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Market Power and the Heterogeneous Pass-through of Corporate Taxes to Consumer Prices*

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Abstract

We study the pass-through of corporate taxes into consumer prices, leveraging 1,058 municipal tax rate changes affecting 4,754 German firms. A 1 p.p. increase in a producer's tax rate raises retail prices by 0.3% on average, consistent with imperfectly competitive producers. Product-level pass-through varies substantially, as it increases in destination-specific product and retailer-category market shares. We find little evidence linking heterogeneous pass-through to differences in retailer efficiency as reflected in relative consumer prices. Instead, our findings align with standard non-CES preferences where pass-through increasing with market shares implies weaker strategic complementarities in price setting than when this relationship is reversed.

JEL classifications: E31, F45, H25, L11

Keywords: Pass-through, Markup adjustment, Market Power, Vertical interactions, Double marginalization

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1 Introduction

How does market power in price setting shape firms' responses to shocks affecting their margins? A vast literature shows that firms adjust prices and markups in response to cost and demand shocks (see, e.g., De Loecker, Goldberg, Khandelwal, and Pavcnik, 2016 and Stroebel and Vavra, 2019), with substantial firm heterogeneity (see, e.g., Berger and Vavra, 2019).[1] In this paper, we examine shocks to local corporate taxes, asking whether firms pass their tax changes on to consumer prices and whether this pass-through is heterogeneous.[2] While relevant for assessing the incidence of corporate taxes, these questions also crucially bear on the role of firms' market power in price setting and markup adjustment, central issues in macroeconomics (e.g., as they shape strategic complementarities in price setting). Specifically, imperfectly competitive firms can pass changes in corporate taxes on to their customers. We delve into the propagation of corporate tax changes through vertical interactions between producers and retailers, addressing the following questions: Does pass-through depend on firm and product characteristics such as market shares?[3] What is the role of retailers in passing producer corporate tax changes through to consumer prices?[4]

To estimate the pass-through of corporate taxes to consumer prices—and how it varies with market shares—we combine high-quality data on retail sales and prices of food and personal care products across many regions and retailers in Germany with detailed information on producer locations and their corresponding municipal corporate tax rates. These taxes are levied by German municipalities on local producers, whose goods are sold by retailers in multiple German regions. We study how retail prices outside a producer's municipality respond to changes in local corporate tax rates (Baker, Sun, and Yannelis, 2020).[5] We use 1,058 changes in these local corporate taxes set by municipalities, affecting 4,754 firms producing 124,705 products between 2013 and 2017.

Our first finding is that producer corporate tax changes affect retail prices, consistent with a key role of firm market power in their propagation. Specifically, a one percentage point increase in a producer's corporate tax rate leads within one year to an average 0.3% increase in the retail

[1] De Loecker et al. (2016) and Stroebel and Vavra (2019), document the response of markups to shocks impinging on the market structure and consumer shopping behavior, respectively, while the corporate tax shocks we consider directly affect the desired markups of imperfectly competitive firms. Berger and Vavra (2019) link time variation in exchange rate pass-through to heterogeneous markup adjustment.

[2] Edmond, Midrigan, and Xu (2015) show that heterogeneous markup adjustment determines the welfare gains of trade. Meier and Reinelt (2024) and Baqaee, Farhi, and Sangani (2024) show that monetary policy affects misallocation and aggregate productivity through firms' differential markup adjustment.

[3] On the link between pass-through and market shares see, e.g., Atkeson and Burstein (2008), Berman, Martin, and Mayer (2012), and Amiti, Itskhoki, and Konings (2019).

[4] See, e.g., Nakamura and Zerom (2010) and Goldberg and Hellerstein (2013) for a study of cost pass-through into both wholesale and retail prices in the coffee and beer sector, respectively.

[5] Using less granular state-level tax changes, Baker et al. (2020) show that changes in corporate tax rates affect retail prices in the US. Beyond providing evidence on the average pass-through, we also analyze heterogeneity in pass-through across different regions (see DellaVigna and Gentzkow, 2019 and Butters, Sacks, and Seo, 2022 on the effects of local shocks on retail prices across jurisdictions). Mertens and Ravn (2013) study the aggregate effects of *federal* corporate tax shocks in the US, finding that national tax hikes are inflationary.

prices of its goods sold in stores in the rest of Germany.[6] Given the limited number of producers in each municipality, our estimates primarily reflect the effects of firm-specific shocks, suggesting that producers use their market power to raise prices in order to shield margins from corporate tax increases, which thus act as shocks to their markups.[7] These (markup) shocks elicit significant adjustment in wholesale prices, which retailers pass through to consumers across German regions.[8]

Second, leveraging their rich variation in our data, we tease out the pass-through effects of market shares, which are a key determinant of heterogeneity in pass-through as established by the previous theoretical and empirical literature (Atkeson and Burstein, 2008, Berman et al., 2012, and Amiti et al., 2019). Documenting that pass-through increases in both product and retailer-category market shares while controlling for product-time variation, our results reveal substantial heterogeneity in structural pass-through at very granular levels.[9] Using variation in product-level market shares across regions and retailers, the pass-through to the retail price of a given product when its market share is in the top decile is estimated to be over 0.3 percentage points higher than when it is in the bottom decile. We find a similarly important role of the retailer market share in its region and within the category to which a product belongs: For a given product, the pass-through when it is sold by a retailer with a large market share in the corresponding product category is around 0.2 percentage points higher than when it is sold by a low-market share retailer. The propagation of upstream shocks to downstream retail prices of the same product thus varies across regions due to different region-specific product market shares and retailer market shares, each defined based on narrow product categories (e.g., lemonades or heavy-duty detergents).

We frame our analysis within a model of upstream producers catering to consumers in multiple locations through destination-specific retailers, similar to Corsetti and Dedola (2005) and Hong and Li (2017), helping to shed light on the structural implications of our findings. Under imperfect competition, the strength of the corporate tax pass-through to retail prices (holding wages and other producer marginal costs constant) is a function of the share of tax-deductible input costs, the producer and retailer markup adjustment, as well as the efficiency of retailers as captured by distribution costs. In turn, markup adjustment is a function of the price elasticity of demand and

[6]In our sample the average change of the tax rate is around 0.6 p.p., while in more than 60% of the municipalities there is just one producer.

[7]Under trade integration and imperfect substitutability of goods, local corporate taxes affect consumer prices in other regions. This can be consistent not only with imperfect competition, but also with specialization in a given set of goods by perfectly competitive producers in each jurisdiction (Gravelle and Smetters, 2006). Nevertheless, given the granularity of our data, our pass-through estimates essentially capture the effects of firm-specific shocks. Therefore, our results are most likely due to individual firms with market power selling differentiated goods.

[8]Our estimates reflect the total price effect of a change in the corporate tax rate possibly due to various factors in addition to producer and retailer markup adjustment, such as adjustment in wages at the producer level (Fuest, Peichl, and Siegloch, 2018). However, in additional analysis using the IAB employer-employee data similar to Fuest et al. (2018), we find only small wage responses to corporate tax changes in our sample. Moreover, we identify the differences in structural pass-through for a given product when it has different market shares by flexibly accounting for all product-specific variation over time, including in wages and other cost-side factors.

[9]All the results hereby are obtained controlling for product-year (or even product-retailer-year) fixed effects, which absorb product marginal costs but also the average pass-through, allowing to identify the relative effects of market shares.

its sensitivity to its own price (the super-elasticity), both possibly depending on market shares, the focus of our empirical analysis.

We show that a positive relationship between market shares and pass-through is consistent with differential markup adjustment not only under non-CES demand systems (Kimball, 1995), but also with a non-trivial role for heterogeneity in retailer efficiency. Specifically, even under CES preferences, downstream pass-through of upstream shocks (such as changes in producer corporate taxes) is stronger for larger market shares when the latter mainly reflect lower consumer prices driven by retailers' efficiency. This is because, for a given change in a product wholesale price, the lower the share of the retailer's marginal cost in the product consumer price, the larger the pass-through (Antoniades and Zaniboni, 2016). At the same time, pass-through in this case is also stronger the lower the product consumer price, as products with larger market shares should also have lower prices in regions and retailers with lower retail costs. We test this prediction in the data, but find only weak evidence of such a link between pass-through and retail prices.

Assuming a standard non-CES demand system widely used in macroeconomics (Dotsey and King, 2005), we characterize analytically the conditions under which a positive link between pass-through and market shares can arise. Specifically, there is a threshold for the parameter determining the super-elasticity, below which pass-through increases in market shares, in line with our empirical findings.[10] Notably, a relatively low super-elasticity, in line, for instance, with estimates in Beck and Lein (2020), implies weaker strategic complementarities in price setting, relative to the case where pass-through decreases with market shares, and hence a lower degree of real rigidities in macroeconomic dynamics (Aruoba, Oue, Saffie, and Willis, 2023).

In our empirical analysis we rely on the same municipality-level variation in corporate tax changes used in Fuest et al. (2018) to identify their impact on local wages.[11] We further refine this identification strategy, building on the analysis of U.S. state-level corporate taxes by Baker et al. (2020), by leveraging the availability of retail prices in stores outside the region where the producers are subject to municipality-level corporate tax changes. By relating these local changes in firms' taxes to changes in their product prices outside the production municipality, and flexibly controlling for destination-specific factors, our estimates are unlikely to be contaminated by shocks jointly driving consumer prices and producers' corporate tax rates. Moreover, because of the high level of geographical disaggregation of our data and the very limited number of firms in each municipality, our corporate tax changes are essentially akin to firm specific shocks; any

[10] Mrázová and Neary (2017) provide several examples of non-CES preferences where pass-through may also increase in market shares. Arkolakis, Costinot, Donaldson, and Rodríguez-Clare (2019) estimate a demand system which is equivalent to the one we consider, obtaining parameter estimates below such a threshold.

[11] That paper, showing that the tax changes also used in our analysis were hardly associated with local business cycles, finds that a one percentage point tax hike lowers firm-level wages by around 0.3% after 3-4 years. Other work using the same exogenous variation in local corporate tax rates in Germany shows that higher rates lower firms' investment (Link, Menkhoff, Peichl, and Schüle, 2022) and R&D spending (Lichter, Löffler, Isphording, Nguyen, Poege, and Siegloch, 2025).

pass-through into their retail prices can thus be directly related to market power.[12]

Our findings contribute to multiple strands of the literature. First, our result that imperfectly competitive firms pass through corporate taxes on to consumer prices adds to a large body of evidence on the effects of these taxes.[13] At the aggregate level, Mertens and Ravn (2013) and Cloyne, Martinez, Mumtaz, and Surico (2023) show that higher federal corporate taxes decrease output and raise inflation in the US. Looking at very decentralized local corporate taxes we specifically isolate the role of market power in their effects on prices, showing that tax changes have price effects akin to markup shocks. Another strand of this literature focuses on the incidence of corporate taxes, e.g., most recently Suárez Serrato and Zidar (2016), Fuest et al. (2018), Garrett, Ohrn, and Suárez Serrato (2020), and Malgouyres, Mayer, and Mazet-Sonilhac (2023). Consistent with Suárez Serrato and Zidar (2016), our evidence that imperfectly competitive producers pass through corporate tax changes into their product prices suggests that the burden of these taxes falls also on firm profits and customers.[14] Our work especially complements similar findings for U.S. state-level corporate taxes in Baker et al. (2020), as we use price data across two-digit ZIP code regions while exploiting the highly disaggregated institutional setup of municipal-level corporate taxes in Germany. The ensuing substantial granular variation in tax changes helps in addressing well-known identification challenges, allowing us to isolate the role of firms' market power. We also explicitly model and empirically examine the role of retailers in the pass-through of corporate taxes on producers to consumer prices. Overall, our evidence points unambiguously to the relevance of heterogeneous firm market power for the analysis of the costs and benefits of corporate taxes.

Second, we contribute to the extensive literature on imperfect competition and market power in price setting, in particular the strand linking heterogeneous pass-through and markup adjustment to market shares. By showing that pass-through of corporate taxes is higher, the larger market shares, we complement empirical findings in the context of exchange-rate pass-through into both producer prices (Berman et al., 2012, Amiti et al., 2019, and Auer and Schoenle, 2016) and retail prices (Antoniades and Zaniboni, 2016). While the latter contribution finds that exchange-rate pass-through into consumer prices increases with retailer size but not with the market shares of producers, we show that product-level pass-through is increasing in both product and retailer-category market shares, measured at highly granular levels.

[12] A further advantage relative to studies based on corporate tax changes at a more aggregate level than our municipalities is that the local business tax is the main fiscal tool of German municipalities that affects firms. Thus, our tax changes are free from comovements with adjustments in other fiscal tools impinging on firms. This strengthens the credibility of our identification of the effects of corporate taxes, while the availability of multiple fiscal levers may be a concern at more aggregate levels.

[13] See Dubois, Griffith, and O'Connell (2022) for a survey of papers using scanner price data to estimate the consumption effects of a wide range of taxes.

[14] Higher corporate taxes directly reduce profits one-to-one and can have an indirect effect due to downward-sloping demand and firms' price setting response under imperfect competition. As a result, following a tax hike, profits fall more than one to one if firms also increase prices (see, e.g., equation (12) in Suárez Serrato and Zidar, 2016).

Third, we contribute to the literature on firm networks and vertical interactions in pass-through (see, e.g., Berto Villas-Boas, 2007, Burstein, Eichenbaum, and Rebelo, 2007), by showing that the pass-through of (markup) shocks to producers into retail prices is substantial and heterogeneous for a wide range of products. Our contribution is to explicitly test for the structural link between pass-through, market shares, and consumer prices arising from differential retailer efficiency (see also Antoniades and Zaniboni, 2016), complementing earlier evidence on the relative importance of wholesalers and retailers in price setting and pass-through using supermarket data for specific product categories (see Nakamura and Zerom, 2010 for coffee and Goldberg and Hellerstein, 2013 for beer).

Fourth, by framing producers in a municipality as exporters of their products to other regions of a currency area, we contribute to the literature on the transmission of (markup) shocks across jurisdictions.[15] Complementing the large literature on exchange rate pass-through and cross-border markup adjustment (see, e.g., the survey by Burstein and Gopinath, 2014), our results suggest that even in a currency area and for exactly the same product, pass-through into consumer prices differs across regions even for stores belonging to the same retail chain. These results on heterogeneous pass-through within national retailers on the basis of their local market shares complement the evidence in Butters et al. (2022) on the effects of local cost shocks on local prices of U.S. supermarkets, in contrast to the uniform pricing hypothesis (DellaVigna and Gentzkow, 2019).

2 Stylized vertical model of corporate tax pass-through

We start by setting up a stylized model of retailers and producers with market power, along the lines of Corsetti and Dedola (2005) and Hong and Li (2017), to describe the pass-through of corporate tax changes to consumer prices. Firms are monopolistically competitive and produce differentiated goods. In line with our empirical application, we consider an economy where each production firm, located in one of many regions, is subject to a local tax rate but exports its products to retailers inside and outside of its region. We assume that there are no trade frictions and a great deal of capital mobility across regions, similar to models of a currency area comprising many (small) open economies. In this setting, local corporate taxes affect prices of differentiated goods independently of whether producers are perfectly or imperfectly competitive. Nevertheless, in our stylized model we focus on the case of monopolistic competition, in line with the fact that our corporate tax changes can be viewed as essentially firm-specific shocks.

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

Retailers. In each region s, retailer r sets the consumer price of product i, P_{isr}, as the standard markup over marginal cost. These marginal costs consist of the wholesale price Q_{isr}, which we allow to be retailer specific, and a local distribution cost D_{sr}, which captures factors related to inventory, advertising, as well as retail inputs like land, capital, and labor, possibly region- and retailer-specific. We assume a final demand curve with elasticity ρ_{isr}, which can vary across retailers, regions and possibly products. The monopolistically competitive retailer has market power and thus sets the optimal price as a markup over marginal costs based on the elasticity of demand:

$$P_{isr} = \frac{\rho_{isr}}{\rho_{isr} - 1}(Q_{isr} + D_{sr}) \tag{1}$$

Producers. The wholesale price is set by a monopolistically competitive production firm, which is generally located in a different region than s. The producer of product i has a Cobb–Douglas production function using labor L_i and capital K_i, with output elasticities α_i and $1-\alpha_i$, respectively, subject to idiosyncratic productivity Z_i. This implies the standard production function

$$\sum_{r,s} Y_{isr} = Z_i L_i^{\alpha_i} K_i^{1-\alpha_i}. \tag{2}$$

Therefore, the firm's marginal cost is the same for all regions it sells to. The firm wage is W_i and the user cost of capital is R (posited to be the same across all firms under the assumption of perfect capital mobility).

The producer is subject to the firm-specific corporate tax rate τ_i on its revenues, after subtracting labor costs and other deductibles.[16] Therefore, abstracting from other deductibles for the sake of clarity, after-tax profits are given by

$$\Pi_i = (1-\tau_i)\left(\sum_{r,s} Q_{isr}Y_{isr} - W_i L_i\right) - RK_i \tag{3}$$

and, based on (pre-tax) cost minimization, marginal costs are given by

$$MC_i = \frac{1}{Z_i}\left(\frac{W_i}{\alpha_i}\right)^{\alpha_i}\left(\frac{R}{1-\alpha_i}\right)^{(1-\alpha_i)}. \tag{4}$$

Standard static profit maximization yields the following optimal price as a markup over marginal costs scaled by the corporate tax rate:

$$Q_{isr} = \frac{\lambda_{isr}}{\lambda_{isr}-1}\frac{MC_i}{(1-\tau_i)^{(1-\alpha_i)}}, \tag{5}$$

[16] In Germany, debt-financed capital is partly deductible, while equity-financed capital is not (see Fuest et al., 2018).

where $\lambda_{isr} \equiv -\frac{\partial Y_{isr}}{\partial Q_{isr}}\frac{Q_{isr}}{Y_{isr}}$ is the elasticity perceived by the producer, which depends indirectly on the retail price, through the vertical interaction between producer and retailer. For instance, assuming as in Corsetti and Dedola (2005) final demand with constant elasticity ρ_s and that upstream producers internalize the effects of the retail price on final demand yields $\lambda_{isr} = \rho_s \frac{\partial P_{isr}}{\partial Q_{isr}}\frac{Q_{isr}}{P_{isr}} = \rho_s \frac{Q_{isr}}{Q_{isr}+D_{isr}}$.

Pass-through and markup adjustment to corporate tax shocks. Our first key result is that, for given marginal costs, corporate taxes affect the (gross) markup of wholesale prices of monopolistically competitive firms, and thus retail prices, effectively acting as a shock to markups. Notably, this effect of corporate taxes on markups will be present even in a closed economy, in contrast to a setting with perfect competition in which case only wages are affected.[17] The effect on markups is inversely proportional to the share of deductible inputs in production costs α_i: Everything else equal, a higher deductible share lowers the tax base. In particular, holding demand elasticities constant, a 1 percentage point increase in the corporate tax rate raises the wholesale price by $(1-\alpha_i)$%, owing to the combined markup and tax base effects:[18]

$$\frac{\partial \log Q_{isr}}{\partial \log(1-\tau_i)} = -(1-\alpha_i) \tag{6}$$

However, perceived demand elasticities may not be constant in general. We can derive the following general expression for pass-through of corporate taxes into retail prices (see also Hong and Li, 2017):

$$\frac{d \log P_{isr}}{d \log\left(1-\tau_i\right)} = -\left(\frac{1}{1+\frac{\partial \rho_{isr}}{\partial P_{isr}}\frac{P_{isr}}{\rho_{isr}}\frac{1}{\rho_{isr}-1}}\frac{Q_{isr}}{Q_{isr}+D_{sr}}\right)\left(\frac{1}{1+\frac{\partial \lambda_{isr}}{\partial Q_{isr}}\frac{Q_{isr}}{\lambda_{isr}}\frac{1}{\lambda_{isr}-1}}\right)(1-\alpha_i) \tag{7}$$

This expression reveals upstream and downstream effects due to the strategic interactions between producers and retailers. Pass-through into retail prices is given by the product of the retail pass-through (given by the first set of brackets in the expression above) and wholesale pass-through (the second set of brackets). Specifically, pass-through is decreasing in the share of distribution cost in retailer's marginal cost, other things equal. In addition to the role of vertical interactions, corporate tax pass-through to retail prices will be larger the lower the retail and wholesale markups (and so the higher the price elasticities ρ_{isr} and λ_{isr}) and the lower the sensitivity of elasticities to prices (as given by the demand super-elasticities $\frac{\partial \lambda_{isr}}{\partial Q_{isr}}\frac{Q_{isr}}{\lambda_{isr}}$ and $\frac{\partial \rho_{isr}}{\partial P_{isr}}\frac{P_{isr}}{\rho_{isr}}$). In particular, a positive super-elasticity implies that a firm's demand elasticity rises and its desired markup falls in response to a corporate tax change raising its price, which lowers pass-through.

[17] As already discussed, in an open economy with perfect competition, local corporate taxes will affect product prices if firms are specialized in a given imperfectly substitutable good.

[18] This is under the maintained assumption that marginal costs and specifically wages do not react to the tax change. However, if manufacturers are able to influence their own wages (or the prices of other deductible inputs) or the latter respond to the shock, then a tax increase can increase retail prices as long as $\frac{\partial \log MC_i}{\partial \log(1-\tau_i)} < 1-\alpha_i$.

Taken together, in response to a 1 percentage point tax increase, while positive distribution costs imply that wholesalers and retailers increase prices by less than $(1-\alpha_i)\%$, both firms have a further incentive to reduce pass-through and increase prices by even less, the lower the demand elasticities and the higher the super-elasticities. The pass-through expression also shows that heterogeneity in elasticities, super-elasticities, and distribution costs may result in different responses of prices to corporate taxes, where all these features can be product-specific in each sales region. Next, we specialize the expression to focus on a crucial driver in many models of heterogeneity in elasticities, market shares.

Heterogeneity in pass-through and market shares. In many non-CES demand systems, a crucial driver of non-constant and heterogeneous demand elasticities and super-elasticities are product-level market shares (see, e.g., Arkolakis and Morlacco, 2017). But even in the CES model of vertical interactions in Corsetti and Dedola (2005), pass-through is related to market shares, as previously shown by Berman et al. (2012) and Antoniades and Zaniboni (2016).[19] Specifically, since in this model the final demand elasticity ρ_s is constant, pass-through into retail prices of a change in corporate taxes simplifies as follows:

$$\frac{d\log P_{isr}}{d\log(1-\tau_i)} = -(1-\alpha_i)\left(\frac{Q_{isr}}{Q_{isr}+D_{sr}}\right)\left(\frac{\frac{MC_i}{(1-\tau_i)^{1-\alpha_i}}}{\frac{MC_i}{(1-\tau_i)^{1-\alpha_i}}+D_{sr}/\rho_{rs}}\right) \tag{8}$$

$$= -(1-\alpha_i)\frac{\frac{MC_i}{(1-\tau_i)^{1-\alpha_i}}}{\frac{MC_i}{(1-\tau_i)^{1-\alpha_i}}+D_{sr}}. \tag{9}$$

As noted above, pass-through is decreasing in the share of distribution costs in the retailer's marginal costs. Notably, since they affect retail prices, these costs are also a determinant of market shares, which under CES preferences are a decreasing function of prices. Therefore, larger market shares can be associated with weaker or stronger pass-through, depending on whether they reflect lower production or distribution costs. In any case, the crucial prediction of this model is that pass-through can be increasing (decreasing) in market shares only if it is also decreasing (increasing) in the retail price, because of lower distribution (production) costs.[20]

Turning to non-CES models where elasticities depend on market shares, we can explicitly analyze the Kimball-type demand system in Dotsey and King (2005) for the special case in which distribution in each region is vertically integrated within the producer at a local cost D_s. Pass-

[19] As noted above, in Corsetti and Dedola (2005), producers' perceived demand elasticity is given by $\lambda_{isr} = \rho_s \frac{\partial P_{isr}}{\partial Q_{isr}}\frac{Q_{isr}}{P_{isr}} = \rho_s \frac{Q_{isr}}{Q_{isr}+D_{isr}}$. In this case producers would face a lower elasticity than retailers depending on the share of distribution costs, because the pass-through of wholesale prices into retail prices is dampened by the presence of additive distribution costs.

[20] A similar result would hold also generalizing the assumption of a linear retail cost structure to a CES retail production function, as long as the elasticity of substitution between the wholesale good and local distribution inputs is less than unity.

through then simplifies to the following expression without double marginalization:

$$\frac{d\log P_{is}}{d\log\left(1-\tau_i\right)} = -\left(\frac{1}{1+\frac{\gamma_{is}}{\rho_{is}-1}}\right)\left(\frac{MC_i}{MC_i+\left(1-\tau_i\right)^{1-\alpha_i}D_s}\right)\left(1-\alpha_i\right), \tag{10}$$

where $\gamma_{is} := \frac{\partial\rho_{is}}{\partial P_{is}}\frac{P_{is}}{\rho_{is}}$ is the super-elasticity. Specifically, the elasticity and super-elasticity are given by the following expressions:

$$\rho_{is} = \frac{\omega}{\omega-1}\frac{-\psi+\left(1+\psi\right)\dfrac{n_{is}y_{is}}{Y_s}}{\dfrac{n_{is}y_{is}}{Y_s}} \tag{11}$$

$$\gamma_{is} = -\frac{\omega}{\omega-1}\frac{\psi}{\dfrac{n_{is}y_{is}}{Y_s}}, \tag{12}$$

where $\frac{n_{is}y_{is}}{Y_s}$ are effective output shares, which are function of the product price, and also depend on a demand shifter (n_{is}, possibly good-region specific), that can affect prices as in Aruoba et al. (2023).[21] The parameter $-\psi \geq 0$ encodes deviations from CES, with both the elasticity and super-elasticity depending on the effective output share $\frac{n_{is}y_{is}}{Y_s}$. Appendix B provides more details.

Both elasticity and super-elasticity are decreasing in the effective output share, resulting in opposing effects on pass-through. However, given that $\rho_{is}-1 = \gamma_{is}+(1+\omega\psi)\frac{1}{\omega-1}$, it is straightforward to show for the limiting case $D_s \to 0$ that pass-through is increasing in effective output shares if $\rho_{is}-1 > \gamma_{is}$, for which a necessary and sufficient condition is that $0 < -\psi < \omega^{-1}$; pass-through is decreasing in effective output shares otherwise. The reason for increasing (decreasing) pass-through is that super-elasticities are declining strongly (weakly) enough to imply that markups fall less (more) in response to the tax shocks.

In the data, effective output shares are generally not observable, but there is an order-preserving map between effective output and market shares, since the demand elasticity ρ_{is} must be larger than 1.[22] Therefore, the same condition, $0 < -\psi < \omega^{-1}$, determines whether pass-through is also increasing in observable market shares. (Appendix B provides the proofs.)

Notably, this property has implications for the strength of strategic complementarities in terms of the sensitivity of a firm's markup to its competitors' prices (equal to the complement of the structural pass-through coefficient to one, $1-(1+\frac{\gamma_{is}}{\rho_{is}-1})^{-1}$). First, when pass-through is increasing (decreasing) in market shares, then this source of strategic complementarities is weaker (stronger) for larger market shares. Second, for given elasticity ρ_{is} and market shares, parameter values of ψ such that pass-through is increasing in market shares also imply weaker strategic complementarities

[21] An important property of this demand system is that (real effective) output of product i is larger than that of product j, $n_{is}y_{is} > n_{js}y_{js}$, if and only if the effective relative price is lower, $\frac{P_{is}}{n_{is}} < \frac{P_{js}}{n_{js}}$.

[22] Because of the standard lower bound on ρ_{is}, we can show that the effective output of product i is larger than that of product j, if and only if the market share of product i is also larger than that of product j (i.e., $\frac{n_{is}y_{is}}{Y_s} > \frac{n_{js}y_{js}}{Y_s}$ if and only if $\frac{p_{is}y_{is}}{P_sY_s} > \frac{p_{js}y_{js}}{P_sY_s}$).

than in the case when pass-through is decreasing in market shares. This is due to the fact that $\frac{\gamma_{is}}{\rho_{is}-1}$ is increasing in $-\psi$.

Testable implications. In Section 5 below we document the role of market shares in affecting the pass-through of corporate tax shocks, and investigate the importance of retailer heterogeneity. Specifically, in our preferred specifications relating pass-through to market shares, we control for product-year fixed effects, which absorb product-specific marginal costs but also average pass-through. Thus, we are able to identify the relative effects of market shares on pass-through due to differential markup adjustment at the product level, highlighting the implications for heterogeneity in strategic complementarities. To further isolate the role of distribution costs in driving the relation between market shares and pass-through, we run similar specifications relating pass-through heterogeneity within products to their (relative) retail prices. As discussed above, the key testable implication is that if pass-through is increasing in product market shares because of lower distribution costs, it must also be *decreasing* in product retail prices (controlling for marginal production costs).

In concluding this section, a caveat is in order: although our framework assumes flexible prices, there is clear empirical evidence that most prices change only infrequently. On the one hand, infrequent price adjustment at both the producer and retailer level may bias estimates of (desired) pass-through downward. On the other hand, optimizing firms facing nominal rigidities in price adjustment will set prices taking into account not only the current changes in corporate taxes, but also their future evolution and their effects on future costs, including wages. If changes in corporate taxes are very persistent, the response of optimal prices will be close to its static counterpart. Moreover, similarly to many studies in the literature, we consider price changes at horizons of at least one year, over which most prices should adjust, especially those of processed food and other groceries, which comprise our sample.[23] Nevertheless, to the extent that other costs also react to corporate tax changes, possibly with a delay, their responses may impact on our estimates, especially dynamically.

3 Institutional setup and data construction

3.1 Local business taxes in Germany

Corporate taxes in Germany are set at the federal and the local level. In this paper, following Fuest et al. (2018), we focus on the *local business tax*, which impinges on corporate and non-corporate

[23]See Gautier, Conflitti, Faber, Fabo, Fadejeva, Jouvanceau, Menz, Messner, Petroulas, Roldan-Blanco, and Rumler (2022) for estimates of the frequency of price changes in euro area countries over a period that overlaps with our sample.

firms.[24] The tax base and the firms subject to the local business tax are defined at the federal level, while the tax rate contains a local component that is set separately in each of the more than 10,000 municipalities (*Gemeinden*). Specifically, the tax base consists of operating profits with some adjustments, for example to account for partial deductibility of debt-based financing costs, while equity-based financing costs are not deductible.

The municipality-specific local business tax rate is computed by multiplying the federally-set basic rate (*Steuermesszahl*) with the local scaling factor (*Hebesatz*) set by the municipality, i.e., local corporate tax rate = 3.5% × local scaling factor. The basic rate has been constant at 3.5% since 2008, i.e., since well before the start of our sample. 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 to at least 2 but is not restricted otherwise (implying that the overall corporate tax rate is at least 7%).[25]

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

3.2 Matched price-firm-tax data

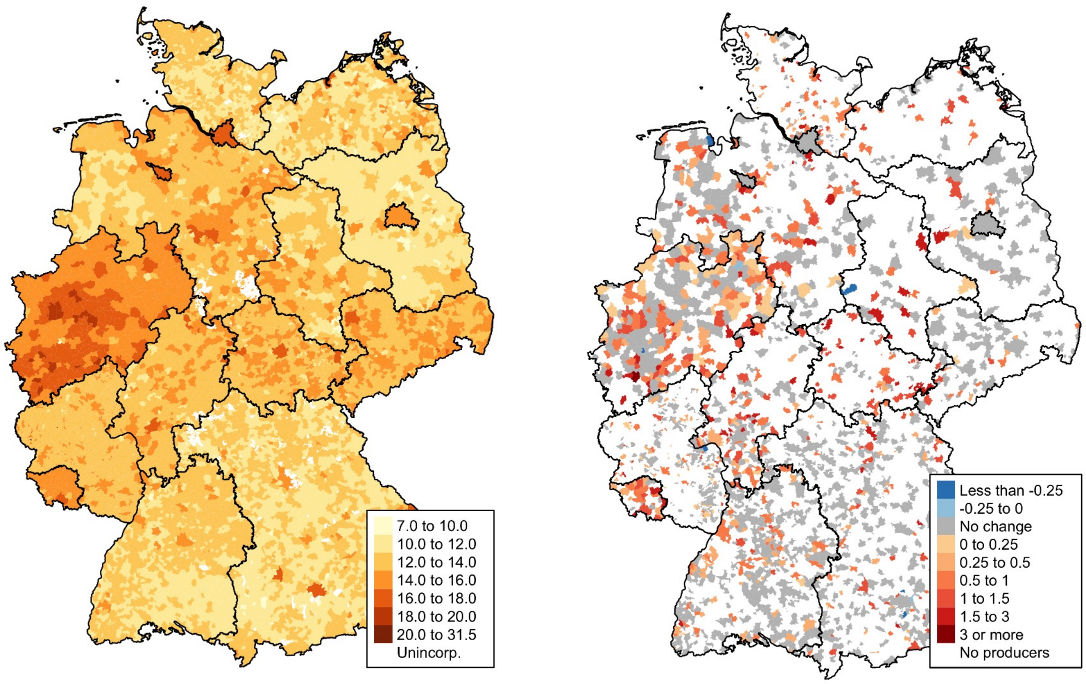
We construct a unique data set that links product-level retail prices to municipality-level tax rates based on the location of the producers.[26] We use product-level prices from the marketing company Information Resources, Inc. (IRi) (Bronnenberg, Kruger, and Mela, 2008). The IRi data are collected in supermarkets, specifically by point-of-sale scanners, and comprise the weekly revenue and quantity sold of 309,099 products, identified by EAN barcodes (also referred to as UPCs or GTINs), across 10,412 distinct stores belonging to 16 different (anonymized) retail chains located in 95 two-digit ZIP codes in Germany between 2013 and 2017. Product prices are recorded also in regions other than the one where producers are located. The data also track the retail chain where the product is sold, although in an anonymized fashion. The products include (mostly processed) food, beverages, tobacco, toiletries, and other personal and household care items. Thereby, the sample covers products in 74 of the 187 COICOP categories for goods that make up the Harmonised Index of Consumer Prices (HICP).

To obtain the municipality-level tax rate that applies to the producer of a given product,

[24] This is unlike in the United States, where corporate income is taxed for C-corporations but not for "pass-through" entities. Incorporated firms in Germany are also subject to the federal corporate income tax (*Körperschaftssteuer*). The local business tax (*Gewerbesteuer*) accounts for about 7% of total tax revenue at the federal, state and local levels. The self-employed as well as firms operating in agriculture and forestry are exempt from the local business tax. However, products from such firms are not present in our sample.

[25] Note that scaling factors are also commonly reported in percentage points, such that the minimum is 200. If a firm has establishments in many municipalities (or an establishment extends over more municipalities), the tax

Figure 1: Geographical variation in local corporate tax rates



(a) Local corporate tax rates (%) in 2017 (b) In-sample cumulative changes (p.p.) between 2013 and 2017

Notes: Panel (a) shows municipality-specific local corporate tax rates in 2017. Panel (b) shows cumulative changes in the local corporate tax rates 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 is observed in our sample.

we match the products in the IRi data with firm information from the GS1 GEPIR database. Specifically, we request the company information contained in the GEPIR database for individual barcodes and keep track of the name and postal address. For example, starting from a soda barcode in our data, the GEPIR query will return the soda's brand, the name of the firm that registered the barcode, and the firm's address. We assume that this address identifies the producer's headquarters and thus where the corporate tax is paid.[27] We are able to obtain the producer location for 72% of all German products, equivalent to 73% of revenues, in the IRi data. Based on the reported addresses, we can attach firms to municipalities and thereby match the applicable corporate tax rates over time. Based on firm name and location, we are also able to match the price data to firm information from the Orbis database provided by Bureau van Dijk (BvD). Orbis allows

is apportioned according to the wage bill in each municipality.

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

[27]This reflects the most recent location of the firm; we are not able to track the historical locations of firms. 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.

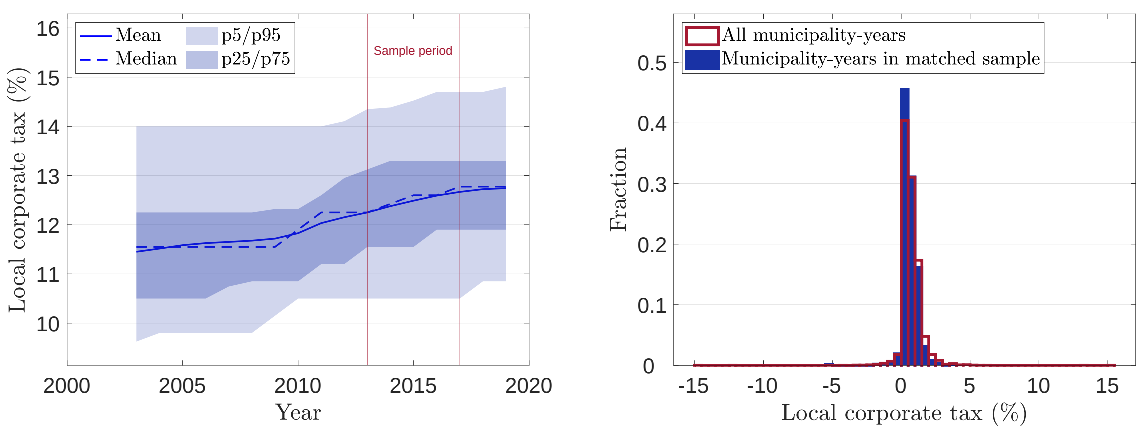
Table 1: Summary statistics of the matched data

	Barcodes	Vendors	Producers	Municipalities	Sales (bn. €)
Universe of products	309,099	11,574	–	–	119,350
Products with German barcodes	173,885	6,292	–	–	59,324
Matched with GS1 and admin data	124,705	4,250	4,754	2,120	43,500

Notes: This table summarizes 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 400–440 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). Each row is a strict subset of the previous row.

Figure 2: Changes in local corporate tax rates

(a) Distribution of tax rates over time (b) Histogram at municipality-year level



Notes: Panel (a) shows moments of municipality-specific local corporate tax rates over time. Panel (b) shows the histogram of municipality-year-specific non-zero changes in local corporate tax rates, for the years 2014–2017.

us to construct a proxy for the existence of establishments and branch offices, which we use for robustness. Appendix A.3 provides details on the matching of products to firms and municipalities.

Table 1 reports summary statistics on the matched data set. Of all 309,099 products sold, 173,885 have German barcodes. For 124,705 of these products, i.e., 72%, we obtain the producer locations and local corporate tax rates.

Figure 1 (b) shows the variation in corporate tax rates in our matched sample, by plotting cumulative changes in local scaling factors between 2013 and 2017 for all municipalities which correspond to at least one producer location in our data (white areas in the figure indicate municipalities in which no firm was identified in the data). Figure 2 (a) shows that our sample period, 2013–2017, is representative of the long-term upward trend in corporate taxes in Germany. Figure 2 (b) and Table 2 report additional descriptive statistics on municipality-level tax changes. Our

Table 2: Changes in local corporate tax rates (in p.p.) in the matched sample vs. all municipalities

	Municipalities	Pop.	Freq.	Mean	p10	p90
All Germany	11,172	83m	15.1%	0.70	0.17	1.40
Matched sample	2,120	52m	14.1%	0.60	0.18	1.23

Notes: This table displays descriptive statistics on municipality-year-specific changes in local corporate taxes for the years 2014–2017. *Freq* indicates the frequency of non-zero tax changes. *Mean*, *p10*, and *p90* indicate statistics for municipality-years with non-zero scaling factor changes.

matched data set contains producers in 2,100 different municipalities, i.e., around 20% of all municipalities in Germany. Nevertheless, the municipalities in our sample account for a population of 52 million, i.e., around 60% of Germany's population. In these municipalities the frequency of tax changes was 14.1%, close to the figure observed in all municipalities (15.1%). The distribution of tax changes is similar in the municipalities in our sample and in all municipalities in Germany. Municipalities change the corporate tax rate by around 0.6 percentage points on average conditional on an increase. The number of firms in each municipality is small, with the share of municipality-years with exactly one firm around 60% and the average number of firms around 2, see Table A.6 in the Appendix.

3.3 Aggregation of micro price data

We aggregate the IRi price data as follows. We start with prices per unit for each product (as identified by a barcode), store, and week, computed as revenue 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 keep only price changes in stores that were operative for the full current and previous year, to avoid possible shop composition effects. We then take the average of the log price changes over all stores within a two-digit ZIP code region, retail chain, and year.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 a formal description of these steps.

For our panel regressions, we trim the yearly distributions of log price changes at their 1% and 99% quantiles. We drop products with only one observation across sold regions, retailers, and years. We exclude in all regressions the price changes which refer to the two-digit ZIP code region where the product is produced, i.e., where the sales region and the production region coincide. 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, aggregated by ZIP code region and retail chain.

4 Empirical strategy and estimates of average effects of corporate taxes on retail prices

In this section, we describe our empirical strategy to estimate the causal effects of local corporate taxes on retail prices. We find that higher local corporate taxes raise retail prices and provide a host of robustness checks.

4.1 Identification

To estimate the causal effect of corporate taxes on consumer prices, we rely on the significant variation in local corporate tax rates across municipalities in Germany over time. Fuest et al. (2018) show that these corporate tax changes are largely exogenous to local business cycle conditions. Relative to this contribution, we further refine our identification strategy by leveraging the fact that our goods are produced in certain locations but sold in many other regions (Baker et al., 2020). This has two advantages. First, this allows us to further control for any aggregate and local demand and supply shocks jointly affecting consumer prices and corporate taxes. Second, due to the high level of geographical disaggregation of our data and the limited number of affected firms in each municipality, our corporate tax changes are alike to firm specific shocks. Thus, any response of retail prices in other regions can be directly related to firm market power rather than reflecting a "terms of trade" effect on the prices of imperfectly substitutable exports (Gravelle and Smetters, 2006).

In detail, we compare the price changes of products of firms located in different municipalities and thus subject to different local corporate tax rate changes, but which are sold in the same two-digit ZIP code regions, outside of the region where producers are located. By doing so, we hold local demand shocks, which affect all prices in a given sales region, constant. Furthermore, by comparing the prices of products of firms producing in the same region but affected by different municipal corporate taxes, we also account for similar supply conditions, while additionally including controls for changes in local labor market conditions and in fiscal space. Finally, the fact that corporate taxes are the main fiscal instrument available to municipalities bearing on firms allows us to cleanly isolate the impact of those taxes, as opposed to the situation where a jurisdiction may enact a complex fiscal package.[28]

We use panel regressions of price changes $\Delta \log p_{isrt}$ of product i in sales region s by retail

[28] Municipalities also can set the local scaling factors of two real estate taxes bearing on households as well as firms, one on arable land (*Grundsteuer A*) and one on built-up areas (*Grundsteuer B*). The local business tax is the main source of income for municipalities. It generated total tax revenues of 55 billion euros in 2019, while the revenues from the tax on arable land amounted to only 0.4 billion euros and the revenues from the tax on built-up areas amounted to 14 billion euros. We show below that our results are robust to controlling for these tax changes as well. Beyond these tax instruments bearing on firms, municipalities have the authority to impose various taxes and fees of secondary importance, such as dog tax, second home tax, tourist tax, waste fees for garbage collection, development contributions for new infrastructure, and gaming machine tax for commercial gaming machines.

chain r in year t on producers' log net-of-tax factor changes $\Delta \log(1-\tau_{it})$, with the understanding that all products produced by firms in the same municipality have the same tax changes. We include fixed effects by sales region-year, α_{st}, where the sales region is a two-digit ZIP code area of the store, and by production region-year, α_{pt}, where the production region p is the two-digit ZIP code of the producer. Formally, using only observations where the sales region is different from the production location, $s \neq p$, we estimate the following specification:

$$\Delta \log p_{isrt} = \alpha_{st} + \alpha_{pt} + \beta(-\Delta \log(1-\tau_{it})) + \Gamma X_{it} + \varepsilon_{isrt} \tag{13}$$

The vector X_{it} includes additional control variables at the municipality or county level. Specifically, we use two lags of changes of the production municipality unemployment rate and two lags of growth rates in the production county-specific debt.[29] Moreover, we control 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. We estimate Huber (1964)-robust regressions to reduce the influence of large outliers in the micro data, but we show that our results are also significant using plain OLS estimation. We cluster standard errors at the municipality level.

The coefficient of interest, β, captures the elasticity of the price with respect to the negative net-of-tax factor $(1-\tau)$, in line with (7). 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. The coefficient β indicates the average across all goods of the change in consumer prices in response to a one percentage point increase in the corporate tax rate on producers in a given municipality. The estimand can differ from structural pass-through as in (7) if firm-level wages or other costs also react to corporate tax changes, possibly with a delay. We address this possible issue below, finding only weak evidence for a response of firm-level wages in our sample.

We can lend causal interpretation to the coefficient β based on the broad exogeneity of corporate tax changes at the municipal level to local business cycle conditions, in line with Fuest et al. (2018). But even in case of residual endogeneity, we can leverage the following two identifying assumptions. First, a local tax change in a municipality within production region p is exogenous to the product demand in the sales region $s \neq p$. Second, the production region by year fixed effects α_{pt} and the local control variables X_{it} (two lags of both unemployment growth and fiscal debt growth) control for any local supply factors related to firms' costs that correlate with local tax changes. Such factors would induce endogeneity if municipalities were to adjust corporate taxes to, e.g., alleviate the impact of wage or other cost changes on firms.

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

Table 3: Effect of a corporate tax change on consumer prices

	(1)	(2)	(3)
		Δ log price	
$-\Delta \log(1 - \text{tax})$	0.301***	0.285***	0.296***
	(0.061)	(0.062)	(0.063)
Observations	19,434,155	19,045,396	19,045,396
Sales region × year FE	✓	✓	✓
Production region × year FE	✓	✓	✓
Debt and unemployment controls		✓	✓
Other municipal tax controls			✓

Notes: This table displays results from estimating $\Delta \log p_{isrt} = \alpha_{st} + \alpha_{pt} + \beta(-\Delta \log(1 - \tau_{it})) + \Gamma X_{it} + \varepsilon_{isrt}$. Prices are observed at the product i, two-digit ZIP code sold location s, retail chain r, and year t level. Corporate tax rates vary by production municipality and year. α_{st} is a two-digit ZIP code sales region by year fixed effect and α_{pt} is a two-digit ZIP code production region by year fixed effect. X_{it} can contain two lags of changes of the production municipality unemployment rate, two lags of growth rates in the production county-specific debt level, and production municipality-specific changes in tax scaling factor on arable land (real estate tax "A") and on built-up land (real estate tax "B"). Huber-robust regressions with standard errors (in parentheses) clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Average effect

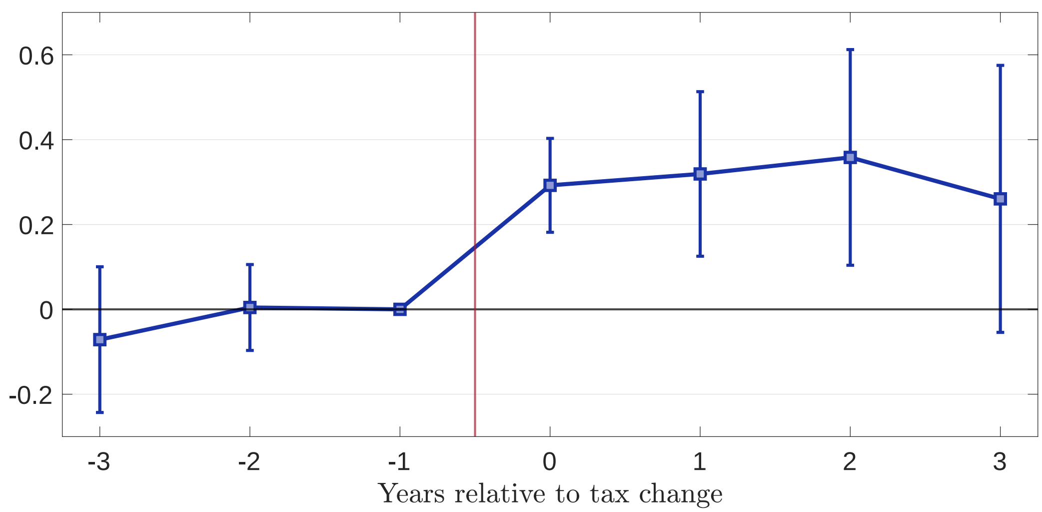
Table 3 reports the estimated effect of corporate taxes on consumer prices, based on three specifications of equation (13). Column (1) uses sales region-year fixed effects, α_{st}, and production region-year fixed effects, α_{pt}, but no further controls. Column (2) adds two lags of changes of the production municipality unemployment rate and two lags of growth rates in the production county-specific debt level. Column (3) adds controls for changes in local scaling factors on real estate taxes, which are two additional fiscal instruments at municipalities' disposal.[30] The point estimates of the coefficient are all positive, narrowly ranging from 0.285 to 0.301, and are highly statistically significant.[31]

These positive coefficients mean that prices increase in response to an essentially firm-specific 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 of a producer causes, on average, an approximately 0.3% increase in the consumer prices of its products. This increase in retail prices is consistent with a significant rise in wholesale prices, which is in turn passed through into higher consumer prices by retailers. As discussed above, this estimate may reflect the total price effect of a higher corporate tax rate that arises from a higher markup but possibly lower wages (Fuest

[30] As noted above, the first real estate tax (*Grundsteuer A*) applies to arable land and the second (*Grundsteuer B*) on built-up areas. Table C.3 reports detailed results.

[31] Table C.1 reports the results from OLS estimators, which are also positive and statistically significant, but somewhat larger. Table C.4 in the Appendix shows these regressions when using directly changes in the tax rate, $\Delta\tau$, as the main regressor. The findings are quantitatively very similar to using changes in the log net-of-tax factor $\Delta \log(1 - \tau)$.

Figure 3: Dynamic effect of a corporate tax change on consumer prices



Notes: 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 distributed-lag regression $\Delta \log p_{isrt} = \alpha_{st} + \alpha_{pt} + \sum_{k=-2}^{3} \beta_k(-\Delta \log(1 - \tau_{it-k})) + \Gamma X_{it} + \varepsilon_{isrt}$. The price path relative to period $t-1$ before the tax change is plotted as $\sum_{k=-1}^{h}(-\beta_{k-1})$. X_{it} contains two lags of changes of the production municipality unemployment rate, two lags of growth rates in the production county-specific debt level, and production municipality-specific changes in the tax scaling factors on arable land (real estate tax "A") and on built-up land (real estate tax "B"). Huber-robust regression with standard errors clustered at the municipality level. Whiskers represent confidence intervals at the 95% level.

et al., 2018) at the producer level. The average structural pass-through coefficient combining upstream and downstream markup adjustment as in (7) would in this case be different from the estimated effect. However, a supplementary analysis of the response of firm-level wages to local corporate taxes in our sample of firms suggests this response is not of first order.[32] In Section 5 below, we identify the structural differences in pass-through for different market shares within the same products by flexibly holding all product-specific characteristics, including wages and other cost-side factors, fixed.

To assess the dynamic effects of corporate taxes on consumer prices, we extend regression (13)

[32] We match the firm-year specific tax changes in our dataset to firm-level wages based on the administrative employer-employee data by the Institute of Employment Research (IAB). Figure C.1 in the Appendix shows that in our sample, which differs from the one in Fuest et al. (2018), the effects of corporate tax changes on wages are small and very imprecisely estimated.

to the following distributed-lag regression:

$$\Delta \log p_{isrt} = \alpha_{st} + \alpha_{pt} + \sum_{k=-2}^{3} \beta_k(-\Delta \log(1 - \tau_{it-k})) + \Gamma X_{it} + \varepsilon_{isrt} \tag{14}$$

Figure 3 plots the cumulative price relative to period $t-1$ following a tax change in period t, which is given by $\sum_{k=0}^{h} \beta_k$ for $h \geq 0$, and $\sum_{k=-1}^{h}(-\beta_{k-1})$ for $h < 0$, which yields the price path relative to period $t-1$. The results show that prior to a tax change, there are only negligible and insignificant changes in retail prices. This flat pre-trend is consistent with no anticipatory effects of tax changes. In the years after the tax change, prices increase significantly and stay persistently higher, in line with tax changes being highly persistent in the data. This strong persistence of the effect also suggests that distortions arising from infrequent price adjustment, as discussed in Section 2, should indeed be of limited concern.

4.3 Robustness

In this subsection we document the robustness of our findings in a number of dimensions, including the use of more granular fixed effects and excluding multi-establishment firms.

Addition of more granular fixed effects. Our results are robust to the inclusion of more granular fixed effects, see Table 4. Column (1) reproduces the baseline specification in Column (3) of Table 3. Column (2) adds retail chain by sales region by year fixed effects, to capture factors that are specific to a given retail chain in a given region. As a result, we then compare the prices of products sold in the same region and by stores belonging to the same retail chain. Column (3) adds fixed effects at the level of product category by sales region by year, thereby analogously comparing relative price changes of products of the same group and sold in the same region. As product categories we use 20 COICOP-level categories, which we manually assigned based on the product categories in the IRi data set. The results show that our benchmark estimates are broadly robust to controlling for more granular sources of unobserved heterogeneity, with point estimates reducing the most to around 0.2 in Column (3), though insignificantly different from baseline estimates.[33]

Exclusion of multi-establishment firms. As an important robustness check of our main finding, we investigate the role of firms with multiple establishments. This is relevant because the apportionment rule in the corporate tax code implies that if a firm produces in several municipalities, the tax base is divided among municipalities according to the wage bill accruing there. Thus, the effective tax rate for a firm is a wage-bill-weighted average over all production establishment

[33] As shown in Table C.2 in the Appendix, our results are also robust to removing any of the granular fixed effects.

Table 4: Robustness to adding more granular fixed effects

	(1)	(2)	(3)
		Δ log price	
$-\Delta \log(1 - \text{tax})$	0.296***	0.273***	0.195***
	(0.0634)	(0.0630)	(0.0620)
Observations	19,045,396	19,045,396	19,045,396
Production region × year FE	✓	✓	✓
Debt and unemployment controls	✓	✓	✓
Other municipal tax controls	✓	✓	✓
Sales region × year FE	✓		
Sales region × retailer × year FE		✓	
Sales region × category × year FE			✓

Notes: This table displays results from estimating $\Delta \log p_{isrt} = \alpha_{s(r/c)t} + \alpha_{pt} + \beta(-\Delta \log(1 - \tau_{it})) + \Gamma X_{it} + \varepsilon_{isrt}$, with different levels of fixed effects. α_{pt} is a two-digit ZIP code production region by year fixed effect. Specification (1) replicates the baseline estimate and uses a two-digit ZIP code sales region by year fixed effect α_{st}. Specification (2) uses a sold location by retailer by year fixed effect α_{srt}. Specification (3) uses a sold location by HICP product category (COICOP) by year fixed effect α_{sct}. X_{it} contains two lags of changes of the production municipality unemployment rate, two lags of growth rates in the production county-specific debt level, and two further municipal tax scaling factors: of *real estate tax A* on arable land and *real estate tax B* on built-up land. Huber-robust regressions with standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

municipalities. To the extent that profits are maximized at the firm instead than at the establishment level, our results may thus be influenced by the presence of such multi-establishment firms. As explained in Section 3, we match IRi data with Orbis firm data in order to identify multi-establishment firms. The Orbis data allow to construct a proxy for the existence of establishments and branch offices, including their location. Specifically, the Orbis data set includes some information about "branches", although there is, unfortunately, no guarantee that this captures all establishments. A branch is a recorded firm presence outside of the location of the headquarter.

Column (1) in Table 5 repeats the estimation for the subsample of all Orbis firms as a benchmark, broadly confirming our estimates for the whole sample. Column (2) then includes only the prices of firms in Orbis without branches. It turns out that our benchmark estimate is robust to excluding the multi-establishment firms identified in Orbis, as point estimates drop somehow but are again insignificantly different from the baseline estimates.

Placebo exercise. Although the fixed effects that we include in our panel regressions control flexibly for common shocks in the production region of each firm, we carry out further tests to address concerns about the exogeneity of the tax changes. This placebo-type exercise checks if randomly re-assigning tax changes across municipalities within a narrowly defined region also results in significantly estimated price effects. In other words, we check if prices change either due to unobserved local shocks not captured by our controls, or spillovers. Specifically, for a given

Table 5: Robustness to excluding firms with multiple establishments

	(1)	(2)
	Δ log price	
	All Orbis firms	without branch
$-\Delta\log(1-\text{tax})$	0.303***	0.269***
	(0.0656)	(0.0562)
Observations	13,564,215	7,807,277
Sales region × year FE	✓	✓
Production region × year FE	✓	✓
Debt and unemployment controls	✓	✓
Other municipal tax controls	✓	✓

Notes: This table displays results from estimating $\Delta\log p_{isrt} = \alpha_{st} + \alpha_{pt} + \beta(-\Delta\log(1-\tau_{it})) + \Gamma X_{it} + \varepsilon_{isrt}$, as in Table 3, 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. X_{it} contains two lags of changes of the production municipality unemployment rate, two lags of growth rates in the production county-specific debt level, and two further municipal tax scaling factors: of *real estate tax A* on arable land and *real estate tax B* on built-up land. Huber-robust regressions with standard errors clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 (13). Table C.5 in the Appendix shows the results, which reveal insignificant or even negative coefficients. This corroborates our finding that prices indeed increase due to municipality-specific hikes in tax rates.

Alternative outlier treatments and exclusion of sales prices. Table C.6 (a) in the Appendix shows that the results are robust to trimming price changes at different cutoffs and Table C.6 (b) shows they are robust to using sales price-filtered data, which exclude V-shaped price movements at the weekly frequency (Nakamura and Steinsson, 2008).

5 Heterogeneous pass-through of corporate taxes into consumer prices

In this section, we provide novel evidence that pass-through of corporate tax shocks increases with product and retailer market shares at very granular levels. Our stylized conceptual framework in Section 2 allows for both general, non-constant demand elasticities, as well as the presence of heterogeneous distribution costs. Both factors generate a link between market shares and pass-through and thereby heterogeneity in pass-through across products and markets. Our data set is uniquely suited to investigate the link between pass-through and market shares because it includes

Table 6: Average product market shares by quintiles (in %)

	Quintile				
	1st	2nd	3rd	4th	5th
Within years	<0.0001	<0.0001	<0.0001	0.0001	0.0018
Within group-years	0.0005	0.0039	0.0176	0.0810	0.8055
Within group-region-years	0.0195	0.0727	0.1990	0.5339	2.1543
Within group-region-retailer-years	0.3430	0.4606	1.0215	1.9848	4.2122

Notes: This table displays the average market shares $s_{isrt}^{(m)} = \frac{\sum_{s',r' \in m} \text{sales}_{isrt}}{\sum_{i',s',r' \in m} \text{sales}_{i's'r't}}$, using different market definitions and across quintile bins. Averages are computed without the top and bottom 1% market shares within each group. The observations are sorted into quintile bins according to product-level sales within the market.

very granular information on sales for each product in many locations. While we find little evidence of distribution costs shaping pass-through heterogeneity, our results are consistent with non-CES demand systems with weak strategic complementarities.

5.1 Pass-through heterogeneity and product market shares

We first document the role of producer size in pass-through, which has frequently been used as a proxy for firms' market power (see, e.g., Amiti et al., 2019). We define firm size s_{it} as the sum of all product sales of a firm in all regions and retailers (for a given year). We assign an observation into decile bin k if the production firm's size is in the k^{th} decile of the firm size distribution (for a given year), denoting the set of observations that are assigned to decile k by q_k. We then estimate an extension of the panel regression (13) where we interact the change in the log net-of-tax factor with indicator variables representing the size deciles:

$$\Delta \log p_{isrt} = \alpha_{st} + \alpha_{pt} + \sum_{k=1}^{10} \alpha_{q_k} \mathbb{1}\{s_{it} \in q_k\} + \sum_{k=1}^{10} \beta_{q_k} \mathbb{1}\{s_{it} \in q_k\}(-\Delta \log(1 - \tau_{it})) + \varepsilon_{isrt} \tag{15}$$

Figure 4 (a) plots the estimates of the decile-specific pass-through coefficients $\{\beta_{q_k}\}$. While point estimates tend to decrease and then increase again with firm size, they are not statistically different from each other. Moreover, only the coefficients of the 8^{th} and 10^{th} deciles are statistically different from zero and close to the average estimate of 0.3. While this seems to suggest that pass-through may be stronger for the largest firms, firm size at the national level appears to be only a weak determinant of the strength of pass-through.

Next, we go beyond firm size as a relatively coarse proxy of market power and investigate the link between product-level market shares and pass-through, leveraging the granularity of our data. For a given definition of a market m, we define the market share of a product i, sold in region s

by retail chain r, as follows:

$$s_{isrt}^{(m)} = \frac{\sum_{s',r' \in m} \text{sales}_{is'r't}}{\sum_{i',s',r' \in m} \text{sales}_{i's'r't}}, \tag{16}$$

where the denominator includes total sales in the entire market, that is, of all products, including those for which we do not obtain the producer identity and whose prices thus drop out of the estimation sample.[34] We use four definitions of product-level market shares with the following definitions of the market m, increasing in their granularity: (1.) All products sold in a given year across all product categories and regions; this is the overall national market share of each individual product in all sales of our German supermarkets. (2.) All products sold in a given IRi product category and in a given year, across all regions; this is the market share of each individual product in all sales of our German supermarkets in its category.[35] (3.) All products sold in a given IRi category, in a given two-digit ZIP code region, in a given year; this is the market share of each individual product in its product category at the regional level. (4.) All products sold in a given product category, in a given two-digit ZIP code region, by a given retail chain, in a given year; this is the same market share as the previous one, but computed within each specific retailer. For the last and most granular definition of market shares, the formula simplifies to $s_{isrt}^{(m)} = \frac{\text{sales}_{isrt}}{\sum_{i'} \text{sales}_{i'srt}}$.[36]

We again sort observations into deciles based on their associated market share. Thereby, we assign an observation to decile bin k if the market share is in the k^{th} decile of the market share distribution of market m. Table 6 shows average product-level market shares for each of the definitions, but across quintiles for the sake of simplicity. Denoting again the set of observations that are assigned to decile k by q_k, we interact the change in the log net-of-tax factor with indicator variables representing the market share decile, see equation (15) where now we include product market shares $s_{isrt}^{(m)}$ instead of firm size s_{it}.

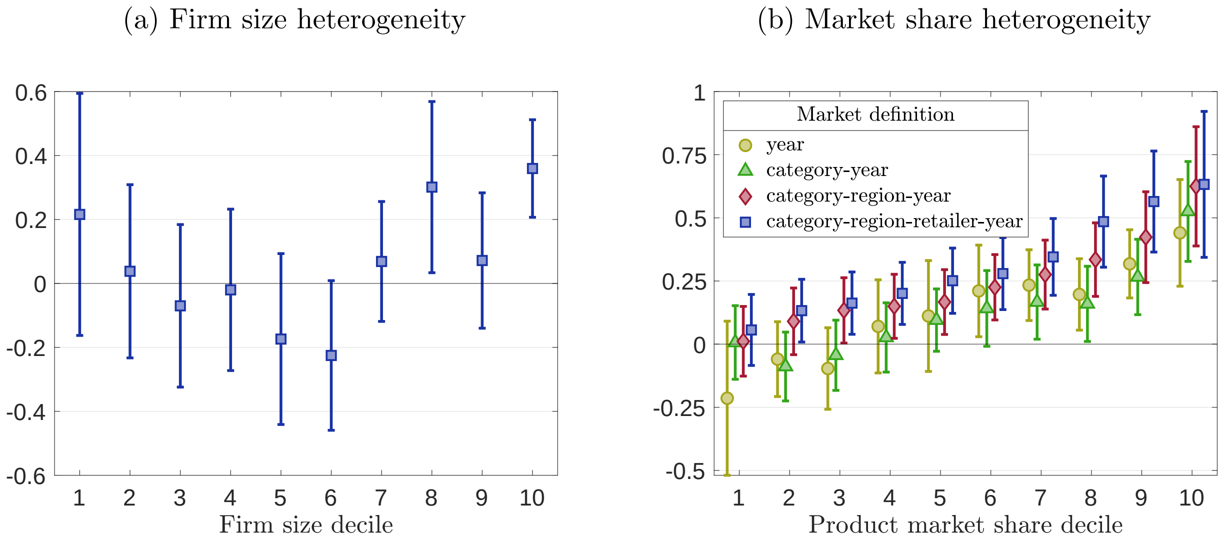
Figure 4 (b) plots the decile-specific pass-through coefficients $\{\beta_{q_k}\}$ for the various definitions of market shares. The following results emerge. First, across all definitions, point estimates are all statistically significant for the top half of deciles. Point estimates of all but the bottom decile are significant for the most disaggregated definition of product market shares, the retailer-regional level (see definition (4.) above). This suggests that not only firms with larger market shares, but even firms with small product market shares at the most disaggregated level enjoy market power, allowing them to pass through corporate taxes to consumer prices.

[34] This also includes products with non-German barcodes and those with private labels.

[35] We use the roughly 500 subcategories from IRi to define our baseline market shares, as they should best capture the competitive landscape in our data. Alternatively, we use the roughly 200 categories from IRi or manually map the 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). The results using these alternative classifications are shown in the Appendix in Figure C.2 and are very similar to the baseline results.

[36] Our retail scanner data do not include 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 product category-region-retailer-year measure, which is retailer-specific and therefore does not depend on sales in other retailers.

Figure 4: Pass-through by firm size and product market share



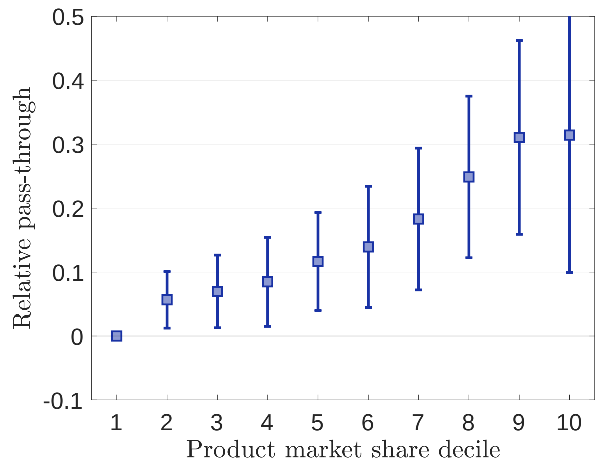
Notes: This figure plots the effect of an increase of corporate tax rates on retail prices by firm size and by product market share. Observations are sorted into decile bins according to total product sales for the producing firms (in the given year) and according to product-level sales within the market. The figure then plots decile-specific coefficients β_{q_k} from the regression $\Delta \log p_{isrt} = \alpha_{st} + \alpha_{pt} + \sum_{k=1}^{10} \alpha_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\} + \sum_{k=1}^{10} \beta_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}$. Huber-robust regressions with standard errors clustered at the municipality level. Confidence intervals are at the 95% level.

Second, point estimates across deciles tend to be larger for products with larger market shares, implying higher pass-through of corporate taxes to consumer prices. For the most disaggregated definition of market shares, estimated coefficients range between 0.0 and 0.65. This pattern holds irrespective of the specific market definition, suggesting that market power may amplify pass-through of corporate taxes. However, differences in point estimates across all definitions of market shares are statistically significant only between the bottom and top deciles. For the most granular market shares differences in point estimates become statistically significant between the bottom three and top three deciles. Therefore, to further isolate the differential effect of market power, we turn to an even more granular approach to identify pass-through heterogeneity, where we exploit the variation in market shares within the same product, sold across different regions and retailers.

Specifically, borrowing from the literature on exchange rate pass-through across different export destinations stemming from Knetter (1989), we control for product-specific time-varying unobserved characteristics as follows.[37] Our data are highly disaggregated, allowing us to observe price changes for the same product in numerous two-digit ZIP code regions and different retail chains, across which the individual product's market share, as defined under (4.) above, varies. Thus, we can estimate the variation in pass-through across different levels of (region-retailer-specific) market shares for the same product, while including product-time fixed effects in our

[37]This strategy builds on the insight in Knetter (1989) that, in a panel regression of prices of a product sold by a firm in different destination markets, a product-time fixed effect can control for unobserved characteristics common to the product including marginal costs, or, in our case, changes in the producers' local corporate tax rate.

Figure 5: Pass-through within product relative to lowest market share decile



Notes: This figure shows the effect of an increase of corporate tax rates on retail prices by product market share. Observations are sorted into decile 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 decile-specific coefficients β_{q_k} from the regression $\Delta \log p_{isrt} = \alpha_{it} + \alpha_{st} + \alpha_{pt} + \sum_{k=2}^{10} \alpha_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\} + \sum_{k=2}^{10} \beta_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\}(-\Delta \log(1-\tau_{it})) + \Gamma X_{it} + \varepsilon_{isrt}$. Huber-robust regressions with standard errors clustered at the municipality level. Confidence intervals are at the 95% level.

specification. To this end, we estimate the following panel regression:

$$\Delta \log p_{isrt} = \alpha_{it} + \alpha_{st} + \alpha_{pt} + \sum_{k=2}^{10} \alpha_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\} + \sum_{k=2}^{10} \beta_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt} \tag{17}$$

This specification now includes product-year fixed effects α_{it} that absorb all product-time-specific variation, including the average effect of the corporate tax change on the product price, as well as any average wholesale and retail markup adjustment. We thereby ensures that differences in the estimated coefficients represent structural differences in pass-through as a function of product-level market shares. This is because this fixed effect will absorb any changes in both the markup and the marginal cost of a given product arising from the corporate tax change that are common across retailers and regions, including any product-specific response in marginal costs, such as wages. Since this specification makes it impossible to identify all β_{q_k}, we drop the coefficient associated with the first decile, β_{q_1}. The remaining variation in price changes comes from wholesale and retail markup adjustments within the same product but across regions and retailers as a function of the product's market shares.

Figure 5 shows that, within products, differences in market shares result in statistically significant differences in pass-through. Compared to an instance with a market share in the bottom decile, the same product with a larger market share in another region-retailer-specific market exhibits a significantly higher pass-through. Namely, the pass-through when a product market share is in the 5th decile is estimated to be around 0.1 p.p. larger than in markets where the product share is in the bottom decile. This difference rises to 0.3 p.p. in the top decile. This difference is smaller than the difference between point estimates in Figure 4 (b) for the bottom and top deciles of product category-region-retailer-year market shares, which compared pass-through within and across products and even firms. As a result, the larger differences in point estimates in Figure 4 (b) may also reflect firm heterogeneity in the share of deductibles, α_i.

Figure C.3 (b) in the Appendix shows that pass-through increases in market shares even when including an even more granular α_{ist} fixed effect to control for common product-region-year variation in price changes. This fixed effect, in addition to absorbing the average pass-through for a given product in a given sales region, also captures changes in destination-specific marginal costs of a product, such as transportation and distribution costs, or product-specific regional demand shocks, which may generate a correlation between market shares and pass-through across regions. The remaining variation is thus driven by differences in wholesale and retail markup adjustments observed in different retail chains as a function of the product's region-retailer-specific market share.[38]

Our finding of substantial heterogeneity in structural pass-through across market shares of the same product is consistent with price discrimination on the basis of destination-specific market power, whereby in response to a given corporate tax hike the price of the same product increases by more in regions and retailers where its market share is larger. Given that we observe retail prices, an important question concerns the role of vertical interactions between producers and retailers in destination-specific markup adjustment, and specifically whether heterogeneity in retailer efficiency matter in shaping heterogeneity in pass-through. We turn to address this question in the next section.

5.2 Pass-through heterogeneity and retailer market shares

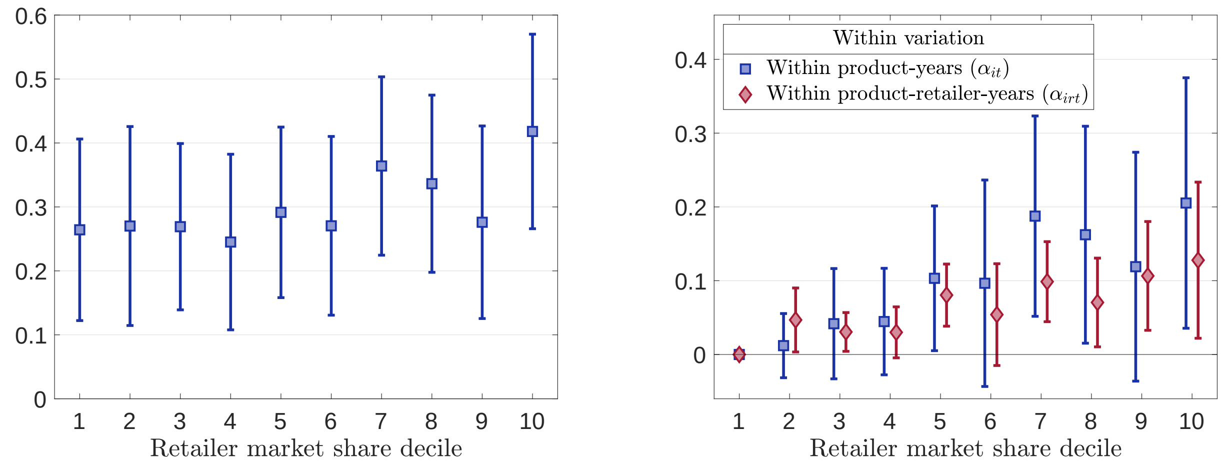
As illustrated in our conceptual framework in Section 2, retailers can also significantly impact the pass-through of upstream shocks to consumer prices. First, the role of market shares in models with general, non-constant demand elasticities also applies to the pass-through from wholesale prices to retail prices. Second, the presence of a retail sector can affect not only the perceived demand elasticities of producers but it directly dampens the pass-through of producer tax shocks when additive distribution costs make up a non-trivial share of the retailers' marginal cost. To shed light on the retailer segment of the vertical interactions between producers and retailers, we consider variation in retailer market shares defined at the category level in our pass-through

[38]Figure C.3 (a) shows that our results are also robust to defining market shares based on the less disaggregated 200 categories from IRi or the twenty COICOP categories underlying the HICP.

Figure 6: Pass-through by retailer market share

(a) Heterogeneous pass-through

(b) Within product (and retailer)



Notes: This figure shows the effect of an increase of corporate tax rates on retail prices by retailer market share. Observations are sorted into decile bins according to retailer sales within the market defined by a region and year. In panel (a), the figure then plots decile-specific coefficients $\beta_{q_k^r}$ from the regression $\Delta \log p_{isrt} = \alpha_{st} + \alpha_{pt} + \sum_{k=1}^{10} \alpha_{q_k} \mathbb{1}\{rs_{srt}^{(c)} \in q_k\} + \sum_{k=1}^{10} \beta_{q_k} \mathbb{1}\{rs_{srt}^{(c)} \in q_k\}(-\Delta \log(1-\tau_{it})) + \Gamma X_{it} + \varepsilon_{isrt}$. In panel (b), the blue line adds a fixed effect α_{it} and the red line adds a fixed effect α_{irt} (both absorbing $\beta_{q_1^r}$). Huber-robust regressions with standard errors clustered at the municipality level. Confidence intervals are at the 95% level.

estimates. We focus on the market share of retailer r in region s and product category c, i.e.,

$$rs_{srt}^{(c)} = \frac{\sum_{i \in c} \text{sales}_{isrt}}{\sum_{i' \in c, r'} \text{sales}_{i'sr't}}. \tag{18}$$

We again sort observations into deciles based on the retailer's market share, assigning an observation to decile bin k if the retailer's market share $rs_{srt}^{(c)}$ is in the k^{th} decile of the product category-region-year specific distribution. Denoting again the set of observations that are assigned to decile k by q_k, we first consider the analogous version of (15) and estimate the average pass-through of corporate taxes to consumer prices for each decile bin.

Our findings, as shown in Figure 6 (a), seem to suggest that the estimated pass-through of upstream corporate taxes to downstream retail prices is broadly invariant to the retailer's category market share. Point estimates range from slightly below 0.3 to around 0.4 but their differences are not statistically significant.

However, the granularity of our data allows us, as in the case of product market shares, to control for product-specific, unobserved differences in pass-through, which may affect the estimation due to correlations with retailer market shares. As discussed in Section 2, this would be the case if more efficient retailers in a given category would systematically sell products with lower wholesale prices (see, e.g., equation (9), whereby pass-through increases with retailer efficiency but decreases with producer marginal cost). We again include product-year fixed effects and estimate the relative level of pass-through for a given product when sold by a higher-market share retailer, compared to a retailer with (product category) market share in the bottom decile. We therefore estimate an analogous version of (17).

The within-product analysis, as presented in the blue lines in Figure 6 (b), shows that estimates of differential pass-through become statistically significant for most of the top 50% of the market share distribution. In particular, comparing a high-market share retailer in the top decile to a low-market share retailer in the bottom decile results in a statistically significant pass-through difference for the same product of more than 0.2 p.p. This difference is just slightly larger than the (statistically insignificant) difference between point estimates of bottom and top deciles in Figure 6 (a).[39] Notably, these results imply that supermarkets with larger category market shares either pay a higher wholesale price for the same product or, more likely, pass-through a larger fraction of similar price increases across stores. In turn, this suggests that it is unlikely that pass-through heterogeneity in retailer market shares reflects downstream monopsony power, given that price changes are larger for larger market shares.

As mentioned above, one issue is that we do not separately observe the wholesale prices that retailers are paying for individual products. Hence, in order to take into account the possibility that producers may price-discriminate across retail chains by charging different wholesale prices for the same product, on the basis of retailers' market shares at the category level, we go one step further and control for product- and retail chain-specific price changes. Specifically, extending specification (17), we estimate the regression

$$\Delta \log p_{isrt} = \alpha_{irt} + \alpha_{st} + \alpha_{pt} + \sum_{k=2}^{10} \alpha_{q_k} \mathbb{1}\{rs^{(c)}_{srt} \in q_k\} + \sum_{k=2}^{10} \beta_{q_k} \mathbb{1}\{rs^{(c)}_{srt} \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}, \tag{19}$$

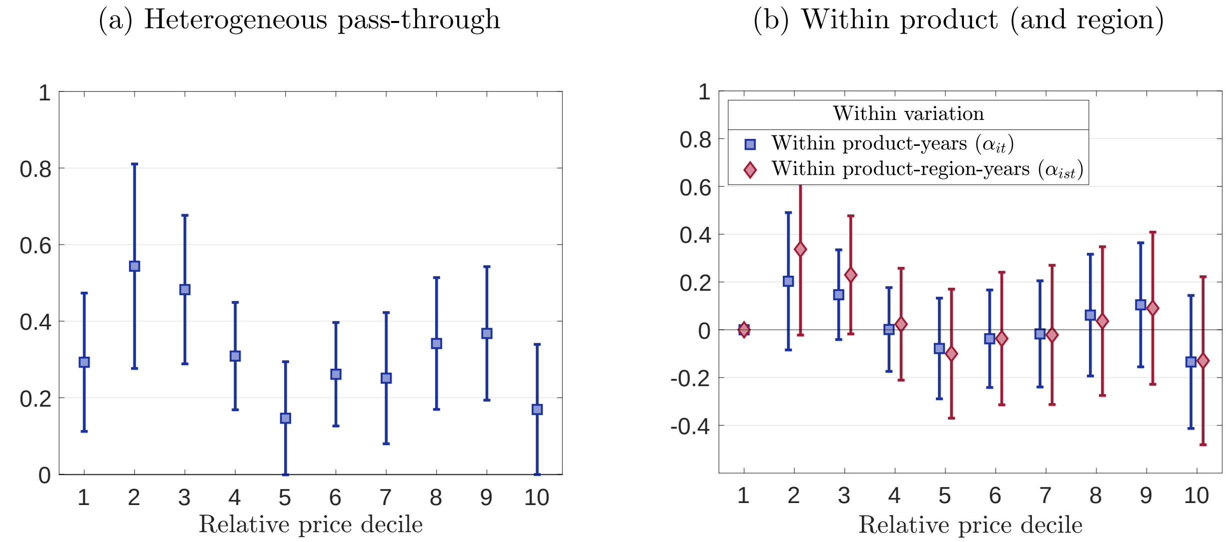
which now includes the product by retail chain by year fixed effect α_{irt}, capturing price changes common to a given product and all stores of a given retailer across Germany. The remaining variation thus stems from differential price changes of the product in stores of the same retail chain across regions with different category-level market shares.

The within-product-retail chain results, shown in the red lines in Figure 6 (b), confirm the previous finding that pass-through increases significantly with the retailer-category market share. The estimated differential pass-through for retailers in the top 10% of the market share distribution, compared to retailers in the bottom 10%, is now around 0.15 p.p., somewhat smaller than in our previous estimates. It implies that a one percentage point increase in the corporate tax of a firm producing a given product leads to a 0.15 percentage points larger price increase for the same retailer, where the latter's market share is relatively larger.[40]

[39] Figure C.4 (a) in the Appendix shows that these results are robust to defining retailer market shares based on the 200 categories from IRi or the twenty COICOP categories underlying the HICP.

[40] Figure C.4 (b) in the Appendix documents the robustness of these results to defining market shares at the less

Figure 7: Pass-through by level of relative retail price



Notes: This figure shows the effect of an increase of corporate tax rates on retail prices by relative retail price. Observations are sorted into decile bins according to their relative prices in the retailer and region. In panel (a), the figure then plots decile-specific coefficients $\beta_{q_k^r}$ from the regression $\Delta \log p_{isrt} = \alpha_{st} + \alpha_{pt} + \sum_{k=1}^{10} \alpha_{q_k} \mathbb{1}\{\hat{p}_{isrt} \in q_k\} + \sum_{k=1}^{10} \beta_{q_k} \mathbb{1}\{\hat{p}_{isrt} \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}$. In panel (b), the blue line adds a fixed effect α_{it} and the red line adds a fixed effect α_{ist} (both absorbing $\beta_{q_1^r}$). Huber-robust regressions with standard errors clustered at the municipality level. Confidence intervals are at the 95% level.

Overall, this evidence is consistent with deviations from uniform pricing across regions within the same retail chain based on local market shares, complementing the U.S. evidence in Butters et al. (2022). Nevertheless, in order to conclude that markup adjustment at the retail level is also relevant for pass-through we would have to rule out that producers charge region-specific wholesale prices to the same retailer on the basis of its local category-level market share. But this kind of producer price discrimination is a prediction of the model of vertical interactions we analyzed in Section 2. For instance, according to equation (9), wholesale markup adjustment and pass-through at the product level can vary with the efficiency of a given retailer across regions, and thus with the latter's market shares. In the next subsection we turn to testing this specific channel of heterogeneity in pass-through.

5.3 Pass-through heterogeneity and relative retail prices

As discussed in Section 2, the key testable implication of heterogeneity in distribution costs as the main driver of the relationship between pass-through and market shares is that pass-through must also be decreasing in product retail prices (given that we control for marginal production costs using the product-time fixed effect α_{it}). Next, we therefore run specifications relating pass-through heterogeneity within products to their (relative) retail prices.

granular level of HICP categories.

For a given product i, we compute its destination-specific relative price as the log difference of the destination-specific retail price p_{isrt} and the average retail price across destinations:

$$\tilde{p}_{isrt} = \log p_{isrt} - \log \sum_{s,r} w_{isrt} p_{isrt}, \tag{20}$$

where w_{isrt} is the share of sales of product i in year t that are sold in region s and retailer r.[41] We then assign an observation to decile bin k, denoted by q_k, if the relative price $\hat{p}_{isrt}$ is in the k^{th} decile of the relative price distribution. We estimate the level of pass-through depending on a product's destination-specific relative price by using specifications analogously to above.

Figure 7 (a) shows a specification similar to (15) where we estimate pass-through conditional on the a product's relative price decile but using variation across all products and destinations. In Figure 7 (b), we absorb product-specific factors such as a product's marginal costs and average distribution costs, and hence the product's average pass-through, by using product-time fixed effects α_{it} as in (17). Alternatively, we include product-sales region-year fixed effects α_{ist} to account also for transportation costs that can vary by product and production location together with the sales location:

$$\Delta \log p_{isrt} = \alpha_{ist} + \alpha_{pt} + \sum_{k=2}^{10} \alpha_{q_k} \mathbb{1}\{\tilde{p}_{isrt} \in q_k\} + \sum_{k=2}^{10} \beta_{q_k} \mathbb{1}\{\tilde{p}_{isrt} \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt} \tag{21}$$

The results show a weak relationship between product-level pass-through and its (relative) retail price. The differences in pass-through across markets with different product retail prices are largely small and generally statistically insignificant. The results thus provide little evidence that pass-through is stronger the lower a product retail price, which would be consistent with heterogeneous distribution costs as the main driver of pass-through increasing in product and retailer market shares, as we found above. Taken together, our results that pass-through increases with market shares seem more consistent with the predictions of non-CES demand systems with a relatively low sensitivity of demand elasticities to firms' prices, in line, for instance, with the evidence in Beck and Lein (2020). This is notable as a relatively low sensitivity of demand elasticities also implies a relatively low degree of strategic complementarities and real rigidities due to price setting.

6 Conclusion

In this paper, we study the role of heterogeneous market power in the pass-through of corporate taxes to consumer prices. We use 1,058 changes in the local business tax rates across German

[41] We trim $\log p_{isrt}$ at the product-year-specific 1% and 99% quantiles before computing the weighted average to avoid the influence of outliers on the relative price distribution.

municipalities and high-quality data on product sales prices across many stores in Germany. We find that a one percentage point increase in a producer's corporate tax rate raises the retail prices of its goods in stores in the rest of Germany on average by 0.3%. Our finding implies that imperfectly competitive upstream producers adjust prices in response to corporate tax changes, which are thus akin to idiosyncratic shocks to their markups. These (markup) shocks thus elicit significant adjustment in wholesale prices, which retailers pass through to consumer prices.

We leverage our data by using granular variation in market shares across regions to show pass-through increases in product and retailer-category market shares. Controlling for time variation in product-specific factors, and thereby holding product-specific marginal costs fixed, we estimate that the pass-through difference between the bottom and the top decile of market shares, for the same product but across regions and retailers, is around 0.3 p.p. We also find a similarly important role for the retailer market share, showing that for the same product, pass-through is stronger for retailers with large category market shares than for low-market share retailers.

We show that a positive relationship between market shares can be consistent with both differential markup adjustment in non-CES demand systems and with a non-trivial role for heterogeneity in retailers' distribution costs, even under CES demand. In the latter case, the products with higher market shares and higher pass-through are sold by more efficient retailers, which implies lower retail prices. We test this prediction in our data controlling for product-time variation, but find little evidence for such a link between product-level pass-through and (relative) product-level retail prices. Instead, our results are consistent with non-CES demand systems widely used in macroeconomics. In these demand systems, pass-through increasing in market shares implies weaker strategic complementarities in price setting and a lower degree of real rigidities in macroeconomic dynamics, compared to the case where the opposite relation holds.

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A Data

This appendix describes the data sources used in the paper and how the data are 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
– ZIP code 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				
State economic indicators	Destatis	State	2d-`AGS` × year	2010–2019
– Total debt				
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 (sub-)category				
– two-digit ZIP code 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 ZIP code				
– 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 files for the years 2003–2019. 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 the 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 those 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, the data contain information about potential territory changes that happened in the corresponding year.

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. These data contain the total population of the municipality and the ZIP code, which helps us to map firms to municipalities. However, note that ZIP codes do not identify municipalities and vice versa. ZIP codes are defined by the German postal service *Deutsche Post*. Single municipalities can have many ZIP codes (in case of large cities), and conversely one ZIP code can be attached to many municipalities. To identify the state of a ZIP code area, one needs to know up to four digits. The ZIP code that is part of Destatis data refers to the ZIP code where a municipality's administration center (*Verwaltungssitz*) is located. Nevertheless, knowing the ZIP code of a municipality approximately helps us in matching firms to municipalities.[42]

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

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

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. These data are only available from 2010 to 2019. For the city-states Berlin, Bremen, and Hamburg, we use state-level debt data.

Municipality map of Germany. From the federal cartography office (*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 ZIP code and population data based on `AGS` and year. Table A.2 shows the number of municipalities, thereof "normal" ones and the 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 obtain 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 (approximate) 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 (or state-level data on total debt for city states).

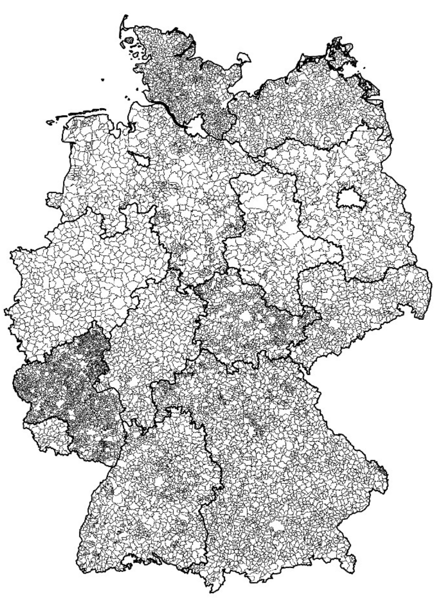
Table A.2 summarizes the number of available municipalities according to data richness. Figure A.1 (b) illustrates the data availability across municipalities for the year 2017.

Table A.2: Number of municipalities across years

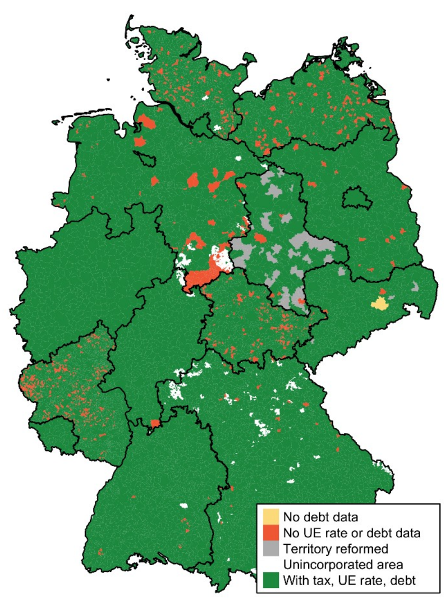
Year	Total	Normal	with UE rate	and with debt	No. of scaling fct. changes
2003	12630	12465			
2004	12434	12321			1031
2005	12342	12249			1341
2006	12313	12227			991
2007	12266	12194			496
2008	12227	12163	9567		486
2009	11996	11917	8306		528
2010	11442	11312	8215	8213	1031
2011	11294	11179	8315	8313	2016
2012	11224	11113	9033	9031	1443
2013	11161	11058	9000	8998	1390
2014	11117	11025	9633	9631	2153
2015	11093	11037	9599	9597	1698
2016	11059	11007	9842	9840	1465
2017	11055	11011	9842	9841	1178
2018	11014	10959			932
2019	10799	10715			700

Notes: *Normal* municipalities are defined as 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 report 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 allow 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 638.25 euros. Moreover, the data contain a product category and subcategory classification (there are 216 categories and 498 subcategories defined by IRi), a coarse name of the manufacturer (vendor), and store characteristics.

Because of data protection, stores are anonymized in our data. That is, we do not know the 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 ZIP code. 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-retail chain-year level. This is for two reasons. First, reducing the number of observations improves computational tractability. Second, tax changes are observed at the annual level and we are interested in the medium-run effects on prices. Since stores are identified only up to their approximate location, keyaccount, 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 retail chain by region by year level. Retail chains are defined by the combination of IRi keyaccount and IRi store type. Regions are defined as two-digit ZIP code 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 ZIP code sales region s, retailer (keyaccount and store type) r, and year t, we compute the *average* year-over-year price change (with slight abuse of notation):

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

where $N_{(r,s),t}$ is the number of stores of retailer r in region s 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 $\Delta \log p_{isrt}$ which are produced by manufacturers that are located in a municipality that belongs to the two-digit ZIP code region s.

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 Article Number. Barcodes around the world are administered 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 3–4 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 exact company prefix 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:	$\underbrace{\underbrace{405}_{\text{country}}\ 3400}_{\text{company}}\ \underbrace{25782}_{\text{product}}\ 2$

For illustration, Table A.4 shows 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. 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, namely, to barcodes beginning with digits 400–440. 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 such that we cover every distinct producer. 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. The subset of barcodes is determined as follows. 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, 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.

Querying barcodes from GS1 GEPIR. 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: 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

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 associated to the same firm. Ex-post, we find that we have obtained information for barcodes of 5,951 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 municipalities. The data contain the address of every producer including the ZIP code and city name. However, this information does not map easily into municipalities. Complications arise because cities/municipalities can have multiple ZIP codes, so the ZIP code in the administrative data does not need to match the ZIP code 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", ", Universitäts- 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 ZIP codes. We also remove municipality-years with territory reforms.

The official data contain two instances where two `AGS` have the same municipality name and ZIP code, respectively: 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 ZIP codes. For a match to be valid, we require that the first two digits of the firm's ZIP code and the municipality ZIP code 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 ZIP code if the combination therewith is unique, otherwise also the third digit, and so on. This way, we are able to match 5,018 of 5,951 firms.

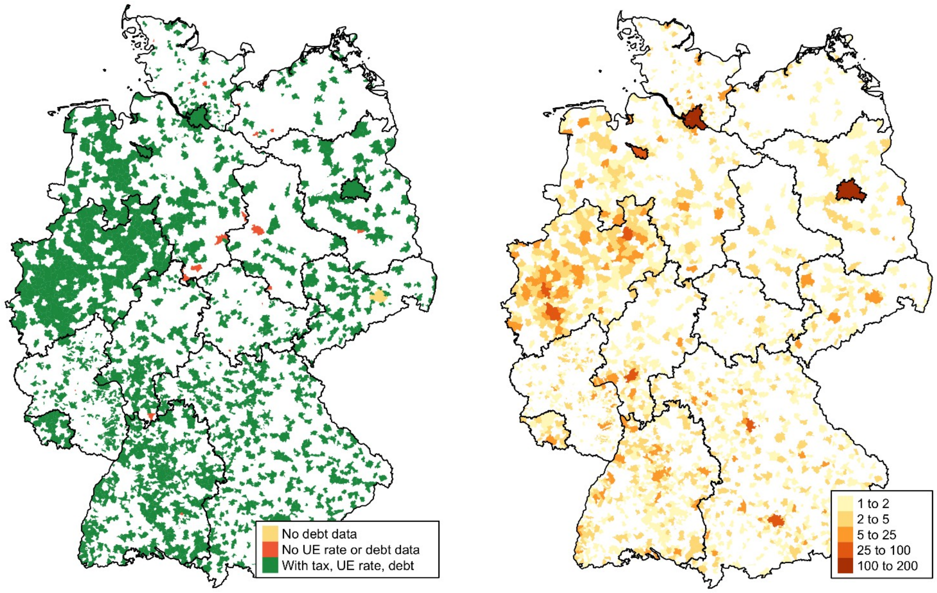
In a second step, we use the Stata function `matchit` to match firms' city to municipalities using fuzzy string matching. This algorithm accounts for typos in the firm locations and other slight perturbations of the city names. The algorithm produces a number of candidate matches with associated similarity scores. We drop candidate matches if the first digit of the ZIP codes does not match. Of the remaining candidates, we directly accept matches if it 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 ZIP codes 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 5,430, 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.

Working with Orbis branch information. Orbis data contain information about branches of firms. We check if for a given `bvdidnumber` there are multiple branch cities that 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 finally match the IRi price data to 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 cover 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.

Table A.6: Number of firms per municipality

No. of firms per municipality	Share of no. = 1	Mean	p90	p99
All municipality-years	63%	2.13	4	14
Municipality-years with $\Delta\tau \neq 0$	60%	1.98	4	11

Notes: This table shows statistics on the number of firms present per municipality in the matched sample. The first line shows the statistics for the full sample. The second line conditions on municipality-years with a tax change.

B Kimball preferences and the relation between market shares and pass-through

B.1 Some useful preliminary properties

We start from the Dotsey and King (2005) version of Kimball preferences as modified by Aruoba et al. (2023) to allow for product-specific demand shifters n_{is}, yielding the following implicit demand for product i in each region s:

$$y_{is}n_{is} = \frac{1}{1+\psi}\left[\psi + \left(\frac{p_{is}}{\lambda_s n_{is} P_s}\right)^{-\frac{\omega}{\omega-1}(1+\psi)}\right] Y_s \geq 0, \tag{B.1}$$

where $\omega > 1$ and $\psi \leq 0$ (with the standard CES case obtaining for $\psi = 0$). The multiplier λ_s and the price level P_s are defined as follows:

$$\lambda_s = \left[\int \left(\frac{p_{ks}}{n_{ks}}\right)^{\frac{\omega\psi-1}{\omega-1}} dk\right]^{\frac{\omega-1}{\omega\psi-1}} > 0$$

$$P_s = \frac{1}{1+\psi}\left[\int \left(\frac{p_{ks}}{n_{ks}}\right)^{\frac{\omega\psi-1}{\omega-1}} dk\right]^{\frac{\omega-1}{\omega\psi-1}} + \frac{\psi}{1+\psi}\int \frac{p_{ks}}{n_{ks}} dk > 0$$

We impose the normalization $P_s = 1$ in the rest of this appendix. Moreover, in order to have a positive demand for each product in (B.1), the individual effective price $\frac{p_{ks}}{n_{ks}}$ must be smaller than the "choke" price:

$$\overline{\left(\frac{p}{n}\right)} = (-\psi)^{-\frac{\omega-1}{\omega(1+\psi)}}\lambda_s \tag{B.2}$$

The demand elasticity of product i, $\eta_{is} > 1$, and its super-elasticity, $\gamma_{is} \geq 0$, are given by the following expressions and crucially depend on the effective output share $\frac{n_{is}y_{is}}{Y_s}$ when $\psi < 0$:

$$\eta_i = \frac{\omega}{\omega-1}\left[\frac{-\psi + (1+\psi)\frac{n_{is}y_{is}}{Y_s}}{\frac{n_{is}y_{is}}{Y_s}}\right] > 1 \Longleftrightarrow -(1+\omega\psi)\frac{n_{is}y_{is}}{Y_s} < -\omega\psi > 0$$

$$\gamma_{is} = \frac{\partial\eta_{is}}{\partial p_{is}}\frac{p_{is}}{\eta_{is}} = -\frac{\omega}{\omega-1}\frac{\psi}{\frac{n_{is}y_{is}}{Y_s}} \geq 0$$

Therefore, under the assumptions in Section 2, the optimal price is given by the following expression:

$$p_{is} = \left(\frac{\eta_{is}}{\eta_{is}-1}\right)\left(\frac{MC_i}{(1-\tau_i)^{1-\alpha_i}} + D_s\right). \tag{B.3}$$

Dropping from now on the subscript s for simplicity, observe that while it is possible in principle that $\dfrac{n_i y_i}{Y} > 1$ because of the effect of the demand shifter n_i, still the condition $\eta_i > 1$ bounds $\dfrac{n_i y_i}{Y}$. Specifically, $\eta_i > 1$ if and only if $\dfrac{n_i y_i}{Y} < \overline{\frac{n_i y_i}{Y}}$, where $\overline{\frac{n_i y_i}{Y}} = \frac{-\omega\psi}{-\omega\psi - 1} \geq 1$ for $-\psi > \omega^{-1}$. Conversely, for $1 > \omega^{-1} \geq -\psi > 0$, the condition $\eta_i > 1$ imposes no bound on $\dfrac{n_i y_i}{Y}$.

Clearly η_i and γ_i are decreasing in ω and increasing in $-\psi$ (though η_i only for $\dfrac{n_i y_i}{Y} < 1$): A larger $-\psi$ thus implies a higher price sensitivity of the demand elasticity. Moreover, both η_i and γ_i are decreasing in $\dfrac{n_i y_i}{Y}$; specifically both diverge for arbitrarily small $\dfrac{n_i y_i}{Y}$ and converge for $\frac{n_i y_i}{Y} \to \left(\overline{\frac{n_i y_i}{Y}}\right)$, namely:

$$
\begin{aligned}
\lim_{\frac{n_i y_i}{Y} \to 0} \eta_i &= \lim \gamma_i \to \infty \\
\lim_{\frac{n_i y_i}{Y} \to \left(\overline{\frac{n_i y_i}{Y}}\right)} \eta_i &= 1 \\
\lim_{\frac{n_i y_i}{Y} \to \left(\overline{\frac{n_i y_i}{Y}}\right)} \gamma_i &= -\frac{\omega}{\omega - 1} \frac{\psi}{\left(\overline{\frac{n_i y_i}{Y}}\right)}
\end{aligned}
$$

where we recall that $\overline{\frac{n_i y_i}{Y}} = \frac{-\omega\psi}{-\omega\psi - 1} \geq 1$ for $-\psi > \omega^{-1}$ and $\overline{\frac{n_i y_i}{Y}} \to +\infty$ for $1 > \omega^{-1} \geq -\psi > 0$.

An important property of the demand system (B.1) is that (real effective) output of product j is larger than that of product i, $n_j y_j > n_i y_i$, if and only if the effective relative price is smaller, $\frac{p_j}{p_i}\frac{n_i}{n_j} < 1$. To see this, note that (B.1) implies that for two products j and i with effective real output $n_j y_j > n_i y_i$, their effective prices must be such that

$$
\frac{1}{1+\psi}\left(\frac{p_j}{n_j}\right)^{-\frac{\omega}{\omega-1}(1+\psi)} > \frac{1}{1+\psi}\left(\frac{p_i}{n_i}\right)^{-\frac{\omega}{\omega-1}(1+\psi)},
$$

which implies the following inequalities:

$$
\begin{aligned}
-1 < \psi \leq 0: \quad \left(\frac{p_j}{p_i}\frac{n_i}{n_j}\right)^{-\frac{\omega}{\omega-1}(1+\psi)} &> 1 \Longleftrightarrow \frac{p_j}{p_i}\frac{n_i}{n_j} < 1 \\
\psi < -1: \quad \left(\frac{p_j}{p_i}\frac{n_i}{n_j}\right)^{-\frac{\omega}{\omega-1}(1+\psi)} &< 1 \Longleftrightarrow \frac{p_j}{p_i}\frac{n_i}{n_j} < 1
\end{aligned}
$$

Therefore, for any $\psi \leq 0, \omega > 1$, $n_j y_j > n_i y_i$ if and only if effective relative prices are such that $\frac{p_j}{p_i}\frac{n_i}{n_j} < 1$; moreover in this case it also holds that both the elasticity and super-elasticity are larger for product i: $\eta_i > \eta_j$ and $\gamma_i > \gamma_j$.

Focusing on the limiting case $D_s \to 0$, we can now analyze the link between market shares and pass-through. Define percentage pass-through (of a generic marginal cost shock), which is determined by the markup elasticity to own price:

$$PT_i \equiv \frac{1}{1 - \frac{\partial\left(\frac{\eta_i}{\eta_i - 1}\right)}{\partial p_i} \frac{p_i}{\frac{\eta_i}{\eta_i - 1}}} \tag{B.4}$$

$$\frac{\partial\left(\frac{\eta_i}{\eta_i-1}\right)}{\partial p_i}\frac{p_i}{\frac{\eta_i}{\eta_i-1}} = \frac{-\frac{\partial \eta_i}{\partial p_i}\frac{p_i}{\eta_i}}{(\eta_i - 1)} = \frac{\gamma_i}{\eta_i - 1} = \frac{-\omega\psi}{-\omega\psi\left(1 - \frac{n_i y_i}{Y}\right) + \frac{n_i y_i}{Y}},$$

where $0 < PT_i \leq 1$ since $\eta_i > 1, \gamma_i \geq 0$. This implies

$$0 \leq \frac{\gamma_i}{\eta_i - 1} < \infty.$$

As a result, PT_i is lower the larger $\frac{\gamma_i}{\eta_i - 1}$.

How does pass-through depend on effective output? Since both η_i and γ_i are decreasing in $\frac{n_i y_i}{Y}$ it is not clear at priori which effect should prevail. Differentiating this expression with respect to $\frac{n_i y_i}{Y}$:

$$\frac{\partial\left(\frac{\gamma_i}{\eta_i - 1}\right)}{\partial\left(\frac{n_i y_i}{Y}\right)} = \frac{\omega\psi\left[1 + \omega\psi\right]}{\left[-\omega\psi\left(1 - \frac{n_i y_i}{Y}\right) + \frac{n_i y_i}{Y}\right]^2},$$

we can establish the following lemma, stating that pass-through is *increasing* in the effective output share $\frac{n_i y_i}{Y}$ when $\frac{\gamma_i}{\eta_i - 1}$ is *decreasing* in it, namely depending on $\omega\psi$.

Lemma 1 *Pass-through PT_i as defined in (B.4) is increasing in the effective output share $\frac{n_i y_i}{Y}$ if and only if*

$$-\omega^{-1} < \psi < 0.$$

Conversely, for $\psi < -\omega^{-1}$, PT_i is always lower for larger output shares such that $\frac{n_i y_i}{Y} < \overline{\frac{n_i y_i}{Y}} = \frac{-\omega\psi}{-\omega\psi - 1}$.

Therefore, according to Lemma 1 above, for $n_j y_j > n_i y_i$ (or equivalently $\frac{p_j}{n_j} < \frac{p_i}{n_i}$), pass-through is larger (lower) for product j when $-\omega^{-1} < \psi < 0$ ($\psi < -\omega^{-1}$).

B.2 Pass-through and market shares

What does Lemma 1 imply for the link between nominal market shares ($\frac{p_i y_i}{PY}$) and pass-through? Using again the demand for each product in (B.1) with the normalization $P = 1$, we obtain the following key condition concerning sales/revenues and market shares:

$$p_j y_j > p_i y_i \Longleftrightarrow \frac{p_j}{p_i}\frac{n_i}{n_j} > \frac{n_i y_i}{n_j y_j} = \frac{\frac{1}{1+\psi}\left[\left(\frac{p_i}{\lambda n_i}\right)^{-\frac{\omega}{\omega-1}(1+\psi)} + \psi\right]}{\frac{1}{1+\psi}\left[\left(\frac{p_j}{\lambda n_j}\right)^{-\frac{\omega}{\omega-1}(1+\psi)} + \psi\right]} \tag{B.5}$$

This condition shows that a larger market share for product j does not necessarily result from a larger relative output ($n_j y_j > n_i y_i$), as the relative effective price must be smaller than 1 but larger than the inverse of relative output ($\frac{n_i y_i}{n_j y_j} < 1$). Nevertheless, as we show next, in general $n_j y_j > n_i y_i$ if and only if $p_j y_j > p_i y_i$, so that the relation between pass-through and market shares is the same as the one between pass-through and effective output. Specifically, the demand function (B.1) expresses effective output as a decreasing function of the effective price, i.e., $n_j y_j / Y \equiv f\left(\frac{p_j/P}{n_j}\right)$, $f' < 0$. Moreover, we can write the market share also as a function of the effective price:

$$g\left(\frac{p_j/P}{n_j}\right) \equiv \frac{p_j y_j}{PY} = \frac{p_j/P}{n_j}\frac{n_j y_j}{Y} = \frac{p_j/P}{n_j} \times f\left(\frac{p_j/P}{n_j}\right) \tag{B.6}$$

Therefore, a sufficient condition for market shares to preserve the ordering of effective output is to be decreasing in the effective price, i.e., $g' < 0$. It is then easy to show that g is a decreasing function if the following condition holds:

$$g' = \frac{p_j/P}{n_j} f' + f < 0 \tag{B.7}$$

In turn, this condition is equivalent to requiring that the price elasticity of the demand function (B.1) is larger than 1. This establishes that market shares are also a decreasing function of effective prices as effective output, preserving the latter ordering. Therefore, if pass-through increases (decreases) in effective output, it also increases (decreases) in market shares.

C Additional empirical results

Table C.1: Results using OLS

	(1)	(2)	(3)
	Δ log price		
$-\Delta \log(1 - \text{tax})$	0.543***	0.511***	0.553***
	(0.173)	(0.174)	(0.183)
Observations	19,434,155	19,045,396	19,045,396
Sales region × year FE	✓	✓	✓
Production region × year FE	✓	✓	✓
Debt and unemployment controls		✓	✓
Other municipal tax controls			✓

Notes: Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See also Table 3.

Table C.2: Results with fewer fixed effects

	(1)	(2)	(3)	(4)
	Δ log price			
$-\Delta \log(1 - \text{tax})$	0.345***	0.301***	0.344***	0.339***
	(0.0837)	(0.0837)	(0.0611)	(0.0805)
Observations	19,434,155	19,434,155	19,434,155	19,434,155
Sold-region × year FE	✓			
Production-region × year FE		✓		
Year FE			✓	

Notes: Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See also Table 3.

Table C.3: Results when controlling for changes in local real estate taxes

	(1)	(2)	(3)	(4)
	Δ log price			
$-\Delta \log(1 - \text{corporate tax})$	0.285***	0.302***	0.290***	0.296***
	(0.0615)	(0.0632)	(0.0631)	(0.0634)
Δ scaling factor real estate tax A		-0.00101**		-0.00119**
		(0.000504)		(0.000557)
Δ scaling factor real estate tax B			-0.000243	0.000383
			(0.000760)	(0.000850)
Observations	19,045,396	19,045,396	19,045,396	19,045,396
Sold-region × year FE	✓	✓	✓	✓
Production-region × year FE	✓	✓	✓	✓
Debt and unemployment 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. Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See also Table 3.

Table C.4: Comparing results using $\Delta\,\tau$ and $\Delta \log(1 - \tau)$

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log price					
$-\Delta \log(1 - \text{tax})$	0.301***		0.285***		0.296***	
	(0.0610)		(0.0615)		(0.0634)	
Δ tax		0.345***		0.326***		0.339***
		(0.0714)		(0.0722)		(0.0745)
Observations	19,434,155	19,434,155	19,045,396	19,045,396	19,045,396	19,045,396
Sold-region × year FE	✓	✓	✓	✓	✓	✓
Production-region × year FE	✓	✓	✓	✓	✓	✓
Debt and unemployment controls			✓	✓	✓	✓
Other municipal tax controls					✓	✓

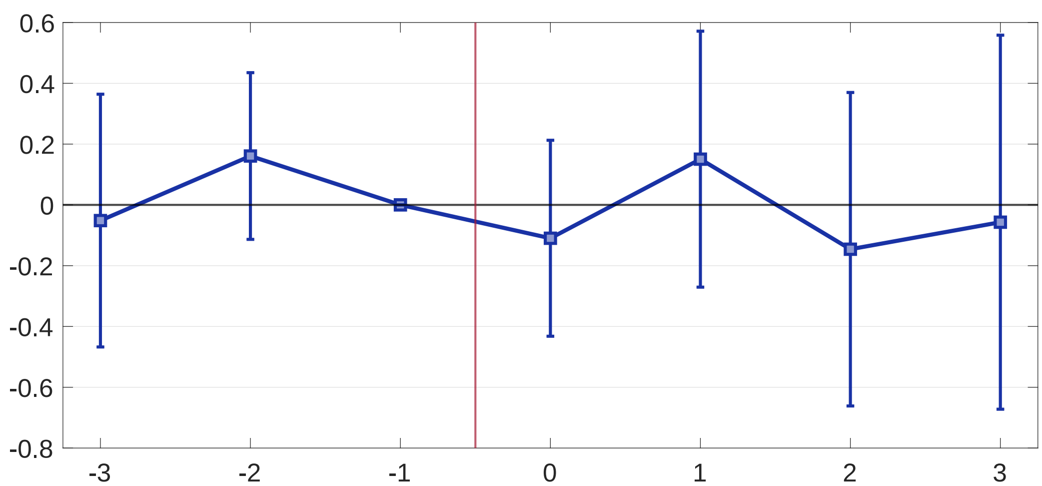
Notes: Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See also Table 3.

Table C.5: Placebo exercise with randomized tax changes

	(1)	(2)
	Δ log price	
$-\Delta\log(1-\text{tax})$, randomized within two-digit ZIP code	-0.168**	
	(0.0727)	
$-\Delta\log(1-\text{tax})$, randomized within district		0.110
		(0.0846)
Observations	15,314,469	9,846,986
Sales region × year FE	✓	✓
Production region × year FE	✓	✓

Notes: This table displays results from estimating $\Delta\log p_{isrt} = \alpha_{st} + \alpha_{pt} + \beta(-\Delta\,\widetilde{\log(1-\tau_{it})}) + \varepsilon_{isrt}$. The regression is specified as in Table 3, but uses randomized regressors. In particular, column (1) randomizes the value of $(-\Delta\,\widetilde{\log(1-\tau_{it})})$ 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 identical to a municipality, in which case we do not consider them for randomization B. Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure C.1: Dynamic effect of a corporate tax change on firm-level wages



Notes: 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 distributed-lag regression $\Delta\log w_{ft} = \alpha_{pt} + \sum_{k=-2}^{3}\beta_k(-\Delta\log(1-\tau_{ft-k})) + \varepsilon_{ft}$. w_{ft} is the firm-level median wage in year t based on the administrative employer-employee data by the Institute of Employment Research as used in Fuest et al. (2018). The wage path relative to period $t-1$ before the tax change is plotted as $\sum_{k=-1}^{h}(-\beta_{k-1})$. Huber-robust regression with standard errors clustered at the municipality level. Whiskers represent confidence intervals at the 95% level.

Table C.6: Comparing results with different trimmings and with sales filtering

(a) Posted prices (baseline)

	(1)	(2)	(3)	(4)
	Δ log price			
	$(p1, p99)$	$(-0.33, 0.33)$	$(-0.2, 0.2)$	$(-0.5, 0.5)$
$-\Delta \log(1 - \text{tax})$	0.296***	0.291***	0.278***	0.295***
	(0.0634)	(0.0616)	(0.0579)	(0.0631)
Observations	19,045,396	18,811,050	18,303,550	19,003,781
Sold-region × year FE	✓	✓	✓	✓
Production-region × year FE	✓	✓	✓	✓
Debt and unemployment controls	✓	✓	✓	✓
Other municipal tax controls	✓	✓	✓	✓

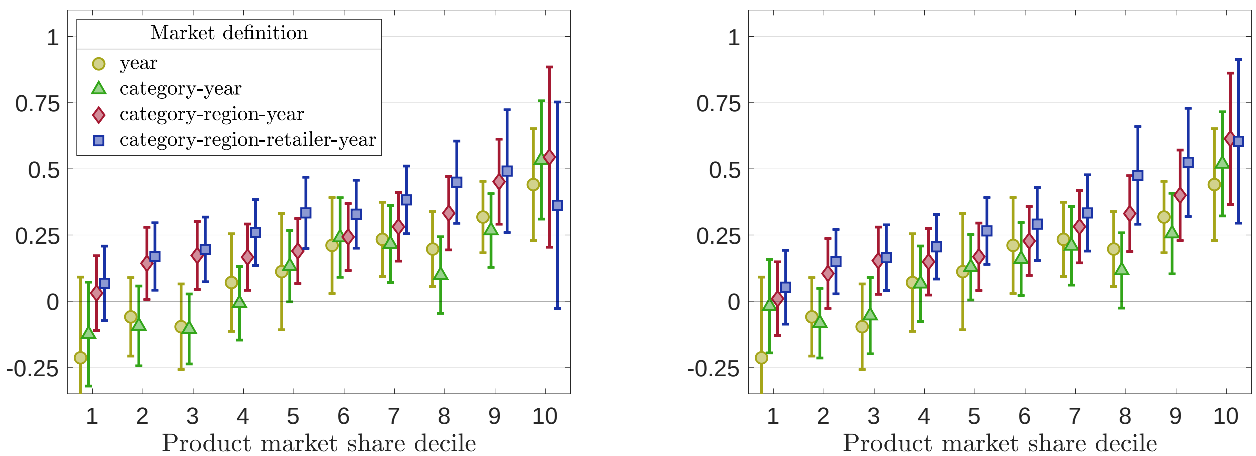
(b) Sales-filtered prices

	(1)	(2)	(3)	(4)
	Δ log price			
	$(p1, p99)$	$(-0.33, 0.33)$	$(-0.2, 0.2)$	$(-0.5, 0.5)$
$-\Delta \log(1 - \text{tax})$	0.249***	0.243***	0.229***	0.248***
	(0.0586)	(0.0569)	(0.0529)	(0.0584)
Observations	19,030,569	18,804,639	18,281,563	19,002,300
Sold-region × year FE	✓	✓	✓	✓
Production-region × year FE	✓	✓	✓	✓
Debt and unemployment controls	✓	✓	✓	✓
Other municipal tax 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. Standard errors (in parentheses) are clustered at the municipality level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See also Table 3.

Figure C.2: The role of product market share for pass-through: Robustness to using market shares based on alternative product category definitions

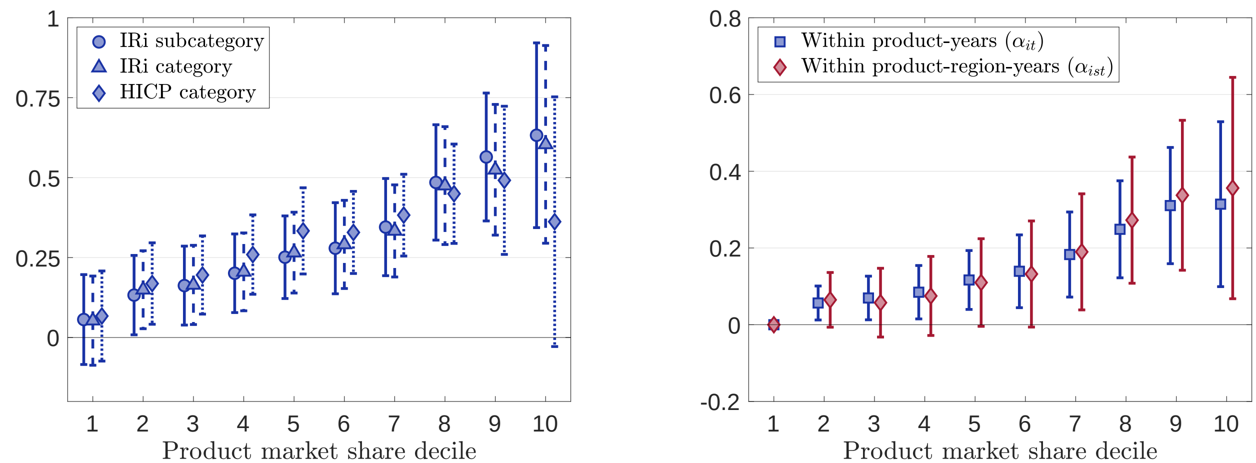
(a) HICP categories (b) IRi categories



Notes: This figure shows the effect of an increase of corporate tax rates on retail prices by product market share. In panel (a), market shares are computed based on HICP product categories. In panel (b), market shares are computed IRi product categories (instead of the more granular "subcategories" used in the baseline results). Observations are sorted into decile bins according according to product-level sales within the market. The figure then plots decile-specific coefficients β_{q_k} from the regression $\Delta \log p_{isrt} = \alpha_{st} + \alpha_{pt} + \sum_{k=1}^{10} \alpha_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\} + \sum_{k=1}^{10} \beta_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}$. Standard errors are clustered at the municipality level. Confidence intervals are at the 90% level.

Figure C.3: The role of market share using variation within products: Robustness

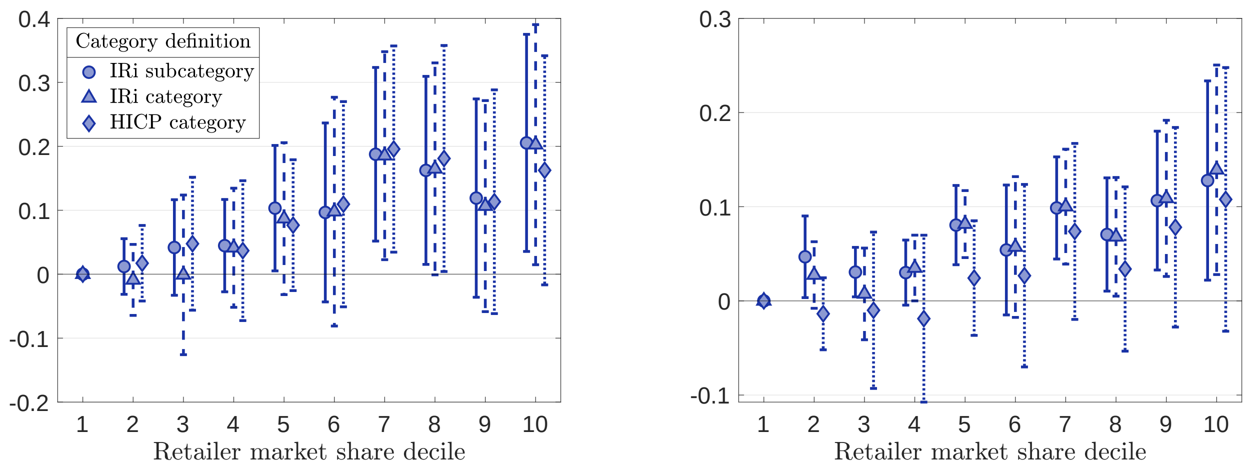
(a) By category definition (b) By within variation



Notes: This figure shows the effect of an increase of corporate tax rates on retail prices by product market share. Observations are sorted into decile bins according to product-level sales within the market. Panel (a) plots decile-specific coefficients β_{q_k} from the regression $\Delta \log p_{isrt} = \alpha_{it} + \alpha_{pt} + \sum_{k=2}^{10} \alpha_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\} + \sum_{k=2}^{10} \beta_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}$. The solid lines reflect the grouping into deciles using market shares based on IRi subcatgories, as in the baseline results. The dashed lines reflect using IRi categories. The short-dashed lines reflect using HICP product categories. Panel (b) compares the baseline estimates (blue lines) with a specification with prouct-region-year fixed effects (red lines), i.e., plots decile-specific coefficients β_{q_k} from the regression $\Delta \log p_{isrt} = \alpha_{ist} + \alpha_{pt} + \sum_{k=2}^{10} \alpha_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\} + \sum_{k=2}^{10} \beta_{q_k} \mathbb{1}\{s^m_{isrt} \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}$. Standard errors are clustered at the municipality level. Confidence intervals are at the 90% level.

Figure C.4: The role of retailer market share using variation within products and retail chains: Robustness for category definition

(a) Within products (α_{it}) (b) Within products and retailers (α_{irt})



Notes: This figure shows the effect of an increase of corporate tax rates on retail prices by retailer market share. Observations are sorted into decile bins according to retailer sales within the market. The figure then plots decile-specific coefficients $\beta_{q_k^r}$, for panel (a) from the regression $\Delta \log p_{isrt} = \alpha_{it} + \alpha_{st} + \alpha_{pt} + \sum_{k=2}^{10} \alpha_{q_k} \mathbb{1}\{rs_{srt}^{(c)} \in q_k\} + \sum_{k=2}^{10} \beta_{q_k} \mathbb{1}\{rs_{srt}^{(c)} \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}$ and for panel (b) from the regression $\Delta \log p_{isrt} = \alpha_{irt} + \alpha_{st} + \alpha_{pt} + \sum_{k=2}^{10} \alpha_{q_k} \mathbb{1}\{rs_{srt}^{(c)} \in q_k\} + \sum_{k=2}^{10} \beta_{q_k} \mathbb{1}\{rs_{srt}^{(c)} \in q_k\}(-\Delta \log(1-\tau_{it})) + \varepsilon_{isrt}$. The estimates with dashed and short-dashed lines reflect the grouping into deciles using market shares based on IRi categories (instead of the more granular "subcategories" used in the baseline results) and HICP product categories, respectively. Standard errors are clustered at the municipality level. Confidence intervals are at the 90% level.