these breaks in the reporting procedure.

In the data, the selection of the population of establishments in the BHP[33] and the LIAB might be biased twofold: First, from 1992 onwards establishments in Eastern Germany are included. We adjust for the potentially resulting biases by excluding Eastern Germany from the analysis. Second, in 1999 marginal part-time workers were integrated into the notification procedure. On the one hand, this leads to a rise in the number of establishments covered in the data set. Before, only establishments with at least one full-time employee subject to social security contributions were reported, whereas from 1999 onwards one part-time employee is a sufficient condition to be subject to reporting. We adjust for this bias by dropping these additional establishments. On the other hand, the inclusion of marginal part-time workers affects employment figures for already reporting establishments (with at least one full-time employee). After the change in the reporting procedure, establishment-level employment figures now include both part-time and full-time workers. The BHP does not allow us to adjust for this bias. For every establishment, the total number of full- and part-time workers is provided, but for other employment data such as the Blossfeld occupational categories, there is no distinction between the two categories. To create a consistent and unbiased data set despite changes in the reporting procedure, we make use of the individual worker-level data provided by the LIAB. For every worker, the data contains the full- or part-time status as well as the classification of occupations by the German occupational classification scheme 1988 (KldB88). We use a crosswalk between KldB88 and the Blossfeld occupational categories provided by Stops (2016) to obtain the Blossfeld occupations at the worker-level. Aggregating the data to the national level, we obtain information about the distribution of part-time workers across Blossfeld occupational categories. This information allows us to clean the BHP by subtracting part-time workers from the sample and also by adjusting for the reporting procedure bias within reporting establishments.

A third alteration that might confound our results is a change in reporting of work

[33] This data set is used and introduced in the subsequent section C.2.1.

hours resulting in a stark break between reported part- and full-time observations in 2011 (Fitzenberger & Seidlitz 2020). For the matched employer-employee data (LIAB), we are able to exclude any workers (all observed years) that changed from full- to part-time employment around 2011, i.e., between 2010 and 2012. This might exclude too many workers, but eliminates the potential bias without strong assumptions or propensity score estimates of being falsely reported as being in full-time employment.

For the establishment-level data (BHP) there is no easy fix. The bias from the reclassification also shows up in total numbers reported per establishment. The bias is even more pronounced in the skill-occupation groups (Blossfeld categories) which also should only report full-time employees. Since we do not observe all workers for all establishments present in the BHP in the worker-level data (LIAB) which would have allowed for a more stringent adjustment, we apply the following procedure. For each of the Blossfeld groups we compute its yearly share in the workforce observed in Blossfeld categories (sum of all Blossfeld categories, i.e., shares add up to one). Then, we take this share to the reported number of full-time employees per establishment and compute the number of full-time employees per Blossfeld category. This corrects for a large part of the observed break in 2011. Still, a minor break in 2011 remains. We take the difference in full-time employees between 2010 and 2012 – adjusted for the annual change – and distribute it evenly across the years in the sample This way, we adjust for the observed change in employment numbers. This effectively reduces the bias and observed discontinuity in 2010 over time and adjusts for the reporting break. Last, we impute employment numbers for 2010 with one- and two-periods lagged and future values.

C.1.2 Imputation procedure

Under social security reporting regulations, in Germany, employers must report the employees' gross wages liable to contribution. There is, however, an assessment ceiling which caps the amount up to which the salary or pension of a person is subject to social security contributions. Since the reported wages are gross wages liable to contribution, gross wages above the income threshold are capped in the data. Hence, the data is top censored for about ten percent of the observations. Due to computational limitations, estimating a suitable Tobit regression in a semi-parametric fixed effects structure on the whole sample as Honoré (1992) suggests is not feasible. To derive unbiased estimates, we follow the procedure of Dustmann et al. (2009) and later refined by Card et al. (2013) and impute censored wages in an initial step. We fit a series of 600 Tobit regressions, by year (24 years), education (missing, no education, vocational degree, some college, and university degree) and age group (ten-year spreads form a group, starting with an age of 20, plus a group for workers between 15 and 19 years of age; 5 groups) of the workers. For each of these groups, we draw the imputed wages from a truncated normal distribution which is scaled to the group by using the fitted standard deviation of the Tobit regression. For a detailed description see Gartner (2005). We use the same line of

controls in the Tobit regressions as Card et al. (2013), i.e., age of the respective worker, the average of the logarithmic daily wage in other years, the ratio of observed years in which the wage is censored over total years the individual is observed, the number of full-time employees at the establishment and the square of it, the mean of years of schooling at the establishment, the share of university graduates, the average of logged daily wages of colleagues and the percentage share of employees at the establishment whose wages are censored, and lastly a dummy equal to one if the individual is only included for one year in the data.

Dustmann et al. (2009) apply a series of tests to validate several imputation methods. They find that a Tobit regression of the whole sample and OLS regressions using imputed wages yield nearly identical results. We verify our results by repeating the estimations on the sample with censored wages. FE regressions on top censored dependent data will generate results biased towards zero (Davidson & MacKinnon 2004). Nonetheless, almost all of our results can be confirmed in sign and magnitude when using the censored data.

C.1.3 Occupational categories

Table 4.5: Occupational classification of Blossfeld (1987)

Name of occupational group	Description of the occupational group	Examples
Manufacturing		
Agricultural occupations (agr)	Occupations with predominantly agricultural orientation	Farmers, agricultural workers, gardeners, fishermen
Unskilled manual occupations (emb)	All manual occupations with at least 60 percent unskilled workers in 1970	Miners, rock breakers, paper makers, wood industry occupations, printing occupations, road and railroad construction workers
Medium-skilled manual occupations (qmb)	All manual occupations with at most 40 percent unskilled workers in 1970	Glassblowers, bookbinders, typesetters, locksmiths, precision instrument makers, electrical mechanics, coopers, brewers
Technicians (tec)	All technically trained specialists	Machinery technicians, electrical technicians, construction technicians, mining technicians
Engineers (ing)	Highly trained specialists who solve technical and natural science problems	Construction engineers, electrical engineers, production designers, chemical engineers, physicists, mathematicians
Service		
Unskilled services (edi)	All unskilled personal services	Cleaners, security guards
Medium-skilled services (qdi)	Essentially order and security occupations as well as skilled service occupations	Locomotive engineers, registrars
Semiprofessions (semi)	Service positions which are characterized by professional specialization	Interpreters, educators
Professions (prof)	All liberal professions and service positions which require a university degree	Statisticians, economists, social scientists
Service (administrative)		
Unskilled commercial and administrative occupations (evb)	Relatively unskilled office and commercial occupations	Postal occupations, office hands, typists
Medium-skilled commercial and administrative occupations (qvb)	Occupations with medium and higher administrative and distributive functions	Credit and financial assistants, foreign trade assistants, data processing operators, bookkeepers, goods traffic assistants
Managers (man)	Occupations which control factors of production as well as functionaries of organizations	Managers, business administrators, deputies, CEOs

Table 4.6: Exemplary occupational hierarchy according to KldB2010 scheme

KldB2010 4-digit	
43	Informatics, information and communication technology occupations
431	Informatics
432	IT system analysis, IT consultancy and IT distribution
4321	Occupations in IT system analysis
4322	Occupations in IT consultancy
43223	Occupations in IT consultancy - complex specialists
43224	Occupations in IT consultancy - highly complex specialists
4323	Occupations in IT distribution
4329	Executive personnel – IT system analysis , IT consultancy and IT distribution

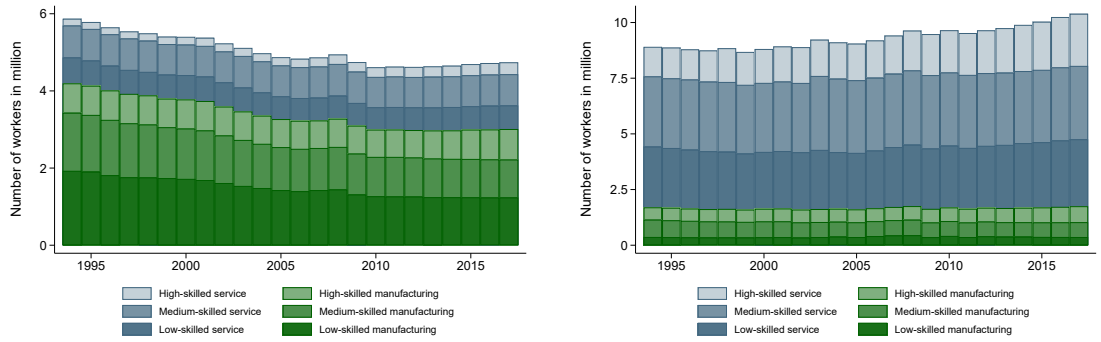
C.2 Complementing descriptives and stylized facts

C.2.1 Servitization in Germany

Figure 4.3 shows the occupational shifts within the manufacturing sector (left) and the service sector (right). For both sectors, the graph depicts the total number of workers and shares from 1994 to 2017 according to six Blossfeld occupation categories divided into service and manufacturing occupations with three levels of skill requirement each. Servitization in manufacturing is driven by two forces. First, the number of workers in manufacturing occupations is shrinking. Only the number of high-skilled manufacturing workers remained about constant (a 4% increase), whereas the number of workers in medium-skilled and especially low-skilled occupations declined (each by more than 30%). Second, the overall number of workers in service occupations increased. The number of workers in low-, and medium-skilled occupations decreased only slightly and the number of workers in high-skilled service occupations increased by 76%.

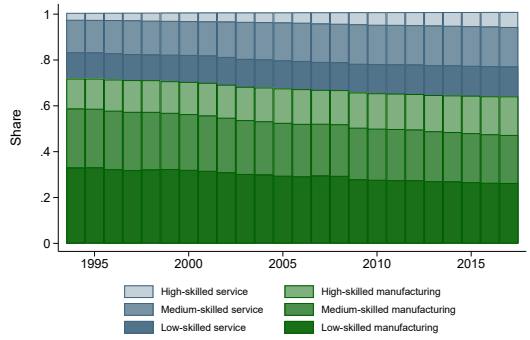
For these statistics, we additionally resort to the Establishment History Panel (BHP), a detailed, representative 50% sample of all establishments in Germany with at least one employee subject to social security contributions (Schmucker et al. 2018). It contains rich information on the labor structure of the establishment such as the labor composition in terms of the occupational mix (12 different occupation categories according to Blossfeld (1987)), the education of the employees (employment by skill categories), the number of female and male workers, the share of foreign workers, the age structure, etc. Additionally, the data set provides information on the wage structure and the industry of the establishment. The data cover between approximately 640,000 and 1,500,000 establishments yearly and constitute an unbalanced panel, as establishments may drop out of the sample or enter the sample. The BHP contains information on the aggregate numbers of workers' occupations by establishment coded in the classification of Blossfeld (1987). The Blossfeld categories are constructed such that educational and task requirements are very homogeneous within and very heterogeneous across Blossfeld categories. In total, there are twelve occupational groups which can be divided into two main fields, i.e., manufacturing and services. Service occupations include the administrative services subcategory. Each of the fields is subdivided further according to the skill requirement of the occupation (low-, medium-, and high-skill).

Table 4.7 shows the development of the within-establishment service share, i.e., servitization as defined in this paper. It becomes apparent that, over the sample period, the service share, i.e., the share of workers with service occupations in all workers within an establishment, increases. This pattern holds for the complete distribution of within-establishment service shares and for all sectors alike as is confirmed by Figure 4.4.

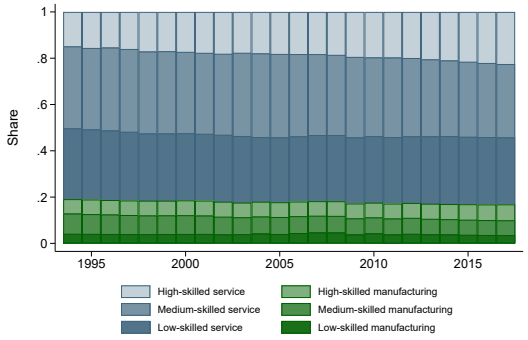


(a) Manufacturing sector

(b) Service sector



(c) Manufacturing sector



(d) Service sector

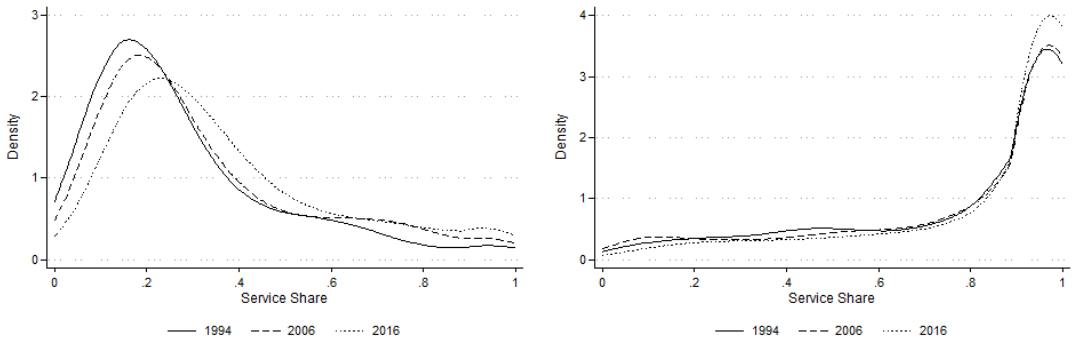
Figure 4.3: Servitization and skills

Notes: Data: BHP. Panel (a) and (c) show employment numbers and shares, respectively, in the manufacturing sector for workers holding low-, medium-, and high-skilled manufacturing and service occupations. Panel (b) and Panel (d) report these figures for the service sector. For Panels (a) and (b) numbers are adjusted to show total employment in the (Western) German economy.

Table 4.7: Servitization across establishments

	1994	2006	2016	1994	2006	2016	1994	2006	2016
	All sectors			Manufacturing			Service		
p10	.111	.142	.200	.077	.095	.125	.313	.284	.400
p25	.226	.297	.412	.133	.158	.198	.628	.647	.760
p50	.619	.769	.879	.221	.251	.308	.917	.925	.956
p75	.962	.984	1	.368	.440	.500	1	1	1
p90	1	1	1	.609	.721	.770	1	1	1
mean	.588	.648	.712	.284	.330	.375	.783	.784	.830
std. dev.	.355	.342	.319	.216	.239	.242	.276	.283	.249

Notes: Data: LIAB. The table shows percentiles and the mean of the service share within establishments for 1994, 2006, and 2016 for all sectors, the manufacturing sector, and the service sector respectively.

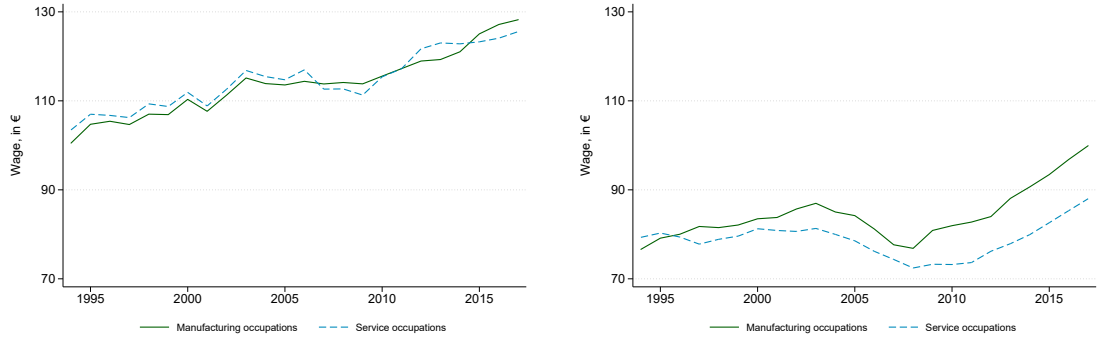


(a) Manufacturing industries (b) Service industries

Figure 4.4: Service share over time

Notes: Data: LIAB. Panel (a) and Panel (b) display kernel densities of the share of workers with service occupations in an establishment's labor force within manufacturing industries and service industries, respectively.

C.2.2 Wages (in levels) of Service and Manufacturing Occupations in Service and Manufacturing Industries



(a) Wage levels for occupation groups in the manufacturing sector

(b) Wage levels for occupation groups in the service sector

Figure 4.5: Wages of service and manufacturing occupations in service and manufacturing sectors

Notes: Data: LIAB. Panel (a) and Panel (b) display wages in levels (in euro) for manufacturing and service occupations within manufacturing industries and service industries, respectively.

C.2.3 Wages by Skill Intensity

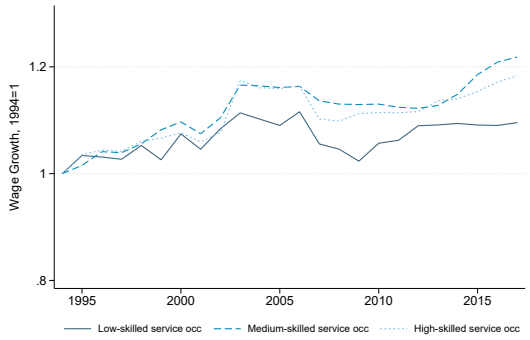
To rule out the possibility that the reported occupation-specific wage dispersion within the service and manufacturing sectors is driven by differences in skill intensity, we break down our analysis further and additionally differentiate between three levels of skill requirement according to Blossfeld categories in Figure 4.6. This classification is identical to the one that we use to analyze occupational shifts (cf., Figure 4.3). Panel 4.6a and 4.6b report wage developments in manufacturing industries for workers employed in manufacturing and service occupations, respectively. Panel 4.6c and Panel 4.6d report wage developments for workers within service industries. The figures are complemented by Figure 4.7 that shows wages in levels.

These graphs yield four notable insights. First, the reported difference in within-sector wage developments between workers in manufacturing and service occupations also persists across different skill categories. Accordingly, we can rule out the possibility that our finding of within-sector remuneration differences by occupations is caused only by a different skill distribution across occupations. The growth in wages for workers holding manufacturing occupations both within the manufacturing and within the service sector is higher than the wage growth for workers holding service occupations except for medium- and high-skilled occupations in the service sector. One likely reason is that high-skilled service occupations include administrative occupations such as managers.

Second, the previous picture that generally manufacturing occupations are higher



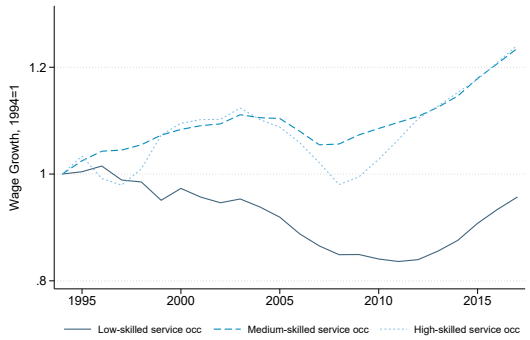
(a) Wage growth of manufacturing occupation groups within the manufacturing sector



(b) Wage growth of service occupation groups within the manufacturing sector



(c) Wage growth of manufacturing occupation groups within the service sector



(d) Wage growth of service occupation groups within the service sector

Figure 4.6: Wage growth across skill and occupational groups in manufacturing and service sectors

Notes: Data: LIAB. Panels (a) and (b) report wage developments in manufacturing industries for workers holding low-, medium-, and high-skill manufacturing and service occupations, respectively. Panel (c) and Panel (d) report wage developments for workers within service industries. Wages are normalized to 1 in 1994.

paid than service occupations does not persist, interestingly enough. Although wage growth is mostly higher for all manufacturing occupations, this does not apply to wages in levels. Although workers in manufacturing occupations experience a higher wage growth than workers in service occupations, they do not earn higher wages in levels. In 2017, average wages in the manufacturing sector were approximately 2.6% (or 2.81 Euro) higher for workers in low-skilled manufacturing occupations than for workers in low-skilled service occupations, but about 23.4% (or 27.13 Euro) lower for workers in medium-skilled manufacturing occupations than for workers in medium-skilled service occupations and 7.4% (or 12.91 Euro) lower for workers in high-skilled manufacturing occupations than for workers in high-skilled service occupations. The picture is similar for the service sector.[34] The previous observation that average wages for workers in man-

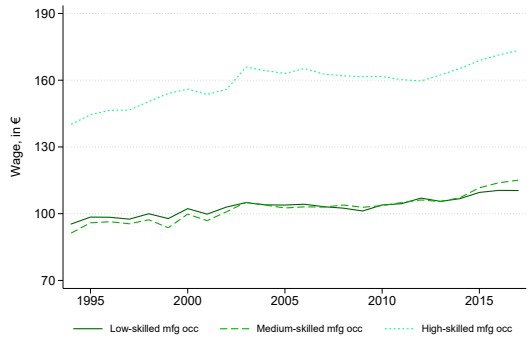
[34]In 2017, average wages in the service sector were approximately 9% (or 7.03 Euro) higher for worker

ufacturing occupations are higher than average wages for workers in service occupations is accordingly driven by the distribution of low-, medium-, and high-skilled service and manufacturing occupations across industries. For example, the proportion of higher-paid high-skilled workers is greater for workers in manufacturing occupations than for workers in service occupations both within manufacturing and service industries (cf., Figure 4.3).

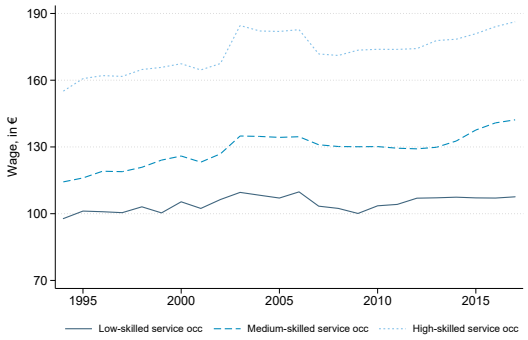
Third, for each of the six occupation-skill categories, wages are lower in the service sector than in the manufacturing sector. On average, daily wages in manufacturing industries are 39.2% or 36.58 Euro higher than in service industries for both service and manufacturing occupations differentiated by low, medium, and high-skilled categories.

Fourth, remarkably, it is medium-skilled workers in both the manufacturing sector and in the service sector whose wages grow strongest. Except for workers holding service occupations in the service sector, we do not establish the decline in (relative) wages for low-skilled workers who according to Bárány & Siegel (2018) are affected most by skill-biased technological change.

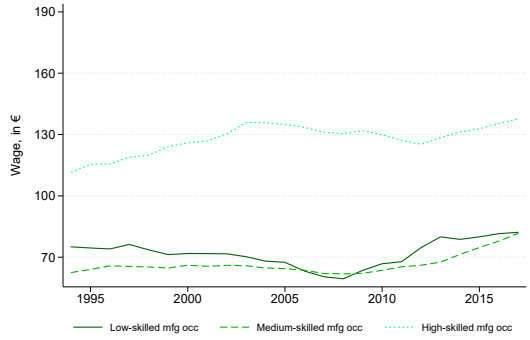
in low-skilled manufacturing occupations than for worker in low-skilled service occupations, about 24.1% (or 25.92 Euro) lower for worker in medium-skilled manufacturing occupations than for worker in medium-skilled service occupations but 17.11% (or 20.14 Euro) higher for worker in high-skilled manufacturing occupations than for worker in high-skilled service occupations.



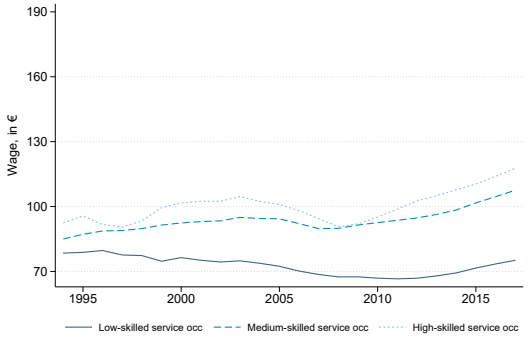
(a) Wage levels of manufacturing occupation groups within the manufacturing sector



(b) Wage levels of service occupation groups within the manufacturing sector



(c) Wage levels of manufacturing occupation groups within the service sector



(d) Wage levels of service occupation groups within the service sector

Figure 4.7: Wage levels across skill and occupational groups in manufacturing and service sectors

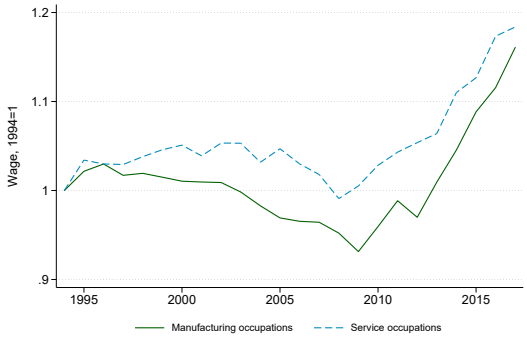
Notes: Data: LIAB. Panels (a) and (b) report wage developments in manufacturing industries for workers in low-, medium-, and high-skilled manufacturing and service occupations, respectively. Panel (c) and Panel (d) report wage developments for workers within service industries. Wages are in levels.

C.2.4 Average wages by occupations within establishments of each sector

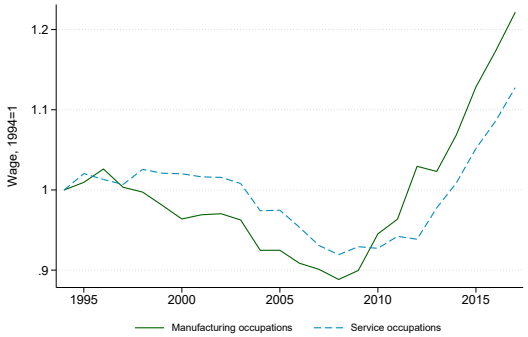
To supplement the foregoing discussion on differential wage growth and within-establishment wage inequality, we additionally report the mean of the average wages by occupations within establishments of each sector in Figure 4.8. Averaging wages by occupations within establishments means that each establishment contributes an equal share to the reported numbers independent of the establishment's size. Workers in large establishments are accordingly under- and workers in small establishments overrepresented, which explains why numbers differ in comparison to Figure 4.2. There, we build averages across for all workers (by occupation) – and not establishments – such that implicitly the establishment's size is considered.

Overall, the trend in both figures is similar: Figure 4.8, displays distinct patterns of average within-establishment wage developments in both sectors which we can reconcile

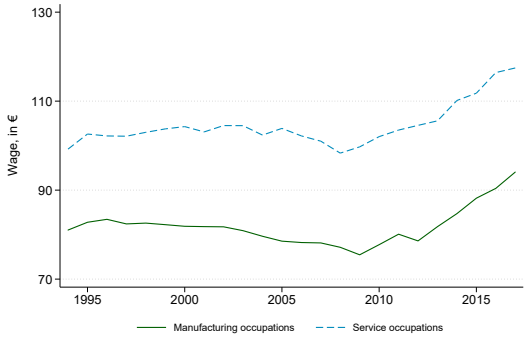
with the development of within-establishment wage inequality as reported in Panel (b) of Figure 4.1. Until shortly before the financial crisis in 2008/2009 within-establishment wage averages are stagnant for service occupations in the manufacturing sector and fall slightly for manufacturing occupations in the manufacturing sector as well as for service and manufacturing occupations in the service sector (cf., Panels (a) and (b) of Figure 4.8). After these years, real wage growth commences for all occupations (in line with the observations in Figure 4.2). A similar picture emerges for establishments of the service sector.



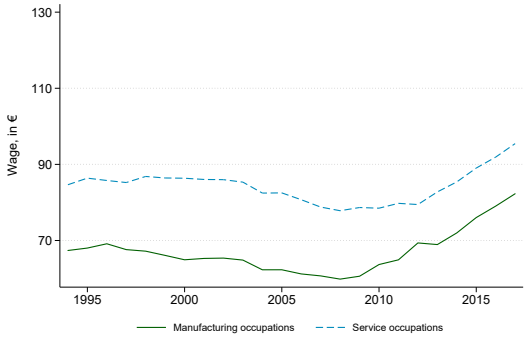
(a) Wage growth of unweighted within-establishment wage averages by occupation groups in the manufacturing sector



(b) Wage growth of unweighted within-establishment wage averages by occupation groups in the service sector



(c) Wage levels of unweighted within-establishment wage averages by occupation groups in the manufacturing sector



(d) Wage levels of unweighted within-establishment wage averages by occupation groups in the service sector

Figure 4.8: Wage growth of unweighted within-establishment wage averages by occupation group and sector

Notes: Data: LIAB. Panel (a) reports the average wage growth of unweighted within-establishment wage averages for manufacturing and service occupations for the manufacturing sector. Panel (b) reports the same figures for the service sector. Wages are indexed to 1 in 1994. Panels (c) and (d) show the wages in levels.

C.3 Servitization and the average worker

To assess the effects of servitization on the average worker's compensation, we make use of the panel structure of the data and estimate the Mincerian wage regression (4.4) using a fixed effects approach.

$$log(wage)_{ijt} = \alpha_i + \beta_1 \frac{\#\ service\ workers_{jt}}{\#\ employees_{jt}} + \mathbf{X}'_{it}\boldsymbol{\gamma}_1 + \mathbf{X}'_{jt}\boldsymbol{\gamma}_2 + \delta_t + \varepsilon_{ijt} \tag{4.4}$$

$\mathbf{X}'_{it}$ ($\mathbf{X}'_{jt}$) contains (time-varying) individual (establishment) confounders[35], α_i are worker fixed effects, δ_t depicts time dummies, and ε_{ijt} denotes the error term. $\frac{\#\ service\ workers_{jt}}{\#\ employees_{jt}}$ is the share of workers holding service occupations at establishment j.

We estimate equation (4.4) for all workers in Germany in our sample that are employed at an establishment with more than ten full-time employees and where the establishment's industry classification never switched between the manufacturing and service sector.[36] Our main interest lies on the effect of the service share on wages, i.e., β_1.

A fixed effects structure is appropriate as it not only time demeans the data but it also excludes any person-specific effects. Combined with the exclusion of establishments and workers switching sectors or occupations, the inclusion of fixed effects controls for match-effects as documented by Card et al. (2013).[37] We regress the logarithmic daily wage of worker i employed at establishment j at time t on worker and establishment characteristics.[38]

Table 4.8 reports the results for equation (4.4). For the economy as a whole the effect of servitization on wages is negative and statistically different from zero at the one percent level. Putting economic meaning to the effect of -0.144, we find that a ten-percentage-point increase in the service share within an establishment leads to a wage decrease of 1.44% for the average employee. Alternatively, a standard deviation (sd($service\ share$) = 0.3387) increase in the service share leads to a wage decrease of 4.9%.

Columns (2) and (3) in Table 4.8 distinguish between the manufacturing and the service sector. The results for the whole economy are primarily driven by the manufacturing sector: The effects of servitization on wages are strongly negative for workers employed

[35] For a full list of regressors see Section C.5, Table 4.10.

[36] This sample selection ensures identification of effects within the sectors that are not caused by a reclassification of establishments.

[37] Indeed, a Hausman test rejects the null that individual effects are orthogonal; hence an RE specification would lead to inconsistent estimates. A Hausman-Taylor (or related) model could potentially lead to more efficient results, but is computationally not feasible. Due to the large number of observations, we are confident that our results do not lack precision. We cannot assume orthogonality between individual time-invariant characteristics and the error term.

[38] We use the previously described imputed wages for all regressions. This approach is computationally and econometrically feasible when dealing with top censored data and a fixed effects structure. The semi-parametric model of Honoré (1992) is again not feasible due to large data and restricted computational power in connection with data access.

in the manufacturing sector. Here, a ten-percentage-point increase in the service share of a given establishment lowers averages wages by .9%.

For the service sector though, we find almost negligible effects. For every ten-percentage-point increase in the service share, the average employee's wage decreases by .08%. However, as mentioned before, the service share within the service sector is on average quite high, which means that we do not observe strong wage effects from servitization. Further, particularly high-paying industries such as banking and insurance employ the fewest manufacturing workers within services, whereas low-paying industries such as traffic and news transmission employ significantly higher numbers of manufacturing workers and are hence the sectors with room for servitization.

Summarizing, the overall effect of the employers' servitization level on employees' wages is negative. This effect is driven by the manufacturing sector, where we find the strongest negative effect.

Table 4.8: FE regressions of logged daily wages on the service share

	Dependent variable: log(wage)		
	(1)	(2)	(3)
	All sectors	Manufacturing sector	Service sector
Service share	-0.144***	-0.090***	-0.008***
	(0.002)	(0.004)	(0.003)
Observations	9,809,082	4,994,141	4,490,122
R-squared	0.34	0.23	0.39
Additional confounders	Yes	Yes	Yes
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Notes: Data: LIAB – estimating equation (4.4)
Only workers at establishments with more than ten full-time employees are included. We do not include establishments that switch industries during our period of observation. The explanatory variable *service share* is the (yearly) share of full-time employees with service occupations over all full-time employees in a given establishment based on the underlying BHP data. Accordingly, the service share is not subject to potential coverage issues. "All sectors" also include establishments in the primary sector, which explains the discrepancy between the sum of observations in *manufacturing* and *service sector* and observations in the *all sectors*sample.

C.4 Robustness

This section presents selected robustness tests of our empirical results. Instead of interacting the service share with the six broad occupational-skill groups as in equation (4.2), we now interact the service share with the even more disaggregated Blossfeld categories so that we can now estimate (4.5). Regressors are the same as before. The

results are presented in Table (4.9).

$$\begin{aligned} log(wage)_{ijt} = \ & \alpha_i + \boldsymbol{\beta_1} \frac{\#\ service\ workers_{jt}}{\#\ employees_{jt}} \times \mathbb{1}\{Blossfeld\}_{it} \\ & + \boldsymbol{\beta_2} \mathbb{1}\{Blossfeld\}_{it} \\ & + \mathbf{X}'_{it}\boldsymbol{\gamma}_1 + \mathbf{X}'_{jt}\boldsymbol{\gamma}_2 + \delta_t + \varepsilon_{ijt} \end{aligned} \tag{4.5}$$

The Blossfeld manufacturing categories are now subdivided according to low-skilled (*emb*), medium-skilled (*qmb*), and high-skilled (*tec*) manufacturing occupations. The additional distinction we make lies in service occupations where we now regard administrative occupations separately.

Generally, the estimation confirms the previous picture that low- and medium-skilled occupations are more negatively affected than high-skilled occupations. This is true for service occupations without administrative services and especially for manufacturing occupations.

Table 4.9: FE regressions: interaction with Blossfeld group

	Dependent variable: log(wage)		
	(1)	(2)	(3)
	All sectors	Manufacturing sector	Service sector
emb × service share	-0.331***	-0.322***	-0.086***
	(0.006)	(0.008)	(0.010)
qmb × service share	-0.057***	-0.127***	0.050***
	(0.006)	(0.015)	(0.010)
tec × service share	-0.114***	0.031***	-0.191***
	(0.006)	(0.010)	(0.011)
edi × service share	-0.106***	-0.100***	-0.037***
	(0.005)	(0.011)	(0.011)
evb × service share	-0.181***	-0.148***	-0.208***
	(0.010)	(0.028)	(0.019)
qdi × service share	-0.173***	-0.208***	-0.045***
	(0.009)	(0.035)	(0.012)
qvb × service share	-0.170***	-0.054***	0.033***
	(0.004)	(0.008)	(0.006)
semi × service share	-0.062***	-0.008	0.029***
	(0.003)	(0.008)	(0.005)
man × service share	-0.243***	-0.109***	-0.100***
	(0.009)	(0.032)	(0.013)
prof × service share	-0.090***	0.051***	-0.055***
	(0.005)	(0.010)	(0.009)
Additional confounders	Yes	Yes	Yes
Observations	9,808,849	4,994,135	6,535,499
R-squared	0.34	0.23	0.406
Robust standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

Notes: Data: LIAB – estimating equation (4.5)
Only workers at establishments with more than ten full-time employees are included. We do not include establishments that switch industries during our period of observation. The explanatory variable *service share* is the (yearly) share of full-time employees with service occupations over all full-time employees in a given establishment based on the underlying BHP data. Accordingly, the service share is not subject to potential coverage issues. "All sectors" also include establishments in the primary sector, which explains the discrepancy between the sum of observations in *manufacturing* and *service sector* and observations in the *all sectors* sample.

C.5 List of regressors

Table 4.10: List of regressors

Variable	Description
Individual level	
age	age of the worker
age sqr	Age of the worker squared, to account for non-linear lifetime earning curves
Abitur	Dummy equal to one if worker has a higher education entrance qualification (A-levels equivalent)
uni	Dummy equal to one if the worker holds a university degree

vocational	Dummy equal to one if the worker holds a vocational degree
days in job	Indicates how long the individual holds this particular job (in years)
manufac	Dummy equal to one if the worker is in a manufacturing occupation
service	Dummy equal to one if the worker is in a service occupation
routine	Indicator if the occupation is routine in nature
lowskill	Indicator if the worker's occupation has low skill requirement
mediumskill	Indicator if the worker's occupation has medium skill requirement
highskill	Indicator if the worker's occupation has high skill requirement – reference group
niveau	Indicates the level of requirement for the occupation (4 categories)
establishment level	
service share	Share of full-time employees in service occupations in total full-time employees ($\in [0, 1]$)
number full-time employees	Establishment size indicator
establishment age	Indicator of the establishmtent's age. Computed as the difference between the respective year and the "year of first appearance". The latter indicates either the founding date of the establishment or the year of change of ownership or legal change. The constructed variable serves as an indicator for how well the establishment is settled in the market.
Manu	Indicator for the industry sector: manufacturing sector
Service	Indicator for the industry sector: service sector
perc female estab	Share of full-time female workers in total full-time employees
shr migrant estab	Share of migrants in total full-time employees
shr age 50 estab	Share of workers over 50 years of age in total full-time employees
shr routine estab	Share of workers in routine occupations in the establishment
perc BL medium estab	Share of workers in medium-skilled occupations in total full-time employees
perc BL high estab	Share of workers in high-skilled occupations in total full-time employees
shr NivAid estab	Share of workers out of the lowest requirement group (*niveau*) in total full-time employees
shr NivNorm estab	Share of workers out of the second to lowest requirement group (*niveau*) in total full-time employees
shr NivComplex estab	Share of workers out of the third to lowest requirement group (*niveau*) in total full-time employees
year fixed effects	
district fixed effects	

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6 Eidesstattliche Versicherung

Ich erkläre hiermit, dass ich meine Doktorarbeit “Essays on Firms and Workers in the Global Economy” selbständig und ohne fremde Hilfe angefertigt habe und dass ich als Koautor maßgeblich zu den weiteren Fachartikeln beigetragen habe. Alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen der aufgeführten Beiträge wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

Kiel, July 06, 2021

Thilo Kroeger

7 Hilfsmittel

Die empirischen Analysen der verschiedenen Kapitel beruhen auf verschiedenen Datensätzen, welche dort jeweils beschrieben sind. Die Datenaufbereitung und -auswertung erfolgten mit der Statistik-Software „STATA 15“. Der Datenzugang für Kapitel 3 und 4 erfolgte über Fernzugriff des IAB sowie über Gastaufenthalte am Forschungsdatenzentrum der Statistischen Landesämter Standort Berlin-Mitte im Gebäude des Deutschen Institut für Wirtschaftsforschung (DIW).

Kiel, July 06, 2021

Thilo Kroeger