Tax thy neighbour: Corporate tax pass-through into downstream consumer prices in a monetary union*

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Abstract

We estimate the response of product-level retail prices to changes in the corporate tax rates paid by wholesale producers (pass-through). Under perfect competition in goods and factor markets, pass-through of corporate taxes should be zero, and their incidence mainly falls on factor prices. We use variation in tax rates across time and space in Germany, where municipalities set the local business tax once a year, to provide estimates of tax pass-through into the retail prices of more than 125,000 food and personal care products sold across Germany. By leveraging 1,058 changes in the local business tax rate between 2013 and 2017, we find that a one percentage point tax increase results in a 0.4% increase in the retail prices of goods produced by taxed firms and purchased by consumers in the rest of Germany, who thus end up bearing a substantial share of the tax burden. This finding suggests that manufacturers may exploit their market power to shield profits from corporate taxes, complicating the analysis of the redistributive effects of tax reforms. We also explore various dimensions of heterogeneity in pass-through related to market power, including producer size, market shares, and retail store types. While producer heterogeneity does not seem to matter, the significant pass-through of corporate taxes to consumer prices in the low inflation period covered by our sample is mostly due to price changes in supermarkets and hypermarkets.

Keywords: corporate taxes, producer pass-through to retail prices, imperfect competition, vertical interactions

JEL classifications: F12, F45, E13, H71, L11

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1 Introduction

Who pays for local corporate tax increases in a highly integrated monetary union? The ability to set different local tax rates is usually extolled as a virtue of fiscal federalism. But goods and capital mobility imply that the tax incidence may fall on shareholders, workers in the jurisdiction setting corporate taxes, or consumers not only in the same jurisdiction but also in other regions in the monetary union, where the goods of taxed firms are exported to. In contrast to a closed economy where the burden of corporate taxes falls fully on shareholders, as shown in the seminal paper by Harberger (1962), full goods and capital mobility and perfectly competitive markets imply that the burden falls mainly on labour, the less mobile (even though generally tax-exempt) factor. If goods markets are not perfectly competitive and firms have market power, then the tax burden will also be borne by consumers, with additional distributive implications. Nevertheless, the effects of corporate tax policies on firms' prices are a rarely analysed issue.

In this paper, we estimate the pass-through of corporate taxes into retail prices in Germany using municipality-level variation in local business tax rates. In this respect, we consider Germany as a highly integrated currency area, comprising many small open economies with no trade frictions and a great deal of capital mobility. We build on Baker, Sun, and Yannelis (2020), who are the first to empirically estimate the pass-through of state-level corporate taxes into retail prices in the United States, using barcode-level retail prices from household scanner data. We complement the results of Baker et al. (2020) by using store-level scanner data and especially by exploiting the German institutional setup of local corporate taxes, which are set at the municipal level.[1] The ensuing much more granular variation in tax changes helps in addressing some well known identification challenges (see also Fuest, Peichl, and Siegloch, 2018).[2] In particular, because we relate local tax changes to price changes outside the production municipality and flexibly control for demand and supply factors separately, the estimated effect is not contaminated by shocks that jointly drive prices and tax rates. Moreover, the local business tax is the main fiscal tool of German municipalities that affects firms, in contrast with central governments and even less decentralised regional fiscal authorities that have multiple

[1]Differently from Germany, where all firms pay corporate taxes, papers on the tax incidence in the US must also take into account whether a firm is incorporated or not, because corporate taxes in the US depend on the legal form of the firm. Harberger (1962) shows that the tax burden falls on all owners of capital, independently of whether they are incorporated or not. Gravelle and Kotlikoff (1988) shows that when accounting for the endogenous decision to incorporate as well as for dual production of the same good by corporates and non-corporates, the incidence does not change much but the excess tax burden increases substantially.

[2]Several other studies focus on the intra-national variation of corporate tax rates, arguing that this makes it easier to control for unobserved factors. For example, Ljungqvist and Smolyansky (2016) use a difference-in-differences approach at the US state-level and show that a one percentage point increase in the top marginal corporate income tax rate reduces employment by 0.3–0.5% and income by 0.3–0.6%.

tools at their disposal.[3] We also analyse determinants of pass-through of corporate taxes to retail prices, especially concerning heterogeneity in producers and retailers, which plays a key role in theories of imperfect competition and firms' market power.

Specifically, we look at 1,058 tax changes between 2013 and 2017, matching German municipalities with firms' headquarters and with the prices of their products from supermarket scanner data. Similarly to Baker et al. (2020), the identification of our empirical results uses the fact that retail product prices are observed in locations different from where producers are subject to the corporate tax. This allows controlling for local business cycles that may jointly influence prices and tax rates. Our main finding is that local corporate tax pass-through into retail prices of goods "exported" to the rest of Germany is substantial. On average, a one percentage point increase in the local corporate tax rate raises the retail prices of the exported products of taxed firms by around 0.4%.

The municipality-level variation in corporate tax rates used in our analysis was previously considered by Fuest et al. (2018), who argue that it is largely exogenous. They find that a one percentage point tax increase lowers firm-level wages by 0.3%. By using the same tax variation, we can compare their result on the corporate income tax pass-through to wages to ours on retail prices more directly, stressing the novelty of our results. An estimated pass-through of taxes to retail prices of about 40% has the following two implications. First, the fact that consumer prices are affected by tax changes implies significant adjustment in wholesale prices, which are then passed-through by retailers. Second, under the mild assumption that supermarkets do not magnify wholesale price changes, corporate taxes elicit changes in the latter prices large enough to keep net-of-tax profit margins, and thus markups, of producing firms broadly constant.

Because firms are located across different German municipalities and sell their products to many other jurisdictions across Germany through retailers, we frame our analysis in a model of a currency area, consisting of many small open economies trading under minimal frictions through a retail sector, similar to Corsetti and Dedola (2005) and Hong and Li (2017). We show in the model that the effect of corporate taxes on prices depends on the elasticity of consumer demand for each product, the share of retail costs relative to wholesale cots, the share of tax-deductible input costs and the effect of corporate tax on input costs (Fuest et al., 2018).

In line with our model, we extend our empirical analysis to allow for heterogeneity in pass-through of corporate taxes to retail prices. In particular, we estimate category-specific pass-through for 20 COICOP-level categories, but find no significant heterogeneity. We also explore the role of producers and retailers heterogeneity. We allow for

[3] German municipalities also set two real estate taxes. One applies to arable land (*Grundsteuer A*) and one on built-up areas (*Grundsteuer B*). Similar to the local business tax, the tax rate is a federally set base level multiplied by local scaling factors. Our estimated pass-through of corporate taxes to prices is robust to controlling for changes in local scaling factors of the real estate taxes.

heterogeneity in producers' size and market shares, but find little evidence of it. This is interesting, because models with oligopolistic competition or non-CES demand curves, would predict lower pass-through for firms with larger market shares, other things equal (Atkeson and Burstein, 2008; Kimball, 1995). Consistently with the above results, we also find no significant effect of competitors' tax changes on prices of other firms' products. Furthermore, we consider pass-through heterogeneity in terms of income (GDP per capita) in the sales region, finding larger point estimates for high-income regions but no statistically significant differences. However, we do find significant difference in pass-through across store types: While prices in drug stores and discounters are hardly affected, we find significant pass-through into retail prices in supermarkets and hypermarkets.

Related literature We contribute to four strands of the literature. First, our finding that consumers bear some of the burden of corporate taxes could be appreciated against the backdrop of a large body of literature that has instead examined the effects of corporate taxes on factor prices in various settings, but mostly focusing on closed vs. open economies. Our findings, together with those in Baker et al. (2020), point to the need to include imperfect competition in goods markets into the analysis of the costs and benefits of corporate taxes. Auerbach (2006) discusses possible consequences of relaxing some of the assumptions in Harberger (1962), e.g., allowing for imperfect competition in goods markets and introducing risk. Gravelle (2013) focuses on relaxing the closed-economy setup and reviews the literature on corporate tax incidence in open-economy general equilibrium models, where the relatively higher mobility of capital versus labour increases the tax incidence on wages when factor substitution is low. The reduced incidence on capital arising from the open economy setting is mitigated when the elasticity of substitution of products is low.

Second, we contribute to the vast literature on the role of imperfect competition and market power in price setting, by showing that corporate taxes affect consumer prices. This constitutes a clear deviation from perfectly competitive markets. Moreover, we contribute to the strand of the literature on imperfect competition that focuses on heterogeneous pass-through and markup adjustment. By showing that products with relatively large market share and firms with relatively high total sales have no significantly different pass-through, we complement theoretical and empirical findings in the context of exchange rate pass-through, which show that pass-through decreases with market power, as proxied by market shares and firm size (Atkeson and Burstein, 2008; Auer and Schoenle, 2016; Amiti, Itskhoki, and Konings, 2019).

Third, we contribute to the literature on networks and vertical interactions (see, e.g., Hong and Li, 2017), by showing that the pass-through of shocks to wholesale producers into retail prices is substantial, in particular for supermarkets and hypermarkets relative to discounters. There could be various structural reasons for this finding. On the one hand, producers may discriminate between discounters and other stores, e.g. since they may perceive little market power for sales by the former, or they may be less able to apply price increases to them. On the other hand, retailers may transmit the shocks differently to their customers depending on their own market power, with discounters absorbing price increases into their profit margins, contrary to supermarkets and hypermarkets.

Fourth, we contribute to the literature on price adjustment in currency areas. Similarly to Fuest et al. (2018), McKenzie and Ferede (2017) use the fact that in Canada corporate taxes change across provinces to cast the problem in an open-economy setting across provinces.[4] In light of the open economy literature they predict a high pass-through on local wages. Using provincial data they estimate that in the long run a 1% tax increase lowers wages by 0.11%. Our contribution shows that tax shocks to producers are passed through not only into their local factor prices, but also into the retail prices of their "exports" to other German regions.

2 Institutional setup and data construction

Corporate taxes in Germany are set at the federal and the local level.[5] The tax base and the firms subject to the tax base are defined at the federal level, while the tax rate contains both a federal component and a component that is set in each of more than 10,000 municipalities (*Gemeinden*). Specifically, the tax base is operating profits with some adjustments, for example to account for non-deductibility of equity-based financing and only partial deductibility of debt-based financing. Unlike in the United States, where corporate income is taxed for so-called C-corporations but not for "pass-through" entities, in Germany both incorporated and not incorporated entities are subject to this tax.[6]

The municipality-specific corporate tax rate is computed by multiplying the federally-set basic rate (*Steuermesszahl*) with the local scaling factor (*Hebesatz*) set by the municipalities. Since 2008, well before the start of our sample, the basic rate has been constant at 3.5%. Each year, usually in the last quarter, municipalities decide on the local scaling factor for the next year, becoming effective on January 1. It must be set at least to 2 but is not restricted otherwise (implying that the overall corporate tax rate is at least 7%).[7]

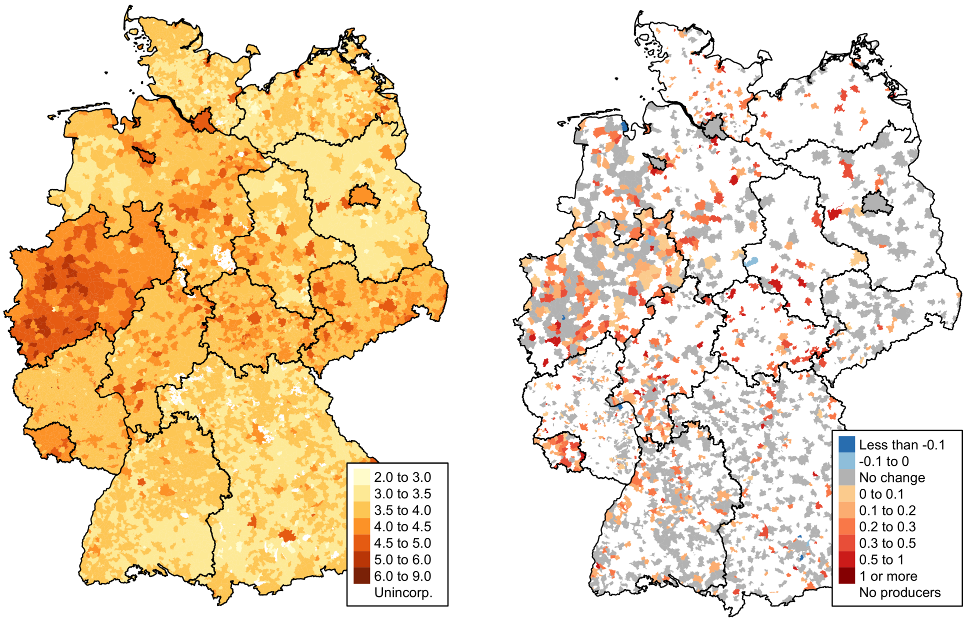
[4] Relatedly, Becker, Egger, and Merlo (2012) show that corporate tax rates have an effect on the location decision of multinational enterprises. In particular, they find using German data that higher corporate tax rates reduces employment and fixed assets of foreign MNEs.

[5] In this paper, we focus on the local business tax component of the corporate tax, following Fuest et al. (2018). There is also the federal corporate income tax (*Körperschaftssteuer*) and the federal personal income tax (*Einkommenssteuer*). The local business tax (*Gewerbesteuer*) yields about 7% of total tax revenue.

[6] Specifically, the self employed as well as firms operating in agriculture and forestry are exempt, but they do not belong in our sample of products.

[7] Note that scaling factors are also commonly reported in percentage points, such that the minimum

Figure 1: Geographical variation in tax scaling factors



(a) Scaling factors in 2017

(b) In-sample cumulative changes between 2013 and 2017

Notes: Panel (a): municipality-specific corporate tax scaling factors in 2017. The effective corporate tax is computed as 3.5% times the scaling factor. Panel (b): Cumulative changes in the municipality scaling factor between 2013 and 2017, which is the sample period for consumer prices used in this paper. Grey areas indicate no change in the scaling factor. White areas indicate municipalities in which no producer location is observed in our sample.

We collect and assemble official data from the Statistical Offices of the 16 German Länder (*Statistische Landesämter*) on yearly municipality-level corporate tax rates. Figure 1a shows the significant geographical variation in the level of municipality-level scaling factors. The average scaling factor is 3.62, which results in a corporate tax rate of 12.7%. The largest scaling factor is observed at 9 in the town of Dierfeld in Rheinland-Pfalz (so that the overall corporate tax rate is 31.5%).

In this paper, we construct a unique dataset that links product-level retail prices to municipality-level tax rates based on the location of the producers.[8] We obtain product-level prices from the marketing company Information Resources, Inc. (IRi) (Bronnenberg, Kruger, and Mela, 2008). The German IRi data are collected by point-of-sale scanners and comprise the weekly value and quantity sold of 309,3228 products, identified by barcodes (UPCs or GTINs), across 10,412 distinct shops from 16 (anonymized) retail chains in 95 two-digit ZIP codes between 2013 and 2017. Thereby, product prices are recorded also in

is 200. If a firm has establishments in many municipalities (or an establishment extends over more municipalities), the tax is apportioned in proportion to the wage bill in each municipality.

[8] Table A.1 in Appendix A contains an overview of all data sources used.

regions other than the one where producers are located.[9] The products are so-called fast-moving consumer goods, including (mostly processed) food, beverages, tobacco, toiletries, and other personal and household care items. The coverage of food, beverages and tobacco accounts for 74 of the 187 ECOICOP categories for goods comprising the Harmonised Index of Consumer Prices (HICP).

To obtain the municipality-level tax rate that applies to the producer of a given product, we match the product-specific barcodes in the IRi data with firm information from the GS1 GEPIR database, which contains producer identity and location. Since we are interested in the pass-through of taxes to prices for German firms, we restrict our attention to barcodes that are registered in Germany.[10] Because the large number of distinct products in the data set prevents us from querying information for every barcode, we focus on a subset of barcodes so as to cover every distinct producer firm. The subset of barcodes is determined as follows.[11] First, for most of the barcodes the first seven digits identify the firm, so we focus on barcodes with different seven-digit starting sequences. Second, because for some firms GS1 identifiers are longer than seven digits (up to eleven digits), we also add barcodes with the same starting sequence but attached to different "vendors", which is a coarse firm/brand name variable in the IRi data.

Given this set of barcodes, we obtain detailed associated producer information, including its location, from GS1, the company administrating and licensing barcodes. It is natural to assume that this official address identifies the producer's headquarter and thus where the corporate tax is paid. Note that this information reflects the most recent address of the firm; we are not able to track the historical locations of firms.[12] We are able to obtain the identity and location for 65% of barcodes representing different firms.

We merge the firm information back to the product-level data based on this firm identifier. This yields the producer location for 61% of all German products in the IRi data. Based on the reported postcode and city, we can attach firms to a municipality and thereby the applicable corporate tax rate for the firm over time.[13] Appendix A.3 provides details on the matching of products to firms and municipalities.

Equipped with the concrete firm name and firm location, we are also able to search

[9]We aggregate the weekly data to annual frequency, as described below, to match the frequency of tax changes.

[10]Namely, to barcodes beginning with digits 40–44.

[11]The information behind different barcodes registered by the same firm is mostly identical, so this approach is sufficient to determine the location of every product's producer.

[12]This is a potential source of measurement error. However, our sample covers recent years, so that the current addresses of the firms should largely be valid. Moreover, due to the short nature of the sample, re-locations are unlikely to have occurred often.

[13]Neither the city name nor the postcode uniquely identifies a municipality. Municipalities may share names or postcodes. Thus, the matching of firm location to municipalities is done in an iterative way. First, we match to municipalities with a unique name. Then, we match to municipalities for which name and one-digit postcodes are unique, then for those whose name and two-digit postcode are unique, and so on. Firms remain unmatched to municipalities if the city and postcode do not match any municipality.

Table 1: Summary statistics of the matched data

	Barcodes	Vendors	Producers	Municipalities	Sales (bn. €)
Universe of products	311767	11581	–	–	118659.4
Products with German barcodes	175255	6378	–	–	59374.6
... with known firm location	127527	4265	4684	2100	45672.5
... with Orbis information	117351	3368	3739	1620	44240.1

Notes: This table summarises the number of barcodes (individual products at the `EAN` level), *vendors* as defined by IRi, producers as defined by the GS1 company prefix, municipalities, and the total sales revenue, for the universe of products in the IRi data (row 1), for products with German barcodes (`EAN`s starting with digits 40–44, and excluding private labels; row 2), and for the subset of German products for which we have producer location information (i.e., producer identity and a matched municipality; row 3), and for the subset of those with a match to the Orbis database (row 4). Each row is a strict subset of the previous row.

for these firms in the Orbis database provided by Bureau van Dijk (BvD). We are able to find 77% of firms in Orbis. The Orbis data then helps us to construct a proxy for the existence of establishments and branch offices and their location. This is relevant because of the apportionment rule in the corporate tax code. If a firm produces in several municipalities, the corporate tax code requires that the tax base is divided among municipalities according to the wage bill accruing there.[14] In other words, the true corporate tax rate is a wage-bill-weighted average across the tax rates of all municipalities in which the firm operates. Unfortunately, no establishment-level wage bill data is available to us, so that we cannot compute this. Instead, we address this issue in a robustness exercise by excluding firms with known establishments located outside the headquarter municipality.

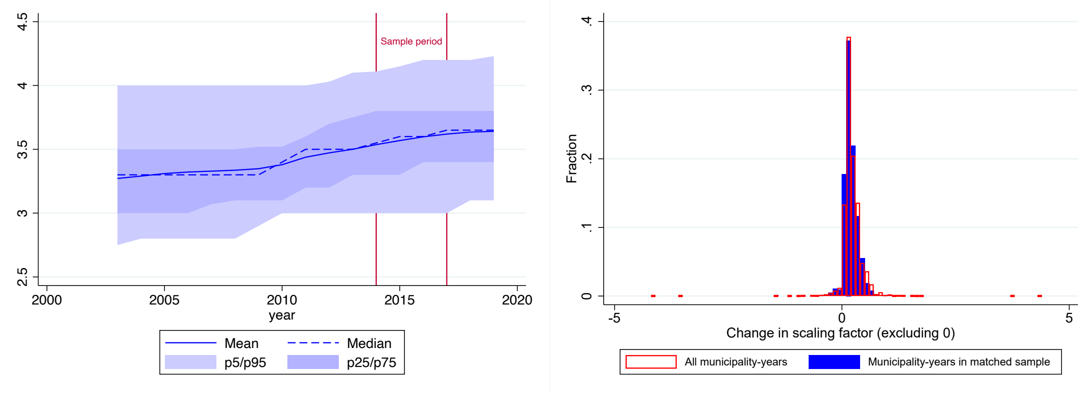
Table 1 reports the number of products sold in Germany by the different levels of information we have on them. First, of all 311,787 products sold, 175,255 have German barcodes. Considering the products for which we find location information – and, hence, tax information – cuts the number of products to 126,527 in 2,100 municipalities. When we also match to those that are present in Orbis the number drops further to 117,351 in 1,620 municipalities (though we will use this subsample only for some robustness checks). Total sales of the sample matched with firm locations covers a large share, roughly 75%, of German barcode sales.

Figure 1 shows the variation in the changes in the scaling factors between 2013 and 2017 across Germany. Panel (b) focuses on municipalities which correspond to at least one producer location in our data (white areas indicate municipalities in which no firm was identified in the scanner data). Figure 2 reports additional descriptive statistics on tax municipality-level changes. Our matched data set contains producers in 2,100 different municipalities, i.e., around 20% of all municipalities in Germany. Nevertheless,

[14] This should be relevant mainly for large firms. We would expect that small firms do not distribute their administration and production across cities.

Figure 2: Changes in the corporate tax scaling factor

(a) Distribution of scaling factors over time (b) Histogram at municipality–year level



(c) Descriptives

	Municipalities	Pop.	Freq. change	Mean	Min	Max
All Germany	11,172	83m	15.1%	0.030	-4.20	4.30
Matched sample	2,120	52m	14.1%	0.025	-1.5	1.01

Notes: Panel (a): moments of municipality-specific corporate tax scaling factors over time. The effective corporate tax is computed as 3.5% times the scaling factor. Panel (b): histogram of municipality-year-specific changes in corporate tax scaling factors, for the years 2014–2017. Panel (c): Corresponding descriptives on municipality–year-specific changes in corporate tax scaling factors, for the years 2014–2017.

the municipalities in our sample account for a population of 52 million, i.e., around 60% of the German population. In these municipalities the frequency of tax change was 14.1%, close to 15.1% across all municipalities (see Figure 2b). The distribution, including the mean, of tax changes is similar in the municipalities in our sample and in all municipalities in Germany, as can be seen from the histogram in Figure 2b and 2c. Our sample period, 2013–2017, is representative of the long-term upward trend in corporate taxes in Germany, see Figure 2a.

We aggregate the IRi price data as follows. We start with prices per unit for each product, store and week, computed as sales over quantity sold. We then compute annual quantity-weighted average prices of each product in each store and year. We then compute log changes of these store-year specific average prices. We include only prices from stores that were operative for the full current and previous year, in order to avoid possible shop composition effects. We then take the simple average of the log price changes over all stores within a two-digit ZIP code region, retail chain and year.[15] We denote these average log price changes as $\Delta \log p_{isrt}$ where i denotes a product, r a retail chain, s a two-digit ZIP code region, and t years. Appendix A.2 provides more details.

For our panel regressions, we trim the yearly distributions of average log price changes

[15] Using quantity-weighted averages yields the same results.

at their 1% and 99% quantiles. We exclude in all regressions the price changes which refer to the two-digit zip code region in which the product is produced, i.e., where sold region and produced region overlap. Effectively, in our empirical analysis we look at how corporate taxes in a municipality affect the retail prices of products originating in this municipality in all other German jurisdictions.

3 Theoretical framework

The German institutional setup, where each production firm, located in one of many municipalities with different local tax rates, sells their products mainly outside of that municipality through retailers, and where interest rates are determined at the national level, can be thought of as a currency area comprising many small open economies with no trade frictions and a great deal of capital mobility. To analyse how corporate tax rates may influence prices, we set up a model similar to Corsetti and Dedola (2005) and Hong and Li (2017).

We consider an economy with many local markets m, where in each market a retailer sets the retail price of product i in sector j, P_{ij}^m, as a markup over marginal cost, taking marginal costs as given. The retailer's marginal cost consists of the wholesale price Q_{ij}^m, which is set by the production firm, and an additional distribution cost D_j^m. This cost, which for simplicity depends only on the sector and market, captures factors related to distribution, inventory, advertising, as well as retail inputs like land, capital and labour. Assuming that the retailer has market power and faces a CES final demand curve, the retail price of product i in sector j, sold in region m is

$$P_{ij}^m = \frac{\rho_j^m}{\rho_j^m - 1}(Q_{ij}^m + D_m^j), \tag{1}$$

where ρ_j^m is the price elasticity of the demand Y_{ij}^m.

The product wholesale price is set by a production firm, which is generically located in a different region than the retailer, but can sell to all regions m. The manufacturer sets the wholesale price, taking into account its own demand elasticity, which depends indirectly on the retail price. The manufacturer of product i in sector j has a Cobb–Douglas production function using labour L_{ij} and capital K_{ij}, with output elasticities α and $1-\alpha$, respectively, subject to idiosyncratic productivity Z_{ij}. The manufacturer pays the firm-specific (in practice municipality-specific) corporate tax rate τ_{ij} on its revenues, after subtracting labour costs and other deductibles.[16] Denoting the firm-specific wage as W_{ij} and the user cost of capital by R (common to all firms under the assumption of

[16]In Germany, equity-financed capital is partly deductible (see Fuest et al., 2018).

perfect capital mobility), the manufacturer's post-tax profits are given by:

$$\pi_{ij} = (1-\tau_{ij})\left(\sum_m Q_{ij}^m Y_{ij}^m - W_{ij}L_{ij}\right) - RK_{ij}, \tag{2}$$

The assumed production function implies

$$\sum_m Y_{ij}^m = Z_{ij} L_{ij}^{\alpha} K_{ij}^{1-\alpha} \tag{3}$$

and, therefore, individual firms' marginal costs are the same for all regions where they sell. Standard static profit maximization yields the following optimal price as a markup over the firm-specific marginal costs, MC_{ij}, scaled by the corporate tax rate:

$$Q_{ij}^m = \frac{\lambda_{ij}^m}{\lambda_{ij}^m - 1}\frac{MC_{ij}}{1-\tau_{ij}}, \tag{4}$$

where λ_{ij}^m represents the possibly region-specific manufacturer's perceived elasticity of demand, $\lambda_{ij}^m \equiv -\frac{\partial Q_{ij}^m}{\partial Y_{ij}^m}\frac{Y_{ij}^m}{Q_{ij}^m} = \rho_j^m \frac{\partial P_{ij}^m}{\partial Q_{ij}^m}\frac{Q_{ij}^m}{P_{ij}^m}$. Firms' before-tax markups are scaled by the corporate tax rate, as the tax reduces the marginal revenue of an additional unit sold by $(1-\tau)$, other things equal. As noted by Hong and Li (2017), producers face a lower elasticity of demand than retailers when the latter do not pass-through wholesale price changes completely: this is the case in our setting if retail costs are strictly positive. Therefore, in general it holds that $\frac{\partial P_{ij}^m}{\partial Q_{ij}^m}\frac{Q_{ij}^m}{P_{ij}^m} < 1$. Namely, under the maintained assumption of CES demand, it holds that $\frac{\partial P_{ij}^m}{\partial Q_{ij}^m}\frac{Q_{ij}^m}{P_{ij}^m} = \frac{Q_{ij}^m}{Q_{ij}^m + D_j^m}$.[17] Using the optimal pricing rules, we obtain the following expression for the equilibrium retail price:

$$P_{ij}^m = \frac{\rho_j^m}{\rho_j^m - 1}\left(\frac{\lambda_{ij}^m}{\lambda_{ij}^m - 1}\frac{MC_{ij}}{1-\tau_{ij}} + D_j^m\right) \tag{5}$$

Under the assumption that firms take wages as given, we have $\frac{\partial \log MC_{ij}}{\partial \log(1-\tau_{ij})} = \alpha$. That is, when the tax rate increases, (after-tax) marginal costs *fall*. In particular, the decrease in marginal costs is proportional to the share of deductible inputs in production costs, here α. This reflects the fact that after-tax costs are given by $(1-\tau_{ij})W_{ij}L_{ij} - RK_{ij}$. While after-tax marginal costs fall by α% after a one percentage point tax increase, post-tax revenues fall by 1%. In response to this, the production firm increases the wholesale price by $(1-\alpha)$% so as to keep the post-tax markup constant.[18]

[17] Note that for $\lambda_{ij}^m = \rho_j^m \frac{Q_{ij}^m}{Q_{ij}^m + D_j^m}$ to be well-defined by being greater than one, it needs to hold that $\frac{Q_{ij}^m}{Q_{ij}^m + D_j^m} > \frac{1}{\rho_j^m}$.

[18] However, if manufacturers are able to influence their own wages (or the prices of other deductible inputs) and shift the incidence of tax changes on workers, then $\frac{\partial \log MC_{ij}}{\partial \log(1-\tau_{ij})}$ can differ from α. In general, a tax increase can increase retail prices as long as $\frac{\partial \log MC_{ij}}{\partial \log(1-\tau_{ij})} < 1$.

We can compute the pass-through from corporate taxes to retail prices as follows:

$$d\log P_{ij}^m = -\left(1 - \frac{1}{\rho_j^m - 1}\frac{D_j^m}{Q_{ij}^m}\right)\frac{Q_{ij}^m}{Q_{ij}^m + D_j^m}(1-\alpha)\, d\log(1-\tau_{ij}) \tag{6}$$

This expression shows that, other things equal, tax pass-through to retail prices will be larger, the higher the price elasticity of retail demand, the lower the share of distribution costs in retail costs, and the lower the share of deductible inputs in production costs.In particular, while production firms raise wholesale prices by $(1-\alpha)\%$ after a one percentage point tax increase, retailers increase prices by less if distribution costs are positive. Moreover, they choose lower pass-through if the retail demand elasticity is higher.

4 Empirical strategy

To estimate the causal effect of tax changes on price changes, we leverage the dichotomy between the location of sales and the location of production, following Baker et al. (2020). This dichotomy allows us to control for region-time fixed effects pertaining to the sold region. In addition we also include production region time fixed effects, exploiting the more granular variation of tax rates in our data at the municipality level, whereas in the US corporate taxes are set at the state level. Specifically, we compare annual price changes of goods produced by firms located in a given two-digit ZIP code area, but being subject to different municipality-level corporate tax rate changes, focusing on the response of price changes in different two-digit ZIP code areas from the production one. By focusing on *within-sold-region and within-production-region variation* in price changes and tax changes, we flexibly difference out supply- and demand-driven business cycle factors that could jointly affect prices and taxes. The remaining variation in corporate tax rate changes due to factors operating at a more disaggregated level than the two-digit ZIP code is thus arguably exogenous. This view is corroborated by the fact that, in the data, local corporate tax changes are not predicted by changes in county-level GDP or unemployment, as shown by Fuest et al. (2018).[19] Another advantage of our setup is that the corporate tax is the main fiscal lever of municipalities on firms. In other words, municipalities do not include corporate taxes in complex fiscal packages like those of state or federal governments, which could affect firms with other tools and would thus blur the signal about the actual shocks impinging on firms.[20]

We run panel regressions of price changes $\Delta \log p_{irst}$ of product i, manufactured in production-region (two-digit ZIP code) p, and sold in retail chain r within sold-region

[19] Counties or districts (*Kreise and kreisfreie Städte*) are the administrative level between municipalities and states in Germany. There are, on average, 25 municipalities in each county.

[20] In a robustness check below, we control for changes in the local scaling factors that apply to real estate taxes, which are two additional instruments of municipalities. Our estimates remain practically unchanged.

(two-digit ZIP code) s, and year t, on net-of-tax factor changes $\Delta \log(1-\tau_{it})$. Therefore, we include fixed effects by sold-region-year, α_{st}, where the sold region is a two-digit ZIP code area, and by production-location-year, α_{pt}, where the production location is either a state or a two-digit ZIP code region.[21] The regression equation, which can be motivated by taking time differences of a suitably extended version of the structural equation (6) is

$$\Delta \log p_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \beta(-\Delta \log(1-\tau_{it})) + \Gamma X_{it} + \varepsilon_{isrt}, \tag{7}$$

where α_i is a product fixed effect, α_{st} is a two-digit ZIP code sold location by year fixed effect, and α_{pt} is a two-digit ZIP code production location by year fixed effect. X_{it} can contain control variables at the municipality and county (*Kreis*) level, specifically, four lags of changes of the production municipality unemployment rate and four lags of growth rates in the production county-specific debt. The coefficient of interest β captures the elasticity of the price with respect to the negative net-of-tax factor. We choose this normalization such that an increase in the regressor corresponds to an increase in the corporate tax rate. Since $-\Delta \log(1-\tau) \approx \Delta\tau$, this elasticity is approximately equivalent to the semi-elasticity of the price with respect to the tax. That is, β indicates the average relative increase in prices in response to a one percentage point increase in the corporate tax rate. We cluster standard errors at the municipality level, which allows for arbitrary serial correlation of shocks within municipalities.

One can lend a causal interpretation to the coefficent β, to the extent that our right-hand side variables, including the location-time fixed effects, control for the co-movement between prices and taxes that arise from business cycle effects. Specifically, the sold-location-year fixed effect differences out local demand conditions. Such factors would induce endogeneity of tax changes if a fall in prices in a sold-region, leading to declining profits, would lead in turn to the municipality reducing the corporate tax rate to support local firms. The production-region fixed effect differences out local supply-related factors that could affect the cost of all goods manufactured in the production region. Such factors would induce endogeneity if municipalities were to be induced to change corporate taxes to, e.g., alleviate the impact of wage or other cost increases on firms. Additionally, the inclusion of local unemployment rates and debt in the regression proxies for changes in production costs and other determinants of prices at an even more disaggregated local level. Indeed, in line with the results in Fuest et al. (2018), the remaining variation in corporate tax changes at the municipal level can be thought of as largely exogenous.

[21]Each two-digit ZIP can contain multiple stores and municipalities, thus this variation helps to estimate, respectively, sold-region-year fixed effects, α_{st}, and production-region-year fixed effects α_{pt}.

Table 2: Estimated pass-through from corporate taxes to consumer prices

	(1) Δ log price	(2) Δ log price	(3) Δ log price
$-\Delta \log(1 - \text{tax})$	0.525***	0.538***	0.425**
	(0.171)	(0.182)	(0.209)
Observations	19434155	18871628	14091803
Product FE	✓	✓	✓
Sold-region × year FE	✓	✓	✓
Production-region × year FE	✓	✓	✓
Production-muni. UE controls		✓	✓
Production-district debt controls			✓

Notes: Results from estimating $\Delta \log p_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \beta(-\Delta \log(1 - \tau_{it})) + \Gamma X_{it} + \varepsilon_{isrt}$. Prices are observed at the product, retail chain, two-digit zip code sold location, and year level. Tax rates vary by production municipality and year. In the panel regression, α_i is a product fixed effect, α_{st} is a two-digit ZIP code ("region") sold location by year fixed effect, α_{pt} is a two-digit production location ZIP code ("region") production location by year fixed effect. Depending on the specification, X_{it} contains four lags of changes of the production municipality unemployment rate and four lags of growth rates in the production county-specific debt level. Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 Results

5.1 Average pass-through of local corporate taxes into retail prices in other jurisdictions

In this section we present the estimated pass-through of corporate taxes into consumer prices in regions outside the production location. Table 2 reports the estimated pass-through coefficient based on three specifications of equation (7). Column (1) uses sold-region-year and production-region-year fixed effects but no further controls, while columns (2) and (3) add four lags of changes of the production municipality unemployment rate and four lags of growth rates in the production county-specific debt level. All specifications include product fixed effects to account for product-specific price trends (Adam and Weber, 2022). The point estimates of the pass-through coefficient are all positive, ranging from 0.425 in column (3) to 0.525 in column (1), and highly significant.

The positive coefficients imply that prices increase in response to an increase in the corporate tax rate. Specifically, the coefficient in column (3) implies that a one percentage point increase in the local corporate tax rate leads on average to an approximately 0.425% increase in the retail price of products exported from the affected municipality, relative to

Table 3: Robustness to excluding firms with branches

	(1)	(2)
	Δ log price	
	All Orbis firms	without branch
$-\Delta \log(1 - \text{tax})$	0.413**	0.581***
	(0.209)	(0.203)
Observations	13564215	6591425
Product FE	✓	✓
Sold-region × year FE	✓	✓
Production-region × year FE	✓	✓
Production-muni. UE controls	✓	✓
Production-district debt controls	✓	✓

Notes: Results from estimating $\Delta \log p_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \beta(-\Delta \log(1 - \tau_{it})) + \Gamma X_{it} + \varepsilon_{isrt}$, as in Table 2, using three different subsamples: Column (1) includes only prices of products for which the producing firm is observed in the Orbis database. Column (2) further restricts to observations for which the producing firm does *not* have recorded branches in Orbis. In this case, we can exclude issues of tax apportionment. X_{it} contains four lags of changes of the production municipality unemployment rate and four lags of growth rates in the production county-specific debt level. Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

the prices of all other products originating from municipalities in different regions.[22,23,24] This result is remarkable given the evidence in Fuest et al. (2018) that firm wages fall with a corporate tax increase, easing producers' costs. In contrast, the fact that retail prices instead increase suggests significant adjustment in wholesale firms' prices, which is in turn passed-through into higher retail prices by supermarkets.

As a first robustness check, we exclude products of firms with multiple establishments. While we only observe the tax rate in the headquarter municipality, the effective tax rate for a firm is a wage-bill-weighted average over all production establishment municipalities. Our results may thus be influenced by the presence of multi-establishment firms. As explained in Section 2, we match IRi data with Orbis firm data in order to

[22]In Table B.2 in the Appendix shows these regressions when using directly $\Delta\tau$ as the main regressor. The findings are quantitatively very similar. The results are also robust to trimming price changes at different cutoffs, see Table B.3a and robust to using sales-filtered price data, see Table B.3b.

[23]Table B.1 in the Appendix shows that the estimated pass-through is robust to controlling for changes in local scaling factors applying to two real estate taxes, which are two additional fiscal instruments at municipalities' disposal. The first real estate tax (*Grundsteuer A*) applies to arable land and the second (*Grundsteuer B*) on built-up areas. While the local business tax generated total tax revenues of 55 billion euro in 2019, the revenues from the real estate taxes were lower. The revenues from the tax on arable land amounted to 0.4 billion euro and the revenues from the tax on built-up areas amounted to 14 billion euro.

[24]During the period covered by our sample, tax changes have been predominantly positive. Of the 1,058 observed tax changes, only 31 were tax cuts. Standard models would predict the effects to be symmetric across otherwise similar tax increases and decreases.

Table 4: Robustness to adding more granular fixed effects

	(1)	(2)	(3)
	Δ log price	Δ log price	Δ log price
$-\Delta\log(1-\text{tax})$	0.425**	0.416**	0.339**
	(0.209)	(0.204)	(0.166)
Observations	14091803	14091803	14091803
Product FE	✓	✓	✓
Production-region × year FE	✓	✓	✓
Production-muni. UE controls	✓	✓	✓
Production-district debt controls	✓	✓	✓
Sold-region × year FE	✓		
Sold-region × retailer × year FE		✓	
Sold-region × category × year FE			✓

Notes: Results from estimating $\Delta \log p_{isrt} = \alpha_{i(rs)} + \alpha_{s(r)t} + \alpha_{pt} + \beta(-\Delta\log(1-\tau_{it})) + \Gamma X_{it} + \varepsilon_{isrt}$, with different levels of fixed effects. α_i is a product fixed effect. $\alpha_{s(r)t}$ is a two-digit ZIP code ("region") sold location by year fixed effect in specification (1), a sold location by retailer by year fixed effect in specification (2) and a sold location by category by year fixed effect in specification (3). α_{pt} is a two-digit production location ZIP code ("region") production location by year fixed effect. X_{it} contains four lags of changes of the production municipality unemployment rate and four lags of growth rates in the production county-specific debt level. Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

exclude multi-establishment firms. Orbis includes some information about what the data provider calls "branches". A branch is a recorded firm presence outside of the location of the headquarter. Column (1) in Table 3 repeats the pass-through estimation for all Orbis firms as a benchmark. Column (2) then includes only the product prices of firms without branches. It turns out that our benchmark estimate is robust to excluding multi-establishment firms, as the pass-through coefficient is again insignificantly different from 0.5 (although there is, unfortunately, no guarantee that the Orbis information perfectly captures establishments).

We further assess the robustness of our results, showing that they are not driven by retailer-specific or product category-specific effects. We do so by adding more granular fixed effects, see Table 4. Column (1) reproduces the baseline specification from Table 2. Column (2) adds retail chain-sold-region-year fixed effects, to capture demand factors that are specific to a given retail chain in a given region. Effectively, we then compare the retail prices of products exported from a municipality subject to a corporate tax change, to those of firms located outside that region's municipality, within a given retail chain. Column (3) adds category-sold-region-year fixed effects to capture factors that are specific to a given product category in a given region, thereby analogously comparing relative price changes of products in the same category sold in the same region. The results indicate that our benchmark estimates are robust to controlling for more granular sources of unobserved

Table 5: Placebo exercise

	(1) Δ log price	(2) Δ log price
$-\Delta \log(1 - \text{tax})$, randomised within 2-digit ZIP code	0.118	
	(0.128)	
$-\Delta \log(1 - \text{tax})$, randomised within district		-0.103
		(0.135)
Observations	16795538	10835955
Product FE	✓	✓
Sold-region × year FE	✓	✓
Production-region × year FE	✓	✓

Notes: Results from estimating $\Delta \log p_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \beta(-\Delta \widetilde{\log(1 - \tau_{it})}) + \varepsilon_{isrt}$. The regression is set up as in Table 2, but uses randomised regressors $(-\Delta \widetilde{\log(1 - \tau_{it})})$. In particular, column (1) randomises the value of $\Delta \log(1-\tau_{it})$ by drawing a random $\Delta \log(1-\tau_{it})$ with replacement from the population of municipalities within the two-digit production location ZIP code. The exercise in column (2) draws a random $\Delta \log(1 - \tau_{it})$ from the population of municipalities within the county of the production location. This leads to fewer observations because some counties are also one municipality, in which case we do not consider them for randomisation B. Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

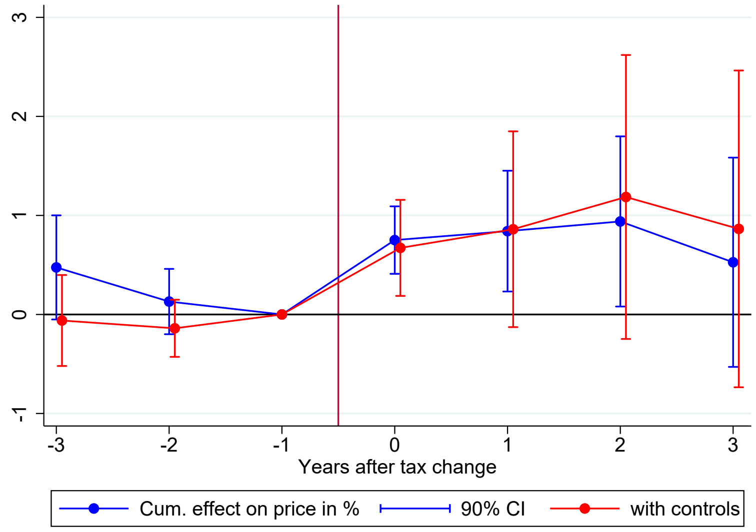
heterogeneity, with the point estimates of the pass-through coefficient ranging from 0.339 to 0.416. However, the differences in these point estimates are not statistically significant.

Although the local fixed effects that we include in our panel regressions control flexibly for common local shocks, we carry out another test to address concerns of exogeneity of the tax rate changes. This placebo-type exercise checks if randomly re-allocating tax changes across municipalities within a narrowly defined region also results in price changes. If this was the case, prices would change either due to unobserved local shocks or due to spillovers. Specifically, for any municipality we randomly draw a tax change from the population of tax changes observed in municipalities that are located in either the same two-digit ZIP code region or the same county. We then re-run the baseline regression as in equation (7). Table 5 shows the results, which reveal small and insignificant coefficients. This corroborates our finding that prices indeed increase due to municipality-specific changes in tax rates.

Finally, we estimate the dynamic effects of municipality-level tax changes on retail prices. To this end, we extend the panel regression (7) to an event study regression:

$$\Delta \log \text{price}_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \sum_{k=-3}^{3} \beta_k(-\Delta \log(1 - \tau_{it-k})) + \Gamma X_{it} + \varepsilon_{isrt} \tag{8}$$

Figure 3: Dynamic effects of a corporate tax change



Notes: In panel (a) this figure plots, for a horizon of h years after the tax change, the sum of coefficients $\sum_{k=0}^{h} \beta_k$ from the regression $\Delta \log \text{price}_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \sum_{k=-3}^{3} \beta_k(-\Delta \log(1 - \tau_{it-k})) + \Gamma X_{it} + \varepsilon_{isrt}$, where β_{-1} is normalised to zero. In panel (b) price changes are replaced by quantity changes. The panel regression is otherwise set up as in Table 2. The whiskers show 90% confidence bands based on standard errors clustered at the municipality level.

Figure 3 plots the estimated coefficients $\{\beta_k\}$. For $k = -3, ..., 3$, β_k indicates the effect of a tax change in period t on retail prices in period $t+k$. The coefficient β_{-1} is normalized to zero. The results show that prior to a tax change, there are no significant changes in retail prices. This flat pre-trend is consistent with the exogeneity of tax changes. In the years after the tax change, prices increase significantly and stay persistently higher.[25]

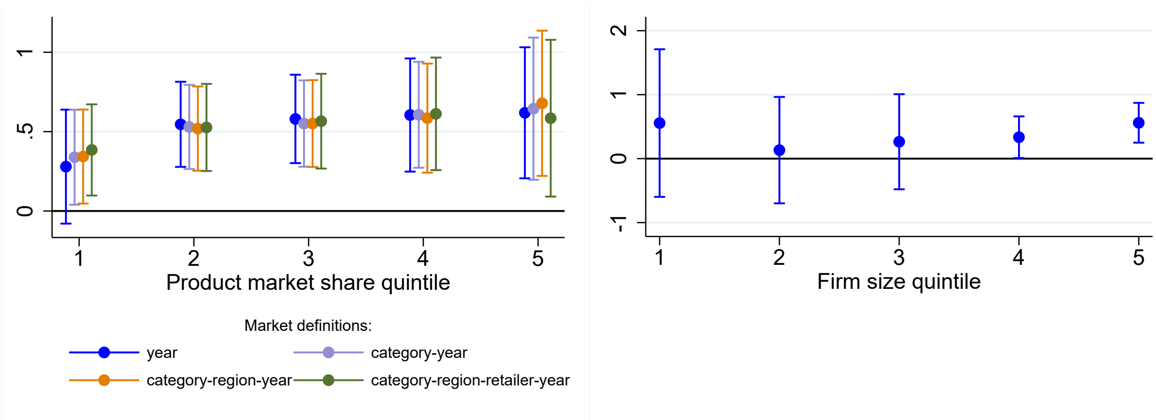
5.2 The role of market shares, firm size, and competitor tax changes

According to models of oligopolistic firms (Atkeson and Burstein, 2008) and models with kinked, non-CES demand curves (Kimball, 1995), pass-through should depend on market shares, and specifically it should fall the larger the latter, possibly increasing again for very large market shares. Since our dataset is uniquely suited to investigate this hypothesis given that it includes very granular information on sales for each "barcode" product, we estimate the pass-through as a function of different market shares. We proceed as follows. For a given definition of a market m, we compute the market share of a product sold in

[25]This is in line with the fact that tax changes are empirically highly persistent.

Figure 4: The role of market share and firm size for pass-through

(a) Market share (b) Firm size



Notes: Effect of an increase of corporate tax rates on retail prices by product market share and by firm size. Observations are sorted into quintile bins according to product-level sales within the market and according to total product sales for the producing firms (in the given year). The figure then plots bin-specific coefficients β_{q_k} from the regression $\Delta \log \text{price}_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \sum_{k=1}^{5} \beta_{q_k} \mathbb{1}\{i \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}$. Standard errors are clustered at the municipality level. Confidence intervals are at the 90% level.

that market as

$$s_{isrt}^{(m)} = \frac{\text{sales}_{isrt}}{\sum_{i's'r' \in m} \text{sales}_{i's'r't}}. \tag{9}$$

where again s and r refer to a sold-region and a retailer. We use the following four market definitions: First, all products sold in a given year across all categories and regions; this is the market share of each individual product in all sales of German supermarkets.[26] Second, all products sold in a given COICOP product category and in a given year, across all regions; this is the market share of each individual product in all sales in its category.[27] Third, all products sold in a given category, in a given two-digit ZIP code region, in a given year; this is the market share of each individual product in its category at the regional level. Fourth, all products sold in a given category, in a given two-digit ZIP code region, by a given retailer, in a given year; this is the same market share as the previous one, but computed within each specific retailer.[28]

We sort observations into quintiles based on market share. Thereby, we assign an observation to the lowest product market share quintile if $s_{i,s,r,t}$ is in the lowest 20% of

[26] The denominator includes therefore also sales of products for which we do not observe the producer identity in our sample.

[27] We manually map the roughly 200 categories in the IRi data set into twenty COICOP level-3 categories. The Classification of Individual Consumption by Purpose (COICOP) is used, for example, in the euro area Harmonized Index of Consumer Prices (HICP).

[28] Our retail scanner data does not observe sales by hard discounters. Therefore, total market sales are only partly captured and thus market shares may be mismeasured. However, this caveat does not apply to the category-region-retailer-year measure, which is retailer-specific and therefore does not depend on sales in other retailers.

Table 6: Estimated pass-through of own and competitor tax changes

	(1)	(2)	(3)
	Δ log price	Δ log price	Δ log price
Market definition m:	Category	Cat.-Region	Cat.-Reg.-Retailer
$-\Delta\log(1-\text{tax})$	0.519***	0.507***	0.521***
	(0.170)	(0.170)	(0.171)
$-\overline{\Delta\log(1-\text{tax})}^{(m)}_{-i}$	1.956	0.488	0.279
	(1.738)	(0.797)	0.552
Observations	19434155	19434155	19434155
Product FE	✓	✓	✓
Sold-region × year FE	✓	✓	✓
Production-region × year FE	✓	✓	✓

Notes: Results from estimating $\Delta\log p_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \beta(-\Delta\log(1-\tau_{it})) + \delta\overline{\Delta\log(1-\tau)}_{-isrt} + \varepsilon_{isrt}$. The average competitor tax change is defined as $\overline{\Delta\log(1-\tau)}^{(m)}_{-isrt} := \sum_{i',s',r'\in m, i'\neq i} s^{(m)}_{i's'r't}\Delta\log(1-\tau_{i't})$ where s is the competitor market share in market m, based on the market definition being applied in the respective column. Prices are observed at the product, retail chain, two-digit zip code sold location, and year level. Tax rates vary by production municipality and year. In the panel regression, α_i is a product fixed effect, α_{st} is a two-digit ZIP code ("region") sold location by year fixed effect, α_{pt} is a two-digit production location ZIP code ("region") production location by year fixed effect. Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

market shares in the market share distribution of market m.[29] We then estimate, as for product categories above, an extension of the panel regression (7) where we interact the net-of-tax factor with dummy variables representing the market share quintile. Figure 4a plots the quintile-specific pass-through coefficients for the various market definitions. There are no statistically significant differences between the estimated effects across market share bins. However, the point estimates and the statistical significance of the individual estimates suggest a modestly stronger effect of corporate taxes on prices for products with larger market shares, across the second to the fifth quintiles. This pattern holds irrespective of the specific market definition.

Similarly, we estimate pass-through conditional on the size of the production firm. We compute firm size as the total sum of all product sales of a firm in all regions and retailers (for a given year). We assign an observation into quintile group k if the production firm's size is in the kth qunitile of the firm size distribution (for a given year), where every firm is only counted once. We then again estimate the panel regression (7) extended to firm size quintile-specific coefficients. Figure 4b plots the quintile-specific pass-through coefficients. While the coefficients are again not statistically different from each other, a similar pattern as for market shares emerges. The point estimates tend to increase

[29] Note that an equivalent binning would arise from sorting according to sales within the market.

with firm size and, notably, only the coefficients for the top 40% of firms are statistically different from zero. This weakly suggests again that if anything pass-through is stronger for larger firms.

This pattern of broad insensitivity of pass-through – both to market shares and firm size – is inconsistent with pass-through in models of oligopolistic firms (Atkeson and Burstein, 2008) and with kinked, non-CES demand curves (Kimball, 1995), and different from previous empirical results on exchange rate pass-through by Auer and Schoenle (2016) and Amiti et al. (2019). Nevertheless, our finding that larger firms are those whose retail prices react more to corporate taxes is best appreciated in light of the evidence in Fuest et al. (2018) that the same set of firms also does not pass-through tax changes to their workers' wages. This is consistent with the presumption that market power allows larger firms to shift the tax incidence to their consumers rather than their workers.

In an imperfectly competitive market environment, firms may respond not only to corporate taxes levied on their own profits, but also to (changes in) the corporate taxes in other jurisdictions that are levied on their competitors and lead the latter to change their prices. We test for this possibility by extending our baseline regression (7) to include a competitor tax change variable defined by

$$\overline{\Delta \log(1-\tau)}^{(m)}_{-isrt} := \sum_{i',s',r' \in m, i' \neq i} s_{i's'r't} \, \Delta \log(1-\tau_{i't}). \tag{10}$$

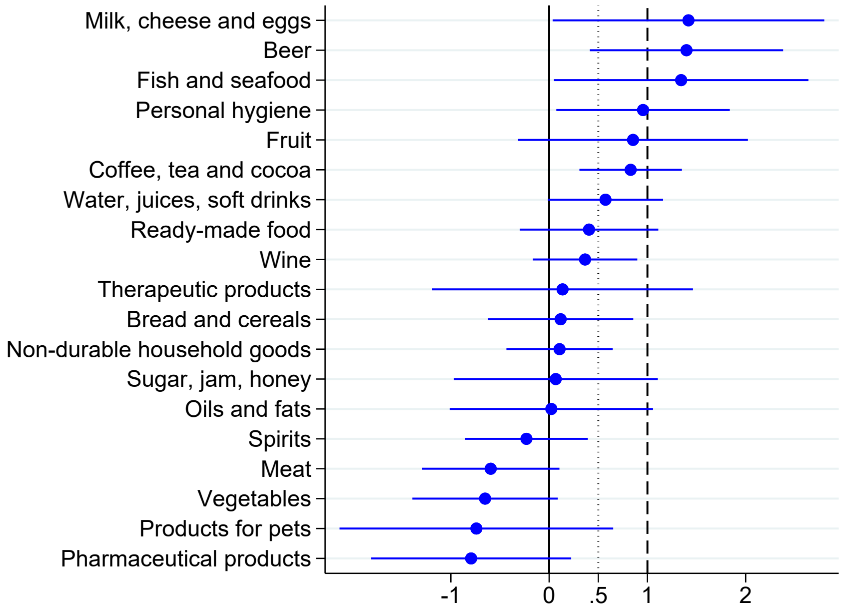
where s is the competitor market share as defined in equation 9, for which the market m is again defined at the category, category-region, or category-region-retailer level.

Table 6 shows the result of the extended regression, revealing that we do not find a significant effect of changes in competitor taxes. The estimates of the own-tax pass-through are unchanged when conditioning on competitor tax changes. This result is consistent with the finding that pass-through does not significantly vary by market shares and thus similarly suggests only weak strategic complementarities.

5.3 Heterogeneous pass-through: Product categories, regional income, and retailer types

In this section we explore possible heterogeneity in pass-through of corporate taxes to retail prices along several broad dimensions: product categories, regional household income, and retailer type. Looking at equation (6), pass-through may be different across these dimensions. First, product categories differ in the price elasticity of demand or distribution costs. Second, price elasticities may also differ across regions, as a function of households income levels (e.g., Anderson, Rebelo, and Wong (2020) find that markups increase with local GDP per capita in the US). Third, retailers may differ in their distribution costs or face alternative levels of price elasticities due to their consumers having different preferences or different degrees search effort, which may in turn make it optimal

Figure 5: Category-specific pass-through



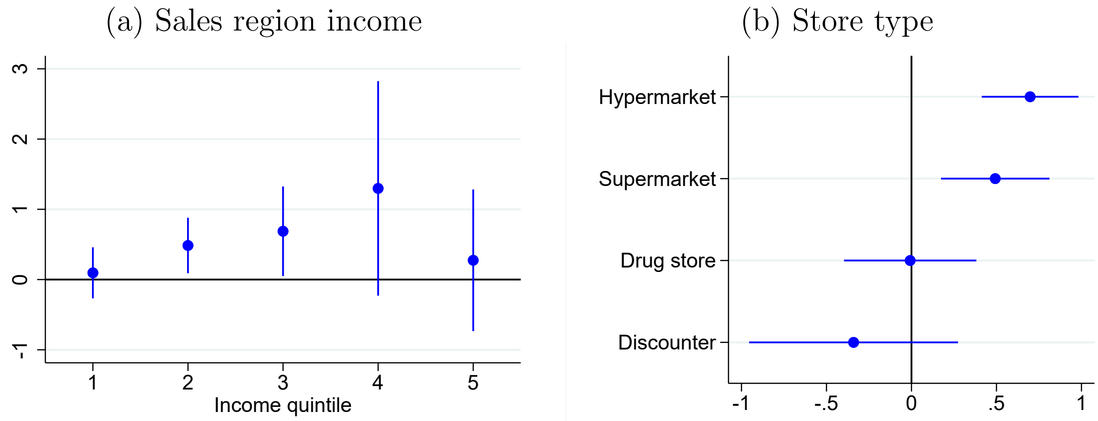
Notes: Effect of an increase of corporate tax rates on retail prices by product category. The figure plots category-specific coefficients $\beta_{(c)}$ from the regression $\Delta \log \text{price}_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \sum_c \beta_{(c)} \mathbb{1}\{i \in c\}(-\Delta \log(1 - \tau_{it})) + \varepsilon_{isrt}$. Standard errors are clustered at the municipality-level. Confidence intervals are at the 90% level.

for firms and retailers to implement different degrees of pass-through.

Pass-through by product categories To estimate pass-through by product category, we estimate an extension of the panel regression (7) where we interact the net-of-tax factor with dummy variables representing each product category in our sample. As product categories we consider COICOP categories, as above. Figure 5 shows the results. We find no categories that exhibit statistically different pass-through from our baseline estimate, partly on account of large uncertainty in some categories. While there is dispersion in category-specific pass-through estimates, there are no extreme outliers. This suggests that the significant estimate of average pass-through comes from pooling all categories, while there is no strong evidence for heterogeneity across product categories.

Pass-through by income in the sales region We also investigate heterogeneity in pass-through for sales regions with different income levels. To do so, we enrich our dataset with GDP per capita at the district level. We then interact the net-of-tax factor with dummy variables representing quintiles of the year-specific distribution of district GDP per capita across observations in the estimation sample (similar to market shares as in Section 5.2). Panel (a) in Figure 6 shows the results. We find that pass-through tends to rise with regional incomes, with the exception of the highest-income regions. However, these differences are statistically insignificant.

Figure 6: Pass-through by sales region income and by retail store



Notes: Panel (a): Effect of an increase of corporate tax rates on retail prices (vertical axis) by sales region income (horizontal axis). The figure plots income quintile-specific coefficients β_{q_k} from the regression $\Delta \log \text{price}_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \sum_{k=1}^{5} \beta_{q_k} \mathbb{1}\{i \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}$. Panel (b): Effect of an increase of corporate tax rates on retail prices (horizontal axis) by retail store (vertical axis). The figure plots store type-specific coefficients $\beta_{(\tilde{r})}$ from the regression $\Delta \log \text{price}_{isrt} = \alpha_i + \alpha_{st} + \alpha_{pt} + \sum_{\tilde{r}} \beta_{(\tilde{r})} \mathbb{1}\{r \in \tilde{r}\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}$, where $\tilde{r}$ denotes a hypermarket, supermarket, drug store, or discounter. Standard errors are clustered at the municipality-level. Confidence intervals are at the 90% level.

Pass-through by retail store type Our dataset covers four types of retail stores: supermarkets, hypermarkets, drug stores, and discounters.[30] We estimate the heterogeneity in pass-through by again interacting the tax change with a dummy indicating the store type. Panel (b) in Figure 6 shows the results. We find significant differences across stores: While drug stores and discounters display both quantitatively and statistically insignificant pass-through, we find that hypermarkets and supermarkets exhibit sizable pass-through of around 50%. This reveals that the significant average pass-through of corporate taxes on retail prices is mainly driven by price adjustments in supermarkets and hypermarkets.[31]

There could be various structural reasons for this result. On the one hand, producers may be following different pricing strategies between discounters and other stores, e.g. they may perceive little market power for sales by the former, or they may be less able to

[30] The types of store are defined as follows. (1) Traditional stores are outlets with a range of goods consisting mainly of groceries (excluding specialty stores) with a surface area from 200 to 799 square metres. This includes supermarkets, which have a surface area larger than 400 square metres, but in the text we use the term "supermarkets" for all traditional stores independent of size. (2) Hypermarkets are self-service retail stores with large surface size (larger than 800 square metres) that are not discounters and offer groceries as well as consumer durables and consumer goods mostly for short to medium-term use. (3) Discounters are self-service stores carrying mainly groceries in a limited range with emphasis on low prices. (4) Drugstores are self-service retail outlets carrying medicines and cosmetics as their core product range.

[31] The heterogeneous effects across store types are not driven by product composition. We directly test for this by including a product by sold-region by year fixed effect as a robustness check, see Table B.4. Thereby we focus on within-product(-region) variation across stores. The differences between store types remain robust.

apply price increases to them. On the other hand, if producers don't discriminate across store types and raise prices across the board, retailers may transmit the shocks differently to their customers depending on their own market power, with discounters absorbing price increases into their profit margins, contrary to supermarkets and hypermarkets.

6 Conclusion

In this paper we estimate how changes in local corporate tax rates in Germany affect retail prices of products of taxed firms that are exported to other German jurisdictions. We find that a one percentage point increase in the local corporate tax rate leads on average to an approximately 0.4% increase in the municipality's retail "export" price relative to the prices of all other products originating from municipalities in different regions. Our results suggest that upstream firms are able to increase prices to protect their markups, and retailers pass-through the wholesale price increases into higher retail prices. This is remarkable given evidence in Fuest et al. (2018) that wages fall with a corporate tax increase, putting downward pressure on producers' costs.

We find that that firms and products with larger market shares do not exhibit lower pass-through, contrary to theoretical predictions and earlier findings in the context of exchange rate pass-through. We also find that competitor tax changes to not lead to significant price changes. These two findings both suggest that strategic complementarities are weak. Nevertheless, our finding that larger firms are those whose prices react more to corporate taxes is best appreciated in light of the evidence in Fuest et al. (2018) that this set of firms also does not pass-through tax changes to their workers' wages. This is consistent with the idea that market power allows larger firms to choose to shift the tax incidence to their consumers rather than their workers, as done by smaller firms. At any rate, the evidence in Fuest et al. (2018) and in our paper strongly points to the fact that shareholders may be able to shield a great deal of the incidence of corporate taxes, at least in Germany.

We also document substantial heterogeneity in pass-through across store types: While drug stores and discounters do not pass-through price increases, we find significant pass-through of tax changes for prices charged in supermarkets and hypermarkets. In contrast, pass-through heterogeneity across other dimensions, including across product categories and in terms of income in the sales region, is limited.

References

Adam, K. and H. Weber (2022): "Estimating the optimal inflation target from trends in relative prices," *American Economic Journal: Macroeconomics, forthcoming.*

AMITI, M., O. ITSKHOKI, AND J. KONINGS (2019): "International Shocks, Variable Markups, and Domestic Prices," *Review of Economic Studies*, 86.

ANDERSON, E., S. REBELO, AND A. WONG (2020): "Markups across space and time," Tech. rep., Princeton University.

ATKESON, A. AND A. BURSTEIN (2008): "Pricing-to-market, trade costs, and international relative prices," *American Economic Review*, 98, 1998–2031.

AUER, R. A. AND R. S. SCHOENLE (2016): "Market structure and exchange rate pass-through," *Journal of International Economics*, 98, 60–77.

AUERBACH, A. J. (2006): "Who Bears the Corporate Tax? A Review of What We Know," *NBER Chapters*, 1–40.

BAKER, S., S. T. SUN, AND C. YANNELIS (2020): "Corporate Taxes and Retail Prices," *National Bureau of Economic Research.*

BECKER, S. O., P. H. EGGER, AND V. MERLO (2012): "How low business tax rates attract MNE activity: Municipality-level evidence from Germany," *Journal of Public Economics*, 96, 698–711.

BRONNENBERG, B. J., M. W. KRUGER, AND C. F. MELA (2008): "Database paper—The IRI marketing data set," *Marketing science*, 27, 745–748.

CORSETTI, G. AND L. DEDOLA (2005): "A macroeconomic model of international price discrimination," *Journal of International Economics*, 67, 129–155.

FUEST, C., A. PEICHL, AND S. SIEGLOCH (2018): "Do Higher Corporate Taxes Reduce Wages? Micro Evidence from Germany," *American Economic Review*, 108, 393–418.

GRAVELLE, J. G. (2013): "Corporate Tax Incidence: Review of General Equilibrium Estimates and Analysis," *National Tax Journal*, 66, 185–214.

GRAVELLE, J. G. AND L. J. KOTLIKOFF (1988): "Does the Harberger Model Greatly Understate the Excess Burden of the Corporate Tax? - Another Model Says Yes," *NBER Working Papers.*

HARBERGER, A. C. (1962): "The Incidence of the Corporation Income Tax," *Journal of Political Economy*, 70, 215–240.

HONG, G. H. AND N. LI (2017): "Market structure and cost pass-through in retail," *Review of Economics and Statistics*, 99, 151–166.

KIMBALL, M. S. (1995): "The Quantitative Analytics of the Basic Neomonetarist Model," *Journal of Money, Credit and Banking*, 27, 1241.

Ljungqvist, A. and M. Smolyansky (2016): "To Cut or Not to Cut? On the Impact of Corporate Taxes on Employment and Income," *Finance and Economics Discussion Series*, 2016, 1–60.

McKenzie, K. J. and E. Ferede (2017): "The Incidence of the Corporate Income Tax on Wages: Evidence from Canadian Provinces," *SPP Research Papers*, 10.

A Data

This appendix describes the data sources used in the paper and how the data is mapped and aggregated. Table A.1 provides an overview of all data sources used. The following sections describe them in detail.

Table A.1: Summary of data sources

Data	Source	Granularity	Identifier	Time
Administrative data:				
Municipality tax scaling factors (*Hebesätze*)	*Statistische Bibliothek*	Municipality	`AGS` × year	2003–2019
– Local business tax scaling factor				
– Real estate tax A scaling factor				
– Real estate tax B scaling factor				
– Indication of territory reform				
Municipality info (*Gemeindeverzeichnis*)	Destatis	Municipality	`AGS` × year	2003–2019
– Postcode of administration (*Verwaltungssitz*)				
– Population				
Municipality economic data	*Regionaldatenbank*	Municipality	`AGS` × year	2008–2017
– Number of employed				
– Number of unemployed				
County economic indicators	*Regionaldatenbank*	County	5d-`AGS` × year	2010–2019
– Total debt				
– GDP (total/per capita/per worker)				
Regional maps of Germany	*GeoBasis-DE / BKG*	Municipality	`AGS`	2017
– Municipalities (*VG-250*)				
– States (*NUTS-250*)				
Retail price data:				
Supermarket sales across Germany	IRi	Barcode/ store/time	`EAN` × store-ID × 2d-ZIP × week	2013–2017
– Weekly unit sales				
– Weekly EUR sales				
– Vendor of product				
– IRi product category				
– two-digit postcode of store				
– IRi store keyaccount				
– IRi store type				
Firm information data:				
GS1 records of individual barcodes	GS1 GEPIR	Barcode	`EAN`	
– Exact firm name				
– City and postcode				
– GS1 Company Prefix				
Orbis data:				
Orbis branch information	Orbis / Bureau Van Dijk	Branch	`bvdidnumber`	
– Branch city				
– Headquarter city				
COICIOP-IRi category mapping:				
COICOP-3 category			`category` (IRi)	

Notes: Regional identifiers: `AGS` is *Amtlicher Gemeindeschlüssel* (official municipality key). *BKG* is the *Bundesamt für Kartografie und Geodäsie*.

A.1 Administrative data

A.1.1 Data sources

Municipality tax scaling factors We obtain annual local scaling factors for each municipality (*Gemeinde*) which are provided by the *Statistische Bibliothek* as *Hebesätze der Realsteuern* in Excel files for the years 2003–2018. These files differ slightly across years with respect to their structure, which needs to be taken into account when appending them to one data set.

Municipalities are uniquely identified by *Amtlicher Gemeindeschlüssel* (`AGS`). `AGS` is an eight-digit key that contains identification of a municipality's state (digits 1–2), *Regierungsbezirk* (given state, digit 3), county (*Kreis*, given the state and *Regierungsbezirk*, digits 4–5), and municipality (given the state, county, and *Regierungsbezirk*, digits 6–8).

In the official data, some `AGS` are less than eight digits long (respecting leading zeroes). This is because the records omit the state identifier from the `AGS` which we then add. The `AGS` of Berlin is sometimes erroneously recorded as a ten-digit code; we delete the superfluous lagging zeroes. Some of the `AGS` are not correct based on the fact that they do not begin with the right state identifier. In this case, we use the *GVISys* (*Gemeindeverzeichnis-Informationssystem*) variable to back out the correct `AGS`.

Moreover it contains information about potential territory changes that happened in the corresponding year. We record such indication as a binary indicator.

Municipality information Additional information on each municipality is provided by Destatis. We obtain these for the years 2003–2018 as well; again, differing column structures have to be taken into account when appending these files. This data contains the total population of the municipality and the postcode, which helps us to map firms to municipalities. However, note that postcodes do not identify municipalities and vice versa. Postcodes are defined by the German postal service *Deutsche Post*. Single municipalities can have many postcodes (in case of a large city), but also one postcode can be attached to many municipalities (small cities). To identify the state of a postcode area, one needs to know up to four digits. The postcode that is part of Destatis data refers to the postcode where a municipality's administration centre (*Verwaltungssitz*) is located. Nevertheless, knowing approximately the postcode of a municipality will help us in matching firms to municipalities.[32]

This data also includes information on unincorporated areas (*gemeindefreie Gebiete*) which are not not governed by a local municipal corporation and hence do not have their

[32]This data also contains the `ARS` key, which is richer than `AGS`. After digit 5 of the `AGS` a four-digit identifier of a *Gemeindeverband* (municipality union) is inserted. Leaving these digits out of the `ARS` gives the `AGS`. However, it is not necessary for our data mapping.

own local business tax scaling factor. We effectively ignore these areas.

Municipality (un-)employment data We obtain the number of employed (subject to social insurance contributions, *sozialversicherungspflichtige Beschäftigte*) and unemployed persons by municipality and year for 2008–2017, which are years relevant for our empirical exercise, from *Regionaldatenbank Deutschland*.

County debt data We obtain total debt for each county (*Landkreis* or *Kreisfreie Stadt*) and year also from *Regionaldatenbank Deutschland*. Counties are identified by the first five digits of `AGS`. Some counties do not report their debt. In general, this data is only available from 2010 to 2019.

Municipality map of Germany From the federal cartography office, the *Bundesamt für Kartografie und Geodäsie*, we obtain shape files that allow producing a map of all municipalities in Germany, which we use to illustrate the geographical variation in our data. We use the map as of 2017 for simplicity. Figure A.1 (a) draws the municipality and state borders.

A.1.2 Matched data

We match the municipality scaling factor with the postcode and population data based on `AGS` and year. Table A.2 shows the number of municipalities, thereof "normal" ones and ones with territory changes, across years. Unincorporated areas are ignored by only considering municipalities that are part of the local scaling factor data.

We then match the (un-)employment data based on `AGS` and year. We obtained only the years relevant for our empirical exercise. Within these years, a number of municipalities are missing, as they do not report these numbers. For the remaining municipalities, we compute an (approximative) municipality level unemployment rate as the fraction of unemployed to unemployed and employed.

Based on the five-digit `AGS` and year we match the municipality data with the county-level data on total debt. Debt data is available for all counties except 11 (including the city states Berlin, Hamburg, and Bremen), a total of 61 municipality-years between 2010 and 2019.

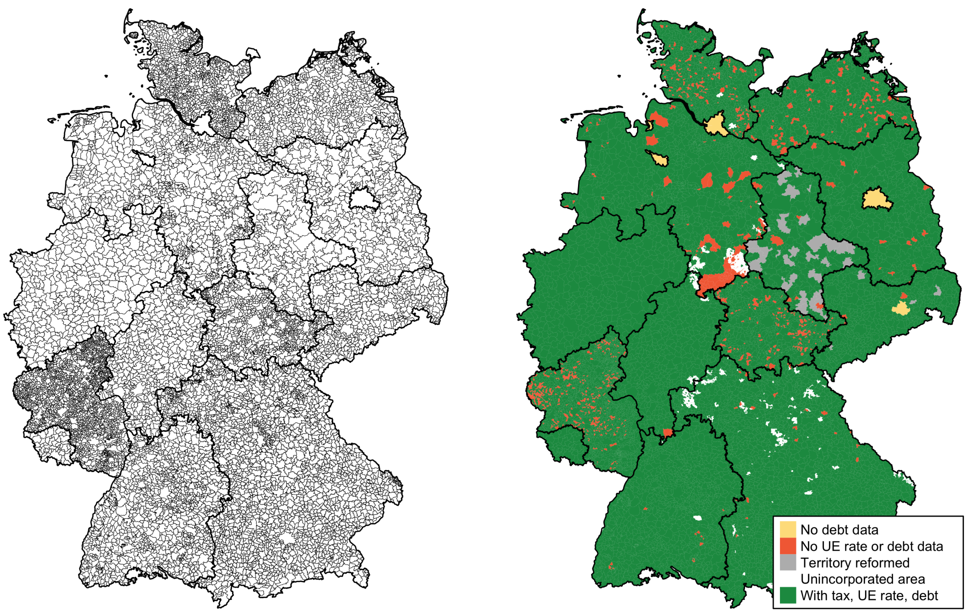
Table A.2 summarises the number of available municipalities according to data richness. Figure A.1 (b) illustrates the data availability across municipalities for the year 2017.

Table A.2: Number of municipalities across years

Year	Total	Normal	with UE rate	and with debt	No. of scaling fct. changes
2003	12630	12465			
2004	12434	12321			1031
2005	12342	12249			1341
2006	12313	12227			991
2007	12266	12194			496
2008	12227	12163	9567		486
2009	11996	11917	8306		528
2010	11442	11312	8215	8209	1031
2011	11294	11179	8315	8309	2016
2012	11224	11113	9033	9027	1443
2013	11161	11058	9000	8994	1390
2014	11117	11025	9633	9627	2153
2015	11093	11037	9599	9593	1698
2016	11059	11007	9842	9836	1465
2017	11055	11011	9842	9837	1178
2018	11014	10959			932
2019	10799	10715			700

Notes: *Normal* municipalities means those without territory change.

Figure A.1: Geography of municipalities and data availability



(a) Municipality and state borders (b) Data availability (year 2017)

Table A.3: An example observation from the raw IRi data

Variable	Example
`EAN`	40015340025782
store-ID	'63386112'
week-ID	'1875'
unit sales	925
value sales [EUR]	638.25
price per unit [EUR]	0.69
category	BIER
vendor	BINDING
volume	500.00ML
zip	63***
keyaccount id	'4'
store type id	'4'

A.2 IRi data

Structure of raw retail scanner price data The retail scanner price data we use observes weekly sales of individual products, identified by barcodes (`EAN`), in individual stores across Germany. An individual product is, for example, a 500ml can of beer with the barcode 40015340025782. Table A.3 shows one individual observation for such a product in the raw data. The data allows us to observe how often a product was sold in a particular store and a particular week. For example, in the week of August 3, 2015 one store in our data sold 925 units of the 500ml can, and thereby generated a revenue of EUR 638.25. Moreover, the data contains a product category classification (there are 217 categories defined by IRi), a coarse name of the manufacturer (vendor), and store characteristics.

Because of data protection, stores are partly anonymised in our data. That is, we do not know the exact identity of a store but only their approximate location and their type. The approximate location is given by the first two digits of their location postcode. The retailer is given by the IRi keyaccount and store type, which can be hypermarket, supermarket, discount, or drugstore.

By means of comparing the sold units to the value of sales, this implies a store-week specific price-per-unit of

$$p_{i,\text{store},w} = \frac{\text{EUR sales}_{i,\text{store},w}}{\text{unit sales}_{i,\text{store},w}}.$$

In our empirical analysis, however, we aggregate our data from the product-store-week level to the product-retailer type-year level. This has two reasons. First, reducing the number of observations improves computational tractability. Second, tax changes are at the yearly level and we are interested in the medium-run effects on prices, and because stores are identified only up to their approximate location and type, we can aggregate the prices to this level of granularity without losing identifying information. The aggregation is explained next, together with sample selection.

Sample selection and aggregation We condition on sales data from individual stores and years for which the store was operative throughout the year. That is, we filter out stores for which we see less than 51 weeks recorded across all products. Then, we aggregate price changes to the store *type* by region by year level. Store types are defined by the combination of IRi keyaccount and IRi store type. Regions are defined as two-digit postcode areas.

First, we compute the store-level average price for product i in year t:

$$p_{i,\text{store},t} := \frac{\sum_{w \in t} \text{EUR sales}_{i,\text{store},w}}{\sum_{w \in t} \text{unit sales}_{i,\text{store},w}}$$

Note that this is equivalent to a unit-weighted average across weekly per-unit prices.

Second, we compute the store-level year-over-year price change:

$$\Delta \log p_{i,\text{store},t} = \log(p_{i,\text{store},t}) - \log(p_{i,\text{store},t-1})$$

Third, for a two-digit postcode region r, store type s, and year t, we compute the *average* year-over-year price change (with slight abuse of notation):

$$\Delta \log p_{i,s,r,t} := \frac{1}{N_{(r,s),t}} \sum_{\text{store} \in (r,s)} \Delta \log p_{i,\text{store},t}$$

where $N_{(r,s),t}$ is the number of type s stores in region r in year t.

As explained in the main text, for our diff-in-diff analysis, we only consider price changes observations that refer to a sales location outside of the producer location. Specifically, we exclude product price changes $\Delta \log p_{i,s,r,t}$ which, according to our further data work explained below, are produced by manufacturers that are located in a municipality that belongs to the two-digit postcode region r.

A.3 Firm information data

Barcode structure and manufacturer identification Individual products are identified by barcodes, called `EAN` in IRi data. EAN stands for European Articel Number. Barcodes around the world are administrated by the firm GS1. According to GS1, the term EAN was superseeded by the GTIN concept, which stands for Global Trade Item Number. In this paper, we call `EAN` the barcode identifier in IRi data and `GTIN` the *equivalent* barcode registered with IRi. `EAN`s can be converted into the `GTIN` form by removing digits 2–3 and adding a check digit according to a known formula. This formula is explained at https://www.gs1.org/services/how-calculate-check-digit-manually.

The GTIN contains two important pieces of information with respect to the producer of the firm, which by definition maintained throughout the paper, is the firm that registered the product with GS1. First, it identifies the country location of the producer through the first three digits of the barcode. In particular, German producers are identified by digits 400–440. The meanings of all country prefixes are listed at https://www.gs1.org/standards/id-keys/company-prefix.

The product barcode also identifies the producer by the company prefix. Whenever a firm becomes a member of GS1, in order to register barcodes, it obtains a company prefix with which all registered barcodes begin. This company prefix is usually seven digits long, but can also be up to eleven digits long. The length of the company prefix cannot be inferred directly. We learn the company prefix precisely in our web-scraping step explained below.

Table A.4: Example: IRi EAN, GS1 GTIN and country/company identification

(1)	IRi EAN:	40015340025782
(2)	Remove digits 3–4:	405340025782
(3)	Add check digit to get GS1 GTIN:	4053400257822
(4)	Identify country and company:	$\underbrace{\underbrace{405}_{\text{country}}\ 3400}_{\text{company}}\underbrace{257822}_{\text{product}}$

For illustration, Table A.4 uses the example of a can of beer to illustrate the conversion of EAN to GTIN.

Selection of individual firm information obtained We want to learn the company identification prefix and the company-related information in the GS1 database for all German products in our sample. We focus on German firms because they are all subject to the same corporate taxation. To this end, we select all barcodes that start with digits 400–440, which are the country prefixes for Germany.

We select a subsample of barcodes that is intended to cover all distinct producers in the sample. At this point we have not obtained firm information for all barcodes individually because downloading this information for more than 150,000 barcodes was infeasible. Instead, we select a subset of GTIN barcodes that (i) start with distinct seven-digit sequences and (ii) have distinct vendor names in the IRi data. The first property makes sure to select one GTIN for every producer, if all company prefixes are seven digits long. However, since some are longer, but this is not visible from the barcode directly, we impose the second property which means that if the first seven digits are the same but the vendor information differs, we sample multiple GTINs, with the intention to obtain information on (at least) one barcode per actual producer.

Table A.5: Success of individual information requests

Return Code	No.
Query Successful	8,384
Company information witheld	1,492
Prefix no longer subscribed	949
Record not found	636
Unknown GS1 Prefix	6
Company prefix mismatch	5
Query successful but links to GS1 company information	221
Total	11,693

Web-scraping of barcodes Ultimately, we request information for 11,693 individual barcodes. The majority of queries, roughly 75%, is successful, yielding company prefix and company information. The remaining quarter of queries is not successful for a variety of reasons. Table A.5 lists the split-up. Most importantly, some company information is not made public by GS1 (row 2). Some barcodes are outdated and cannot be obtained any more (row 3) or are invalid (row 4 and row 5). For some barcodes, the returned company prefix does not match with the requested barcodes (row 6). We also drop such pathological cases. Lastly, some barcode requests are successful, but the barcode contains only the information about GS1 itself (row 7). We also ignore these.

Note that the 8,384 successful queries are for individual barcodes, which are partly produced by the same firm. Ex-post we find that we have obtained information for barcodes of 5951 different firms, based on the GS1 company prefix.

Attaching firm information to remaining barcodes For the 8,384 barcodes for which we successfully gathered firm information, we attach the received producer information back to all barcodes in the following way. The information contains the exact company prefix, which can be seven digits or longer. Based on this, we attach this information to all products for which the `GTIN` starts with this sequence.

Using postal addresses to determine municipality The information contains for every producer their address including the postcode and city name. However, this information does not map easily into municipalities. Complications arise because cities/municipalities can have multiple postcodes, so the postcode in the administrative data does not need to match the postcode of the firm address. Municipalities may also have "suburbs" that show up as firm locations or the cities are spelled slightly differently, e.g., by omitting parts of the official municipality name (e.g., Frankfurt instead of Frankfurt am Main).

We first prepare the administrative data as follows: We remove all parts of the municipality names that describe the city level, i.e.: ", Stadt", ", St.", ", Hansestadt", ", Landeshauptstadt", "Universitätsstadt", ", Hochschulstadt", ", Kreisstadt", ", Wissenschaftsstadt", ", Univeristäts- und Hansestadt", ", gr.kr.St". Moreover we remove all suffixes in brackets (such as "(Main)") and replace both Frankfurt am Main and Frankfurt an der Oder by "Frankfurt", and later distinguish the two based on the different postcodes. We also remove municipality-years with territory reforms.

The official data contains two instances where two `AGS` have the same municipality name and postcode, resepectively: Hamfelde (`AGS` 01053049 and 0153070) and Köthel (`AGS` 01062026 and 01062040). We delete these from the data before matching to firms.

To match firms to municipalities, we rely on municipality names and postcodes. For a match to be valid, we require that the first two digits of the firm's postcode and the municipality postcode are the same. We then match based on municipality names if the municipality name is unique. If it is not unique, we additionally use the first two digits of the postcode if the combination therewith is unique, otherwise the also the third digit, and so on. This way, we are able to match 5018 of 5951 firms.

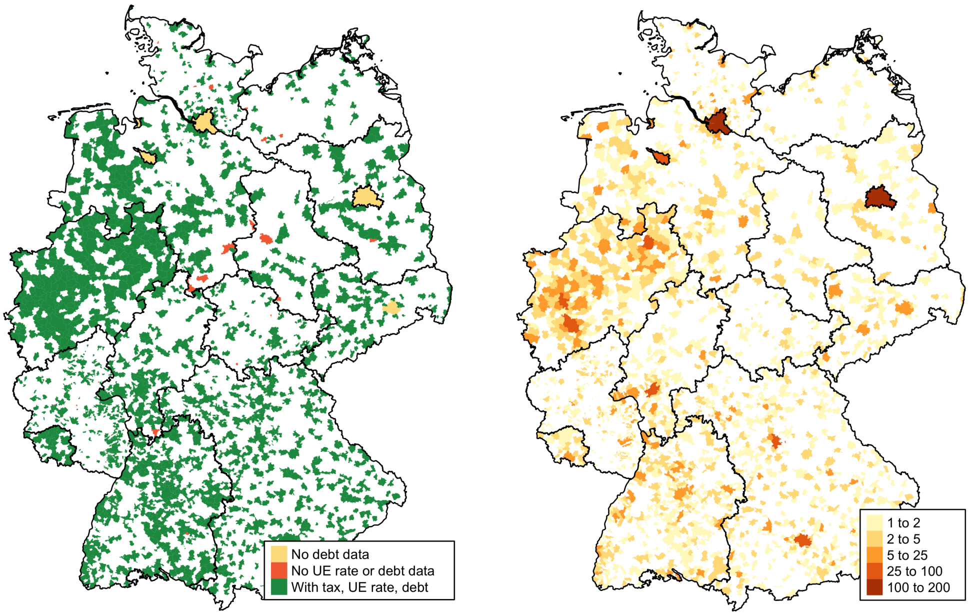
In a second step, we use the Stata function `matchit` to match firms' city to municipalities using fuzzy string matching. This algorithm accounts for typos in the firm locations and other slight perturbations of the city names. The algorithm produces a number of candidate matches with associated similarity scores. We drop candidate matches if the first digit of the postcodes do not match. Of the remaining candidates, we directly accept matches it if turns out that the address city name is an exact match to the corresponding first part of the municipality name (e.g., Radolfzell instead of Radolfzell am Bodensee). We then focus on matches with the highest similarity score. If postcodes match exactly, we accept the match. Apart from this, we accept matches with a similarity score of more than 0.75 and screen each match manually. This increases the number of matched firms by another 412 to 5430, i.e., 91% of the ones identified in the producer-level information.

A.4 Orbis data

Matching to Orbis based on firm name and location To match the firm information from the web information to Orbis data, we use the matching software on the web platform of Orbis. We supply the tool with firm name and location, which the tool matches to Orbis records, yielding the Orbis identifier `bvdidnumber`. We manually go through all matches and check them for correctness. We find 4585 matches, i.e., 77%, in the Orbis database.

Work with Orbis branch information Orbis data contains information about branches of firms. We check if for a given `bvdidnumber` there are multiple branch cities which are different from the firm's main city. In this case we record it as a multi-branch firm. Of the firms we identify in the previous step and linked to Orbis, 74% have more than one branch.

Figure A.2: Geographic coverage in matched data



(a) Data availability (2017) (b) Number of firms (2017)

A.5 Matched price data with producer information and administrative data

We ultimately enrich the IRi price data with the additional data sources described above. Table 1 (in the main text) summarises the sample after each step. First, we condition on German barcodes, i.e., `EAN`s starting with digits 40–44. This reduces the sample of products, as shown by row 2 in the table. Second, we attach the producer–municipality data. This step includes the matching of producer information to products and the matching of municipalities to producers, as explained above. This leads to the sub-population of products described by row 3. Finally, we also attach the Orbis information, which leads to row 4.

The matched data covers production in all regions of Germany with no abnormal geographic clustering, as shown by Figure A.2. North Rhine-Westphalia stands out in being especially densely covered. The number of firms in individual municipalities varies between one firm for most to up to 173 in Hamburg.

B Additional results

Table B.1: Results when controlling for changes in local real estate taxes

	(1) Δ log price	(2) Δ log price	(3) Δ log price
$-\Delta \log(1 - \text{corporate tax})$	0.488**	0.524***	0.531***
	(0.208)	(0.203)	(0.204)
Δ scaling factor real estate tax A	-0.00303		-0.00163
	(0.00201)		(0.00218)
Δ scaling factor real estate tax B		-0.00349	-0.00253
		(0.00214)	(0.00244)
Observations	14091803	14091803	14091803
Product FE	✓	✓	✓
Sold-region × year FE	✓	✓	✓
Production-region × year FE	✓	✓	✓
Production-muni. UE controls	✓	✓	✓
Production-district debt controls	✓	✓	✓

Notes: *Real estate tax A* refers to the tax on arable land. *Real estate tax B* refers to the tax on built-up land. See also Table 2.

Table B.2: Comparing results with $\Delta\,\tau$ and $\Delta \log(1 - \tau)$

	(1) Δ log price	(2) Δ log price	(3) Δ log price	(4) Δ log price	(5) Δ log price	(6) Δ log price
$-\Delta \log(1 - \text{tax})$	0.525***		0.538***		0.425**	
	(0.171)		(0.182)		(0.209)	
Δ tax		0.606***		0.622***		0.490**
		(0.198)		(0.211)		(0.242)
Observations	19434155	19434155	18871628	18871628	14091803	14091803
Product FE	✓	✓	✓	✓	✓	✓
Sold-region × year FE	✓	✓	✓	✓	✓	✓
Production-region × year FE	✓	✓	✓	✓	✓	✓
Production-muni. UE controls			✓	✓	✓	✓
Production-district debt controls					✓	✓

Notes: See Table 2.

Table B.3: Comparing results with different trimmings and with sales filtering

(a) Posted prices (baseline)

	(1) $(p1, p99)$	(2) $(-0.33, 0.33)$	(3) $(-0.2, 0.2)$	(4) $(-0.5, 0.5)$
$-\Delta\log(1-\text{tax})$	0.425**	0.452**	0.393**	0.482**
	(0.209)	(0.201)	(0.178)	(0.209)
Observations	14091803	13998007	13528490	14183456
Product FE	✓	✓	✓	✓
Sold-region × year FE	✓	✓	✓	✓
Production-region × year FE	✓	✓	✓	✓
Production-muni. UE controls	✓	✓	✓	✓
Production-district debt controls	✓	✓	✓	✓

(b) Sales-filtered prices

	(1) $(p1, p99)$	(2) $(-0.33, 0.33)$	(3) $(-0.2, 0.2)$	(4) $(-0.5, 0.5)$
$-\Delta\log(1-\text{tax})$	0.375*	0.393**	0.352**	0.419**
	(0.205)	(0.196)	(0.174)	(0.204)
Observations	14092680	13992737	13519954	14182186
Product FE	✓	✓	✓	✓
Sold-region × year FE	✓	✓	✓	✓
Production-region × year FE	✓	✓	✓	✓
Production-muni. UE controls	✓	✓	✓	✓
Production-district debt controls	✓	✓	✓	✓

Notes: Panel (a) uses observed, posted prices as in our baseline. Panel (b) uses price changes based on a simple V-filter at weekly frequency. Column (1) represents the baseline data treatment where price changes are trimmed at the year-specific 1% and 99% quantiles. Columns (2)-(4) represent different trimmings, where, price changes are trimmed instead at alternative absolute cut-offs. See also Table 2.

Table B.4: Heterogeneous pass-through across retail store types: Product-region-year FE

	(1) Δ log price	(2) Δ log price
Discounter $\times -\Delta \log(1 - \text{tax})$	-0.340	
	(0.373)	
Drug store $\times -\Delta \log(1 - \text{tax})$	-0.00755	0.520
	(0.236)	(0.395)
Supermarket $\times -\Delta \log(1 - \text{tax})$	0.493**	0.929**
	(0.194)	(0.459)
Hypermarket $\times -\Delta \log(1 - \text{tax})$	0.698***	1.284***
	(0.173)	(0.452)
Observations	19434155	14677639
Product FE	yes	(red.)
Sold-region $\times$ year FE	yes	(red.)
Production-region $\times$ year FE	yes	(red.)
Product $\times$ sold-region $\times$ year FE	no	yes

Notes: Column (1) repeats the estimates shown in Figure 6 (b). Column (2) adds a product by sold-region by year FE. *(red.)* indicates that other fixed effects and regressors become redundant due to this. The disounter-specific coefficient is used as the base category and becomes unidentified.