Labour Scarcity and Productivity: Insights from the Last Nordic Plague

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Abstract

I study the causal impact of labour scarcity on productivity growth, a key driver of long-run economic growth. Exploiting a natural experiment from a 1710s plague outbreak in Northern Europe, I show that plagued regions shift into capital-intensive exports and see an export expansion. Using rich port-level trade data and a Ricardian model, I trace this shift to productivity growth driven by capital deepening. While population levels recover within four decades, the productivity and trade effects persist for almost a century, suggesting long-run changes in comparative advantage. My findings imply that labour scarcity can induce productivity-enhancing reallocation.

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1 Introduction

What determines economies' long-run growth rate? One of the main drivers of economic growth are sustained increases in total factor productivity. A long-standing hypothesis holds that labour scarcity, by raising wages and altering relative factor prices, may spur productivity-enhancing innovation and reallocation (Voth, Caprettini, and Trew, 2025, Habakkuk, 1962). However, the opposing view holds that labour scarcity hampers growth as firms are unable to scale production and competitiveness is harmed by higher wages (OECD, 2024). This debate has taken on an increased importance as advanced economies face both low productivity growth and a shrinking workforce.

In this paper, I study a context where labour scarcity leads to productivity growth. I combine granular geographical variation in labour scarcity from a natural experiment, the last Nordic plague, with novel port-level trade data. This allows me to document how labour scarcity affects the composition and volume of trade. I find that plagued regions shift their exports into capital-intensive goods and conquer larger market shares abroad. While the prior reflects changes in factor proportions, I argue that a Ricardian productivity component is required to explain the latter. I thus rationalise these findings in a Ricardian model with immobile labour and link capital deepening to productivity growth. Finally, I show that these plague-induced comparative advantage changes are still in place half a century after population recovery.

The historical setting of this natural experiment is uniquely suited to study this question. I exploit the 1708-1712 Great Northern War plague outbreak as a plausibly exogenous shock that generated labour scarcity. While earlier plagues affected all of Europe, this later outbreak left many other Northern European regions unaffected. These nearby and similar regions form an ideal comparison group. Further, I study a period decades before the Industrial Revolution, which allows me to abstract from the diffusion and adoption of novel technologies.

Exceptionally detailed trade data allow me to track plagued regions' trade patterns for decades while rigorously incorporating the gravity structure of trade. Two features make the Danish toll records used in this paper the ideal source. First, origins and destinations were recorded at the level of ports rather than countries. I therefore observe trade at the same granular spatial resolution as the treatment. Second, cargoes were disaggregated into goods, which I assign into labour- and capital-intensive sectors. I can thus differentiate between goods of different factor intensities. In sum, these data permit an unprecedentedly detailed analysis of trade following this labour supply shock.

I establish two novel empirical findings. First, I find that plagued regions' share of capital-intensive exports rises by 10pp, compared to a pre-plague mean of 6.6%. New capital-intensive export goods contribute significantly to this finding. As capital became relatively more abundant, the shift into capital-intensive exports is reminiscent of the Rybczynski theorem, which states that a relative rise in a factor's endowment leads to an expansion in sectors using that factor intensively. However, this framework's key ingredient – factor price equalisation – is rejected by the data.

Second, plagued regions expand their market shares abroad. Their destination market shares rise by 1pp, compared to a pre-plague mean of 0.9%. This finding is surprising as labour scarcity should increase wages and reduce regions' competitiveness. Instead, I find evidence for a pattern of forced experimentation and innovation as plagued regions also add novel goods to their export baskets. While the export expansion is strongest in capital-intensive sectors, it holds across sectors and factor intensities, along both the intensive and extensive margins. This suggests an important role for productivity growth in the post-plague market share expansion.

Finally, these trade results display path dependence beyond population recovery. By 1750, about four decades after the plague, populations had returned to their pre-plague trends. However, trade and comparative advantage patterns reflect past labour scarcity for almost a century. Thus, the plague's effects on trade patterns outlive population recovery by half a century. This suggests that adjustments to labour scarcity produce persistent changes in comparative advantages.

Next, I build a Ricardian model following Eaton and Kortum, 2002 to rationalise my reduced-form findings. The model's Ricardian nature is motivated by the fact that exports expand across sectors and factor intensities, which a Heckscher-Ohlin model cannot explain. Another argument against a pure factor-content model is that factor price equalisation is rejected by the data. Instead, a Ricardian model with labour immobility can reproduce both the shift into capital-intensive exports and the observed export expansion. In this way, Ricardian forces are married to factor-content forces. The proposed model features two competing channels. First, a Ricardian channel that permits Hicks-neutral changes in productivity (Davis and Weinstein, 2001). I follow Costinot, Donaldson, and Komunjer, 2011 in modelling Ricardian forces within sectors. Second, the model nests non-homothetic preferences as an alternative demand-side channel (Fieler, 2011). I use this model to quantify the relative importance of these channels.

I argue that productivity growth, the first channel, is best-suited to explain my findings. I propose a three-step mechanism that matches my empirical results. First, labour scarcity leads to higher wages. Second, producers employ relatively more capital and exports shift into capital-intensive goods. Third, sectoral productivity growth accelerates as the capital-to-labour ratio rises. I argue that productivity growth as a Ricardian component is necessary to explain the export expansion across sectors and factor intensities. Thus, I suggest that capital deepening increases productivity, and I allow the elasticity between capital deepening and productivity to vary by sector. This reduced-form dependence of productivities on factor proportions allows the model to match the empirical findings.

In support of this mechanism, I show that plagued regions add significantly more novel goods, not exported by them before, to their export baskets. This reflects investments in new production lines, requiring investment capital, and innovation. I also show that this innovation and investment is significantly more frequent in capital-intensive sectors. Micro-foundations for the ascending relationship between productivity and the capital-to-labour ratio include learning by doing (Krugman, 1987), cost discovery (Hausmann and Rodrik, 2003), technology choice (Bustos, 2011), and learning by exporting (Loecker, 2013). From the model's gravity equation, I recover productivity growth as fundamentals (Costinot, Donaldson, and Komunjer, 2011) and project these recovered values onto factor proportions, where institutions and geography are absorbed by fixed effects (Chor, 2010).

Using the model, I first show that wages rise as labour scarcity bites and validate this prediction with historical evidence. The shift into capital-intensive goods, the second step, is attributed to three channels by the model: differences in labour intensity between sectors; relative price effects passed on to destination markets; and sectors' different elasticities of productivity with respect to the capital-to-labour ratio. While all sectors face the same regional factor proportions, they may differ in their labour shares and in their productivities' responsiveness to investment capital. In this historical setting, the latter mainly reflects the availability of productivity-enhancing technologies requiring capital. Such technologies were very limited in labour-intensive sectors (Atack, Margo, and Rhode, 2019, Gallardo and Sauer, 2018, Coleman, 1956). Investments in capital-intensive sectors should produce larger productivity increases as such technologies were more readily available; thus, their productivities' elasticity with respect to capital deepening should be higher.

In support of the third step, I show that productivity growth accelerates after the plague. Capital-intensive agriculture and manufacturing see faster productivity growth than their labour-intensive counterparts. These productivity changes, too, last for almost a century and illustrate path dependence in comparative advantages. I thus argue that labour scarcity leads to productivity growth. However, there is a caveat: institutions shielding producers from these changes stand in the way of the necessary adjustments. I consider one such institution, serfdom, and show that my findings do not apply to regions with serfdom. Labour scarcity was most severe in cities, but serfs could not move there, keeping the hinterland artificially abundant in labour. The lack of productivity effects under serfdom suggests that producers did not face the right set of incentives.

I find no support for the alternative demand-side channel of non-homotheticity frequently discussed in the plague literature (Voigtländer and Voth, 2012). My model nests non-homothetic preferences (Fieler, 2011), under which demand may shift into income-elastic goods as wages rise. However, I find no evidence for this in a direct test and in implied price effects. Similarly, I argue against directed technical change, venting out, and market power as explanations. I conclude that the mechanism I propose is well-suited to explain my empirical findings. Finally, I establish that in the counterfactual absence of a productivity channel exports would have contracted. Therefore, I propose that productivity growth is necessary to reconcile theory with empirics.

This work builds on several strands of literature. First, I provide novel evidence that labour scarcity leads to productivity growth. I use an exogenous mortality shock, instead of migration or fertility that present endogeneity challenges, to establish these findings. I also go beyond existing work to link labour scarcity not only to the adoption of machines and innovation (as in Voth, Caprettini, and Trew, 2025, Franck, 2024, and Andersson, Karadja, and Prawitz, 2020) but also to productivity growth. This is the ultimate outcome of interest in this debate to which my paper makes a crucial contribution.

Second, this paper makes a key contribution to the literature on path dependence in the spatial economy. My paper demonstrates that temporary labour scarcity is reflected in comparative advantages for almost a century. Thus, I argue that a shock to factor proportions explains persistent changes in comparative advantages. I bring Ricardian theory to unprecentedly granular trade data, which also allows me to go beyond existing work (Lane, 2025, Juhász, 2018) in establishing path dependence in comparative advantages in a general equilibrium framework. Further, the historical setting of this natural experiment allows me to avoid the pitfalls of technology diffusion and policy endogeneity.

Third, I provide granular evidence and plausible micro-foundations for the mechanisms behind regions' recovery after shocks (Jedwab, Johnson, and Koyama, 2024, Voigtländer and Voth, 2012, Davis and Weinstein, 2002). I show that this recovery entailed active adjustments reflecting economic decisions rather than mechanical forces.

This paper proceeds as follows. The following section summarises the related literature. Section 2 introduces the historical context and the data. Section 3 holds the trade results and section 4 the model. In section 5, I discuss the mechanisms behind my results. Section 6 shows a counterfactual analysis of trade in the absence of a productivity channel and section 7 concludes.

Related Literature

Labour Scarcity & Productivity

The view that labour scarcity promotes productivity growth is well-established in the literature. Habakkuk's seminal work postulates that labour scarcity in the United States led to labour-saving technological progress (Habakkuk, 1962). Acemoglu, 2010 generalises the relationship between factor proportions and the factor bias of technological progress. He shows that labour scarcity encourages technological progress if the latter reduces the marginal product of labour. Allen, 2009 considers Britain a high wage, cheap energy economy and argues that British innovations resulted from these factor proportions.[1]

Recent work has sought to add causal identification to this debate. Franck, 2024 exploits temperature variation to analyse how labour scarcity led to technology adoption and innovation. Andersson, Karadja, and Prawitz, 2020 use an instrumental variable approach to identify the causal effects of emigration on technological change, linking higher capital intensity to innovation. Voth, Caprettini, and Trew, 2025 use variation in warships' access to coastal areas to identify the positive effect of labour scarcity on the adoption of labour-saving machines.

In current-day debates, labour scarcity is considered an obstacle to economic growth (OECD, 2024, Caldara, Iacoviello, and Yu, 2024). An emerging literature shows that firms respond to labour scarcity by competing for workers, adjusting their input mix, and innovating in management techniques (Börschlein, Bossler, and Popp, 2024, Groiss and Sondermann, 2023).

The key empirical contribution of my paper is to test existing theories. In particular, my paper forms the first test of the Habakkuk thesis in an open economy setting. Further, the novel commodity-origin port-destination port-level trade data set is an empirical contribution in itself. On the theoretical side, I link labour scarcity and investment-driven productivity growth in a general equilibrium framework. This addresses the criticism of Temin, 1966 towards Habakkuk, 1962 regarding factor proportions in general equilibrium.

Path Dependence in Comparative Advantage

An established literature proposes micro-foundations for path dependence in comparative advantage. Krugman, 1987 shows how learning-by-doing feeds into lasting productivity changes. A related explanation lies in learning by exporting. Clerides, Lach, and Tybout, 1998 find no general evidence that firms become more productive after entering export markets. Loecker, 2013 argues to overcome previous identification challenges and finds that entering export markets leads to productivity growth. More generally, Allen and Donaldson, 2022 build a model to explain persistent effects of temporary shocks.

A growing body of literature tests this empirically. Juhász, 2018 interprets the British blockade of France as temporary trade protection. She finds that more protected regions increased their spinning capacity and had higher value added per capita in industry for several decades. Lane, 2025 studies industrial policies in South Korea and argues that they successfully changed comparative advantages.[2]

[1] This assertion is subject to criticism by Humphries and Schneider, 2020, Humphries and Weisdorf, 2019, and Stephenson, 2018.

[2] More broadly on the time path of changes in trade patterns, Hanson, Lind, and Muendler, 2018 stress the empirical relevance of dynamic comparative advantage.

I contribute to this literature by showing that an exogenous increase in capital intensities is followed by a lasting shift in comparative advantages. Juhász, Lane, and Rodrik, 2024 argue that assessing the effects of policies is complicated by identification challenges. Instead, I study an exogenous shock, which largely exempts my findings from this criticism.

Economic Effects of Plagues

My paper also relates to the literature on plagues. Population recovery after the Black Death took about two centuries (Jedwab, Johnson, and Koyama, 2024). Wages, however, did not recover in all parts of Europe (Jedwab, Johnson, and Koyama, 2022, Álvarez-Nogal, Prados de la Escosura, and Santiago-Caballero, 2020).[3] Living standards rose: Broadberry et al., 2014 document that the caloric composition in England shifted towards dairy and meat. Gelman, 1982 finds that English agriculture shifted from arable into pastoral farming. Bosshart and Dittmar, 2025 and Dittmar and Meisenzahl, 2019 stress the political economy of plague outbreaks. Voigtländer and Voth, 2012 argue that sustained wage increases were maintained by directly creating downward pressure on urban populations. Jedwab, Johnson, and Koyama, 2022 document the increased bargaining power of workers beyond higher wages.

My paper adds to this literature by focusing on granular trade in a general equilibrium framework and establishing novel empirical facts. My findings reject the predictions of Malthusian models (Cantoni, 2015) and of models of non-homothetic demand (Voigtländer and Voth, 2012). Instead, I find productivity growth effects that have been implicit to findings in existing work. A theoretical contribution lies in my model's ability to explicitly parse out non-homotheticity (Voigtländer and Voth, 2012, Fieler, 2011). This paper thus helps to establish a firmer foundation of our understanding of the economic effects of plagues.

2 Context and Data

This paper studies the last plague outbreak in Northern Europe, which coincided with large-scale warfare. The war that broke out in 1700 between Sweden, Russia, and their allies affected most countries on the Baltic Sea. Early campaigns led the Swedish army into the Baltics and later deep into the Polish-Lithuanian Commonwealth. As the war turned in Russia's favour, Swedish troops receded to Northern Germany, and Russian troops marched far into Sweden. This so-called Great Northern War ended in 1721 and marked the end of Sweden as a great power. Swedish territories in the Baltic were lost to Russia, and about half of Swedish Pomerania to Prussia. This war was accompanied by a severe outbreak of the plague.

The plague mostly followed army routes, reaching East Prussia in 1708, most of the Baltic Sea by 1711 and Hamburg by 1712. At this point, the Swedish army was on her way back from what is today Ukraine and sought refuge and fresh supplies in Swedish Pomerania. Appendix Figure 6 shows digitised army marching routes based on Spruner and Menke, 1880 and Barraclough, 1997 to illustrate how armies spread the plague. This historical evidence speaks towards war, not trade, spreading the plague. Figure 1 shows

[3] In the short-run, Jedwab, Johnson, and Koyama, 2022 find that wages actually dropped. They explain this through Smithian growth going into reverse.

plagued regions in my sample.[4] 22 regions contain cities that were besieged during the war, while seven regions were both plagued and besieged.[5] Most plagued cities caught the plague from their hinterlands through which armies marched.

2.1 Plague & Mortality Data

Appendix Table 9 presents the plague data I collected. While it cannot be ruled out that more regions suffered plague outbreaks than are recorded in these data, I suggest that this is not a major issue. First, the secondary literature covers all areas around the Baltic, and it is reasonable to assume that a plague incident will have been recorded. I note that even Bremen's mortality rate of 0.7% is recorded, suggesting no omission at the lower end of mortality rates. Second, incorrectly coding a plagued city as an unplagued one will only result in my estimates being an underestimate.

I restrict myself to coding plagued regions and their mortality rates. While Raster, 2023 presents hand-collected rural mortality data for Northern Estonia, this remarkable effort can hardly be extended to the entire region. The plagued ports appearing in the trade data are also recorded as plagued by Raster, 2023, and there are no plagued towns in his data that are not coded as plagued in mine. My assumption is therefore that urban mortality rates correlate strongly with mortality rates in the hinterland.

Mortality estimates are available for half of plagued cities, with the median mortality rate at 36%. For the remaining plagued cities, I predicted mortality with the timing of the plague, geographical controls, and the proximity to army routes. The proximity to armies, displayed in Appendix Figure 6, is motivated by the finding that armies spread the plague. Appendix Table 11 shows the regression results.

While both mortality estimates and a plague dummy are used, there is doubt about the quality and comparability of mortality figures (Roosen and Curtis, 2018, Dittmar and Meisenzahl, 2019), pointing to the plague dummy as being more robust. Demographic heterogeneity in mortality may matter, too. Alfani and Murphy, 2017 finds no systematic evidence that mortality differed by sex or age. Raster, 2023 finds no significant differences in mortality by age, sex, and social status.

Figure 1 shows the 55 out of 594 regions that caught the plague. As only seven plagued regions were additionally directly besieged, I expect the destruction of physical capital to play a minor role. Appendix Table 12 shows that plagued cities were not significantly larger before the plague. I also show that plagued cities were not significantly smaller by 1750 than those of unplagued cities.[6] In Appendix B.2, I discuss the contributions of increased fertility, lowered mortality, and migration to this population recovery. I present evidence from birth registers which show no significant drop after the plague (Appendix Figure 7 and Appendix Table 13). As populations had declined, this is consistent with an increased fertility rate. Given low urbanisation rates, rural-to-urban migration within small regions is sufficient for population recovery.

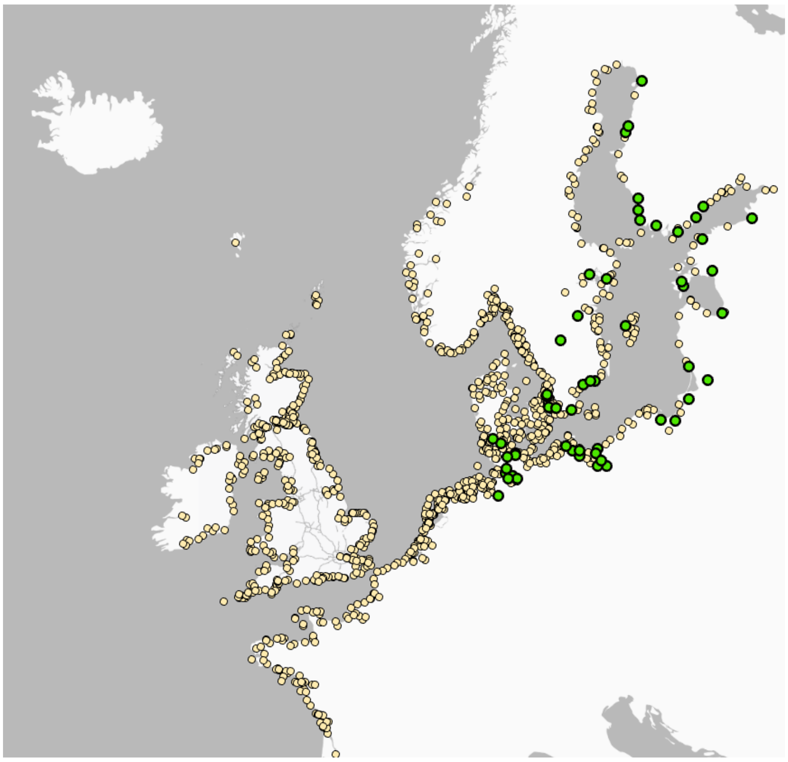
The main analysis identifies treatment as a plague outbreak in a region. As a robustness check, I incorporate plague outbreaks across all of Europe, for most of which I do not have trade data. In Appendix Table 23 and Appendix Figure 27, I present all outbreaks of the Great Northern War plague in Europe. For all regions in my trade data,

[4] Appendix Table 23 lists plagued region across all of Europe, even outside my sample.

[5] See Appendix Table 10.

[6] These data are based on urban and not regional population. Given low urbanisation rates, I consider urban population recovery indicative of regional population recovery.

Figure 1: Plagued regions



Notes: **Green circles:** plague. **Beige circles:** no plague.

I construct an indirect plague treatment variable that assigns higher weights to closer by and larger plagued regions. All details can be found in Appendix C.5. In Appendix Table 24, I show that the indirect plague treatment variable is never significant, and that the main results established for the direct plague treatment mostly go through as before. Therefore, I continue to focus on the direct effects of the plague.

2.2 The Little Ice Age

The period after the plague coincided with climate warming at the end of the Little Ice Age (Waldinger, 2022). It is important to control for temperature change when recovering agricultural productivity as warming in a cold region marked by long winters raises agricultural productivity and lengthens growing seasons.[7] To do so, I use temperature data from Luterbacher et al., 2004 and Xoplaki, 2005 and match regions to the four closest observations, weighting by the inverse distance to these grid points. I define growing seasons as the average over spring and summer.

2.3 Serfdom

Serfdom varied greatly over space and time, with the rise of the so-called second serfdom a notable historical development in this region. Appendix Figure 9 shows regions by

[7]The documented shift into capital-intensive agriculture actually runs counter to climate warming. Under warmer temperatures, regions were likely to reverse their shift into pastoral farming that had occurred during the Little Ice Age (Degroot et al., 2022, Degroot, 2018). This reversal should go in the opposite direction of what I document below.

their serfdom status. While Denmark (including Norway and large parts of modern-day Schleswig Holstein) is the only country in this area that re-introduced serfdom in 1733 (Gary et al., 2022), recent work by Raster, 2023 argues that labour coercion increased in Northern Estonia as a result of post-plague labour scarcity. My paper does not seek to disentangle the margins of labour coercion due to insufficient data coverage across the whole region. Instead, I will conceptualise serfdom as a mobility restriction. I collect data on the presence of serfdom only along the extensive margin, as increased labour coercion would not change the fact that unfree peasants in the countryside could not move to urban areas. While serfs accounted for less than 10% of the population in Estonia and 10-30% in Lithuania (Baten, Szołtysek, and Campestrini, 2016), a significantly higher share of the rural population will have seen their mobility severely restricted as a result of labour coercion (Raster, 2023).

My main sources for the prevalence of serfdom are Raster, 2023 and Peters, 2022. There is disagreement over three areas: the historical provinces of Estonia, Livonia and Pomerania. Siding with Raster, 2023, I code these areas as having had serfdom. Raster, 2023 presents evidence for significant labour coercion in Estonia and Livonia. The German peasant-owning nobility successfully resisted Swedish attempts to abolished serfdom in 1681 (Tammisto, 2020, Seppel, 2019). Laws were passed in the early 1800s that replaced serfdom with villeinage, ascribing peasants to a parish rather than an individual landowner. This, however, still left peasants without the ability to move. By 1819, Peasant Laws had come into force, abolishing serfdom and permitting freedom of movement (Blūzma, 2019). There is evidence that even for several decades after this, mobility restrictions remained in place. (Merkel, 1800) Therefore, when judging serfdom from the perspective of mobility restrictions, Estonia and Livonia certainly were areas with serfdom. For Pomerania, Millward, 1982 notes that during the 17th century, all peasants were liable for unlimited service. In Swedish Pomerania, legislation permitted the sale of landless serfs as late as the 1780s, suggesting that serfdom was present in Pomerania, too.

2.4 The Soundtoll Data

A novel granular trade panel is constructed based on the Soundtoll data. For a discussion of this data set, see also Marczinek, Maurer, and Rauch, 2025. It is plausible that almost all trade between the Baltic Sea and the North Sea is recorded in these data.

Classification of Goods

I map 143,855 cargo descriptions in Old Danish to 227 goods in English and assign these to one of five sectors: labour-intensive agriculture, capital-intensive agriculture, labour-intensive manufacturing, capital-intensive manufacturing, and remaining unclassified goods. All details on the classification and grouping of goods are reported in Appendix A.1.

In Section 4, I argue that the differentiation between labour- and capital-intensive goods is crucial, and that land intensities are not a driving factor. To briefly foreshadow the arguments below: land was, first, abundant in the Baltics which featured low population densities. Second, the production of land-intensive rye and barley drops after the plague, whereas that of capital-intensive calves and foals increases. Third, all my findings hold true also within manufacturing, where land intensities should play almost no role.

Thus, I seek to differentiate labour- from capital-intensive goods.

This distinction follows the principle that capital-intensive goods require a high baseline amount of capital, contained in buildings, furnaces, machinery, tools, carts, and animals. Labour-intensive goods, on the other hand, are dominated by labour-intensive tasks and limited in the degree to which labour can be saved. Following this principle, most goods can be classified in a straightforward fashion.

Labour-intensive agriculture is arable farming. Such farming certainly uses some capital in the form of implements such as carts and ploughs. However, arable farming is dominated by the numerous labour-intensive tasks it entails, such as ploughing, sowing, weeding, harvesting and threshing (Heblich, Redding, and Zylberberg, 2024).

Pastoral farming, mining, and processed foods including alcohols are capital-intensive agriculture. The infrastructure and tools required to mine and process foods naturally make them relatively capital-intensive. For pastoral farming, the importance of capital is well-established in historical studies, with livestock itself classified as capital (Broadberry et al., 2014, Allen, 2005). Cattle, sheep, horses, and hoggs require capital-investments for grazing (such as fencing, drainage, and roads) and for milking and slaughtering (such as buildings and tools) and otherwise graze freely in fields, requiring little labour input.

In manufacturing, I classify textiles as labour-intensive. Broadberry and Gupta, 2009 and Pomeranz, 2006 discuss how traditional production methods in textiles were very labour-intensive, with tasks such as spinning, weaving, and dyeing requiring high labour inputs. Textile production in the early 18th century Baltic region will have employed traditional production methods as these were agrarian societies before the Industrial Revolution. Iron and metal works and ship building, on the other hand, are naturally more capital-intensive in that they use furnaces, buildings or docks, and tools.

Figure 2 shows the most common goods for each sector by overall traded value between 1668 and 1750. Appendix Table 5 ranks the top 30 goods, accounting for 90% of traded value during this period, and shows their assignments into sectors. While the vast majority of these goods can be clearly assigned, I run a robustness exercise in which I reassign four debatable goods: wine and tow to labour-intensive agriculture and planks and ash to labour-intensive manufacturing. This does not change my results.

Classification of cities, duties, currencies, and units

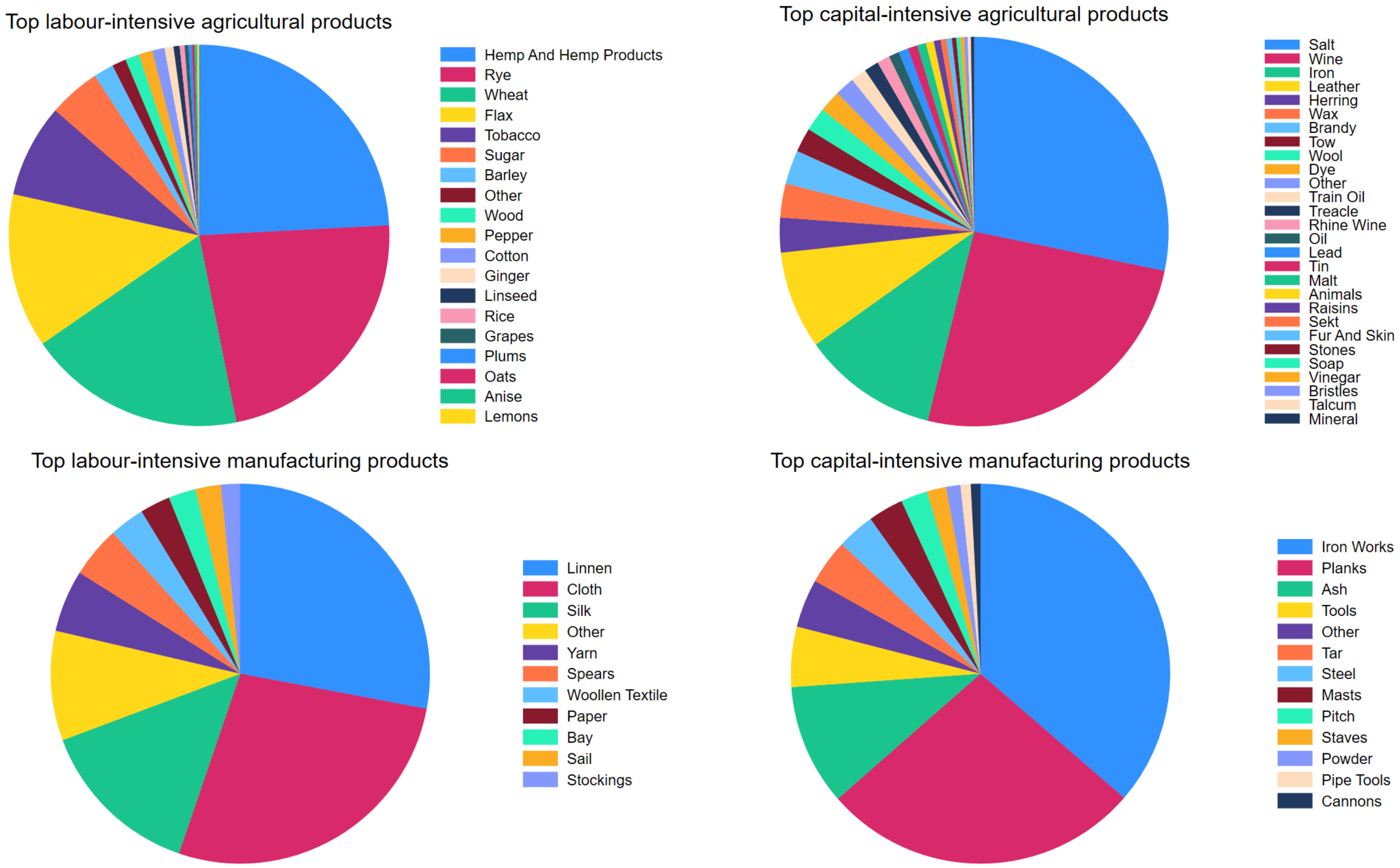
The Soundtoll data record origins and destinations at the level of ports rather than countries. To clean the trade data, I map 90,737 original city names to 3,085 unique place identifiers and assign them into one of 68 areas. Appendix B holds further details.

The Soundtoll data further pose selection issues as I only observe trade between the Baltic Sea and the North Sea. As the Sound was hard and costly to avoid, I observe all trade between Saint Petersburg and London, but none between Amsterdam and London, which are both on the same side of the Sound. However, a lot of Baltic exports were sent only to Western Europe and are thus entirely observed. I also present simulation results in Appendix Figure 28 on a simulated productivity increase. Both in the hypothetical full and in the actually observed sample the productivity increase is recovered. In both cases the estimates are centred around the simulated effect, suggesting no bias.

Details on tolls and duties are given in Appendix A.4. Duties paid by each passing ship are recorded and disaggregated by goods. Most authors interpret the proportional duty as a proxy for value (Waldinger, 2022.[8] I follow this approach but additionally verify

[8]Indeed, the 'hundred money' was introduced in 1548, a 1% duty on value (Gøbel, 2010). Further,

Figure 2: Goods by sector



Notes: This figure shows the most common goods per sector by overall traded value. The 2% least common goods have been summarised as 'other' for legibility's sake.

that duty rate variation does not bias my findings. In a robustness check, I flexibly allow for variation in the rate of duty and construct underlying values. Specifically, I allow duty rate variation along dimensions stressed in the historical literature. I show robustness results, which are very similar to my main results. All details are held in Appendix A.5. A final advantage of value data is that they account for empty ships, whose value is at 0.

Currency concerns, as elaborated in Appendix A.2, are minor as the vast majority of transactions are carried out in Danish coins. While there are reasons to doubt the accuracy of reported tolls and to suspect corruption, there were also institutions in place to mitigate incorrect reporting. Importantly, the Danish crown implemented a truth telling mechanism: the Crown could choose to purchase goods at the stated (and taxed) value to induce truth telling. I also use shipments' weights to construct unit prices. To this end, I convert historical units to kilograms as documented in Appendix Table 7.

3 Trade

This Section presents novel descriptives on trade following a plague outbreak. Labour scarcity, resulting from the mortality shock, will have increased the marginal product of labour and accordingly wages, which is confirmed by the literature (Jedwab, Johnson, and Koyama, 2022).[9] Capital, on the other hand, will have become cheaper relative to labour, inducing producers to adjust to changed relative factor prices.

Two adjustments could appear. First, an adjustment *within* sectors. As long as factor prices are not equalised across regions, a higher capital-to-labour ratio will be employed in the production of goods. In the case of arable farming, this might take the form of swapping easily farmed land for more fertile grounds that require drainage, as seen in post-plague Sweden and described in Section 5. In manufacturing, machinery and tools reflect a common way of increasing the capital-to-labour ratio. The historical literature finds that the plague induced higher wages (Jedwab, Johnson, and Koyama, 2022), thus supporting the expectation of a higher capital-to-labour ratio in the absence of factor price equalisation. This adjustment *within* sectors is difficult to observe in trade data, as the researcher observes products but not their production methods. We can observe the second adjustment, however, which is a compositional effect taking place *across* sectors. Labour scarcity should induce regions to increase their production of capital-intensive goods relative to labour-intensive goods as goods using relatively little labour should be less affected by labour scarcity. This adjustment *across sectors* is predicted by the Rybczynski theorem as part of the Heckscher-Ohlin theory of trade. At constant relative goods prices, it states that the rise in the endowment of capital, compared to labour, ought to lead to a more than proportional expansion of output in capital-intensive sectors. This change in regional relative factor endowments does not lead to changes in regional factor prices as long as the region is sufficiently small. While the Ricardian model introduced in this paper does not feature factor price equalisation, it nevertheless predicts an adjustment *across sectors*. This observed effect, however, is an understatement of the adjustment to labour scarcity as many labour-intensive goods will have been produced with higher capital intensity after the plague.

throughout the Soundtoll's existence, the ad valorem duty varied between 1-2%.

[9] While the terms scarcity and shortage are used interchangeably in the literature (Caldara, Iacoviello, and Yu, 2024), I view shortages as an imbalance between supply and demand upheld by a friction or rigidity. Instead, I will speak of scarcity throughout, in the sense that labour became scarcer compared to capital after the plague.

To proceed, one needs to classify goods as labour- or capital-intensive. For agriculture, I classify arable farming as labour- and pastoral farming as capital-intensive (Heblich, Redding, and Zylberberg, 2024, Broadberry et al., 2014, Allen, 2005). For manufacturing, I distinguish labour-intensive production of textiles from capital-intensive metal works, ship building, and machinery-intensive production (Broadberry and Gupta, 2009). I will assume that the remaining unclassified goods are labour-intensive, but my results are virtually unchanged when instead dropping them. Details on goods classifications can be found in Section 2.4.

Overall exports should fall as wages rose after the plague. This effect should be larger in labour-intensive sectors, yielding the predicted relative increase in capital-intensive exports. These adjustments ought to be visible almost immediately after the plague hit a region. This plague outbreak's median mortality rate of 36% suggests a sizeable increase in labour scarcity and a median increase in the capital-to-labour ratio of 56%. As the Great Northern War plague outbreak was geographically very concentrated, neither supply nor demand would have changed in most regions, permitting the researcher to focus on plagued regions' trade responses. These, given the sudden and large shock to regional populations, should become visible almost instantly.

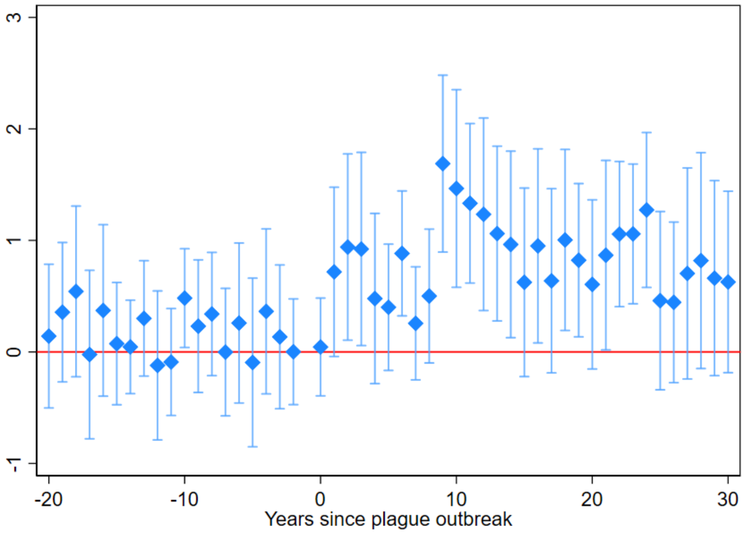
A key identification challenge is that the plague may be endogenous to trade. To rule out this concern, I present historical evidence, provide a balance test, and confirm the absence of pre-trends in the below trade regressions. In the historical literature, it has been argued that armies spread the plague and rarely directly targeted cities or trading hubs. There is further no evidence of the plague having been used as a biological weapon. As for the balance test, to-be-plagued cities do not differ in population size before the plague, as shown in Appendix Table 12. For trade, Table 1 shows two results for the intensive margin (columns 1 and 2) and two for the extensive margin (columns 3 and 4). A future plague dummy does not predict a different volume, composition, or number of exports. The only dimension along which to-be-plagued regions differ is that they are signficantly likelier to export at all. However, Table 1 shows that to-be-plagued ports do not differ in their trade growth. The level difference will be absorbed below with origin fixed effects and the analysis will focus on trade growth. Balancedness in this regard is confirmed in that I tend to not find any significant pre-trends in event studies.

Table 1: Pre-plague balance checks

	Log Exports	Export Growth	Log # of Exported Goods	Export Probability
	(1)	(2)	(3)	(4)
To be Plagued	0.588	-0.055	0.221*	0.090***
	(0.427)	(0.064)	(0.120)	(0.018)
To be Plagued x Capital-Int.	-0.437	0.080	0.043	-0.048***
	(0.367)	(0.063)	(0.107)	(0.006)
Fixed Effects:				
– Destination x Year	✓	✓	✓	✓
Years	1668-1708	1689-1708	1668-1708	1668-1708
Observations	15,826	47,160	31,604	496,920

Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variables are log export volumes (column 1), annual export volumes divided by total exports between 1668 and 1688 (column 2), the log number of exported goods (column 3), and a dummy for any exports (column 4). The independent variable is a plague dummy, equal to one for to-be-plagued regions, and this dummy's interaction with a dummy for a capital-intensive sector. Years are restricted to before 1708 to exclude any plague years. Additional controls are annual growing season temperature, latitude, and longitude.

Figure 3: Capital-intensive exports expand relative to labour-intensive exports



Notes: Estimation of equation 1. Standard errors clustered at the origin level.

Fact #1: Capital-intensive exports increase more than labour-intensive exports.

The plague induced labour scarcity, which will have translated into higher wages and an increased capital intensity of production. The plague's effects should thus differ by sectors' factor intensities. To test this, I estimate an event study using OLS on log exports, weighted by exports in levels.[10] In particular, I estimate:

$$T_{ikt} = \sum_{l=-20\backslash -1}^{30} \beta_l^f \cdot \mathbb{1}(K_{it} = l) + \alpha_{ik} + \alpha_{kt} + \gamma_f x_{it} + \epsilon_{ikt}, \tag{1}$$

where i are origin ports, k one of 5 sectors, f is factor intensity (capital- or labour-intensive), and t are years. T_{ikt} are (log) exports. K_{it} is the time difference to the plague, α_{ik} are origin-sector fixed effects, α_{kt} sector-time fixed effects, and x_{it} are annual growing season temperatures. I am particularly interested in the difference between β_l^C and β_l^L. Throughout, standard errors are clustered at the origin-level.

Figure 3 shows the difference between β_l^C and β_l^L: after the plague, capital-intensive exports expanded significantly more than labour-intensive exports. These estimates imply a 10pp increase in the share of capital-intensive exports, compared to a pre-plague mean of 6.6%.

In the Appendix, I present further results on this fact. Appendix Figure 10 shows that an alternative assignment of four debatable goods (wine and tow as labour-intensive agriculture; planks and ash as labour-intensive manufacturing) produces almost identical

[10]This approach is chosen to recover estimates similar to PPML while using a straightforward OLS event study. Without such weights, OLS on logs tends to produce results very different from PPML: Mayer, Vicard, and Zignago, 2019 and Head and Mayer, 2013 show that PPML places more weight on high trade flows as it minimises distances in real vs. expected trade in levels rather than in logs. Weighting OLS on log trade by levels thus brings OLS close to PPML results, as shown in Mayer, Vicard, and Zignago, 2019.

results. Appendix Table 14 shows PPML and OLS results in a differences-in-differences-in-differences set up. Appendix Table 15 repeats this specification to test if army proximities and sieges are also associated with a labour scarcity-induced shift into capital-intensive exports. Appendix Figure 11 confirms the above finding using the imputation estimator in Borusyak, Jaravel, and Spiess, 2021. Appendix Table 16 shows that the relative expansion of capital-intensive exports occurred both in manufacturing and in agriculture. This alleviates concerns that the finding is driven by differential land intensities of agricultural products, as the same shift operates in manufacturing. At a more granular level, I analyse the plague's effects on the composition of exports at the goods level in Appendix Figure 12.

In Section 5, I present historical evidence relating this finding to data on Swedish farms. I show that after the plague farms switched out of labour-intensive rye and barley production and into raising calves and foals. These effects are stronger the closer a farm is located to a plagued city, implying that they increase in the mortality rate and thus the degree of labour scarcity. I conclude that the plague induced a shift across sectors as predicted by the Rybczynski theorem: when faced with an adverse mortality shock, regions relatively increased their capital-intensive exports.

This shift into capital-intensive exports outlasts the shock to factor proportions by at least half a century. In Appendix Table 12, I show that by 1750 plagued cities were no smaller than unplagued cities, and argue that the same is true for regional populations. Given population recovery, factor proportion theories of trade would suggest that the shift across sectors should be reversed. To the contrary, Appendix Figure 13 shows that the shift into capital-intensive exports persists for almost 90 years after the plague. Capital intensity thus remains significantly elevated despite population recovery.

Fact #2: Plagued regions capture larger shares of destination markets.

Higher wages should have reduced plagued regions' competitiveness in destination markets. To test this, I estimate a second event study incorporating the gravity structure of trade:

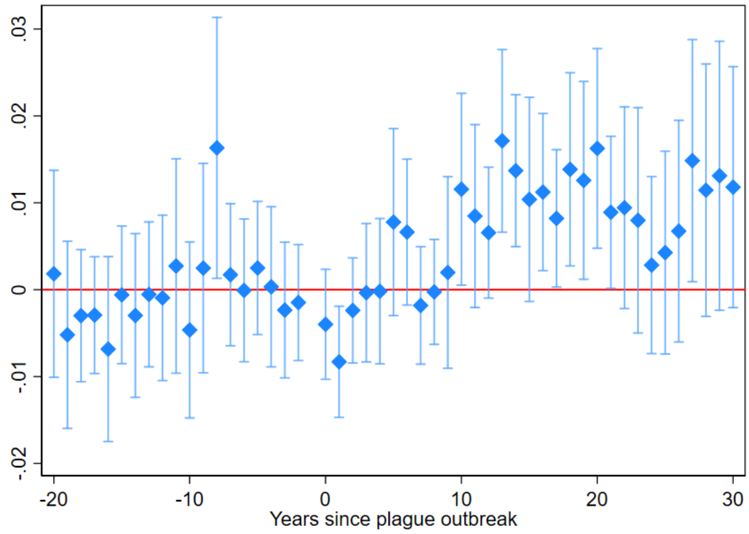
$$T_{ijt} = \sum_{l=-20\backslash-1}^{30} \beta_l \cdot \mathbb{1}(K_{it} = l) + \alpha_{ij} + \alpha_{jt} + \alpha_{at} + \gamma x_{it} + \epsilon_{ijt}, \tag{2}$$

where T_{ijt} is one of several outcomes for trade from origin i to destination j in year t. K_{it} is the time difference between the current year and the plague, α_{ij} is a bilateral fixed effect, and α_{jt} are destination-time fixed effects absorbing the demand side. ϵ_{ijt} is the error term. α_{at} are area-time fixed effects.[11] These permit for different time trends for each area and thus permit heterogeneity by area. x_{it} are time-varying origin controls, in particular growing season temperature, longitude x year, and latitude x year. β_l are the outcomes of interest.

For Fact #2, T_{ijt} is either the volume of exports from i to j in t, or the export share

[11] 57 areas with 12 regions on average: provinces of Belgium, Finland, Ireland; regions of Denmark, England, France, Norway; states of Germany, each Baltic state, Scotland, and Wales, oblasts of Russia, autonomous communities of Spain, national areas of Sweden, and voivodeships of Poland. Details in Appendix B.

Figure 4: Market shares expand



Notes: Estimation of equation 2 on i's share of j's imports, $T_{ijt} = \frac{x_{ijt}}{\Sigma_{i \in I} x_{ijt}}$. Standard errors clustered at the origin level.

that origin i captures in destination j: $T_{ijt} = \frac{x_{ijt}}{\Sigma_{i \in I} x_{ijt}}$.[12] This formulation of T_{ijt} as the share of exports from origin i in destination j in year t motivates the Ricardian model below, which will predict trade shares. For results on the extensive margin and on new exports, T_{ijt} is the number of different goods exported from i to j in t.

Contrary to concerns of an export contraction, Figure 4 shows that plagued cities increase their export shares by about 1pp, which is close to the pre-plague mean export share of 0.9%. Appendix Figure 14a also shows an expansion of export volumes.

The export expansion begins shortly after the plague, with the first significant point estimates for export volumes three years later. Ten years after the plague, these regions capture significantly larger market shares in destination markets.

The onset of the export expansion in terms of market shares coincided with the end of the Great Northern War in 1721. Nonetheless, these results reject the hypothesis that trade simply bounced back. There is about a decade of peace and normal trade during which cities did not display different export patterns. Appendix Figure 15a extends the pre-period to 30 years and similarly finds no pre-trends.

Appendix Figure 15b constructs market shares from cleaned underlying value correcting for duty rates, as introduced in Section 2.4 and detailed in Appendix A.5. Appendix Figure 16 implements the estimator by Borusyak, Jaravel, and Spiess, 2021. Chaisemartin and D'Haultfoeuille, 2022 point out that the summation of average treatment effects may involve negative weights, obscuring the relationship between the estimated coefficient and the ATEs. I allow for treatment effects to change over time but maintain the common trends assumption; I find that all weights are positive and conclude that the standard estimator is appropriate.

Appendix Figure 17 decomposes the intensive margin results into sectors. Two decades after the plague, I find that capital-intensive manufacturing and agriculture con-

[12] I set market shares of i in j to 0 whenever j shows no imports in my data. As the data capture only trade between the North and Baltic Seas, I thus assume that every region has some imports, even if unobserved to me.

tribute each a quarter to the overall export expansion, with the remaining half accruing to labour-intensive agriculture. Labour-intensive manufacturing plays virtually no role. The outsized role of labour-intensive agriculture is not surprising as it makes up 55% of traded value between 1668 and 1750. Aggregating sectors by factor intensity instead, Appendix Figure 18 shows that both saw export expansions. These results choose T_{ijft} to be the volume of exports by factor intensity. The fact that labour-intensive exports only briefly decrease and then recover attests to factor adjustments *within* sectors, making up for some effects of labour scarcity. At a more granular level, Appendix Figure 19 presents results at the goods level.

These results confirm the finding that a few years after the plague had induced a shift into capital-intensive exports, plagued regions captured a significantly larger share of destination markets. This is indicative of a productivity adjustment as plagued regions became more competitive compared to others.

This export expansion outlives population recovery which had been achieved by 1750. Appendix Figures 20a and 20b show that up to 80 years after the plague, market shares abroad and export volumes are still larger in previously plagued regions.

Extensive Margin: Plagued regions export a larger variety of goods.

The export expansion documented above could take place along two margins. First, the intensive margin, with plagued regions exporting larger volumes of goods while keeping the number of goods unchanged. Second, the extensive margin, with plague regions exporting a larger variety of goods. I find that the extensive margin plays an important role: Appendix Figure 14b shows that plagued regions increased the number of goods they export. The mean number of goods exported per year is at 0.43, which is roughly the average point estimate.

Through the lens of a Ricardian model (Eaton and Kortum, 2002), it is the extensive margin expansion that drives the results on market shares. Plagued regions becoming the most competitive suppliers of a larger variety of goods to destination markets is therefore an indication of productivity growth and observationally consistent with an export expansion along the intensive margin. In this historical setting, it is also plausible that the plague pushed self-sufficient farming communities over the productivity threshold for exporting, thus explaining the large extensive margin results.

How do sectors contribute to this extensive margin expansion? Appendix Figure 21 decomposes the extensive margin expansion by sector and finds that capital-intensive manufacturing and agriculture contribute each roughly a third and labour-intensive agriculture roughly a quarter, with only about 5% of the increased number of exported goods attributable to labour-intensive manufacturing. Appendix Figure 22 shows these results overall for capital- and labour-intensive sectors, confirming that about three quarters of this expansion occur in capital-intensive sectors. Appendix Figure 23 shows results at the level of goods.

3.1 Other Robustness Results

I provide results from a panel regression in Appendix Table 19. Defining the plague as a bilateral dummy for whether at least one side suffered an outbreak, I include a full set of bilateral, origin-time and destination-time fixed effects, and regress export levels using PPML (Santos-Silva and Tenreyro, 2006). The results show that trade between regions increased after one side suffered a plague outbreak. Considering the set of fixed effects, however, this result draws on different variation from my main result. Further, Appendix Table 20 shows results for the probability of a region exporting in a given year. After a plague outbreak, regions' probability to be active exporters increases significantly. For all four facts, I present heterogeneity results in Appendix Table 21. While the effects are larger for regions that exported more before the plague, they are significant even for regions that had no exports before the plague. Appendix Table 22 shows that the presence of a besieged city does not affect the post-plague trade findings. Finally, I check if the specification of treatment is sufficient in focusing on plague outbreaks in regions themselves. In Appendix C.5, I describe how I construct a continuous indirect plague treatment variable that captures plague outbreaks across all of Europe. I show in Appendix Table 24 that the indirect treatment variable is never significant. Further, my findings on the direct plague treatment are robust to including the indirect plague treatment.

3.2 Mechanical Explanations

The finding of an export expansion could be driven mechanically by two forces, against both of which I will present evidence. The observed export expansion might reflect a reallocation of exports from within the Baltic Sea to the North Sea, explained by a severe economic downturn in the Baltics. In this case, regions' trade would appear in the Soundtoll data while it did not use to. There are several issues with this explanation. First of all, heterogeneity within sectors speaks against a simplistic reallocation of trade. Second, competing against existing exporters in new destination markets is a costly adjustment and raises the question of how regions became competitive in these markets. Third, the combination of new markets and longer distances implies that regions in the Baltics would not simply have become the least-cost suppliers of their goods in North Sea regions. They would have had to overcome the cost of distance and higher wages through higher productivity to be competitive. Thus, if anything, I am underestimating trade expansion, as plagued regions would have also exported more to nearby harbours.

To more rigorously address this concern, I show simulation results in Appendix Figure 28 for a simulated productivity increase and its effect on trade flows. The simulated productivity growth raises capital-intensive exports. I show that both in the hypothetical full and in the actually observed sample, where only trade passing the toll station is registered, the productivity increase is reflected in significantly higher capital-intensive exports. For both samples, the point estimates are centred around the simulated effect, suggesting no bias. Appendix Figure 28 runs similar simulations, focussing on whether sample selection affects the recovered productivity growth estimates. I conclude that the geographical limitations of the Soundtoll data do not drive my results.

A second mechanical explanation concerns the role of harbours as export hubs. If a harbour attracts production from the hinterland to export it, some share of these products will be consumed in the city itself. Following a plague outbreak, this local consumption would have dropped, and, assuming constant hinterland production, exports should indeed have gone up. I challenge the notion that the hinterland's production would not have been affected. The plague was spread by moving armies, which plundered the hinterland and disrupted production. To test whether local demand contraction in export hubs may be driving my results, I show in Appendix Figure 26 that the share of exports that is shipped to plagued regions increases. This speaks against the mechanical explanation which predicts a decline in imports into plagued regions. Further, Appendix Table 21 shows that also the smallest harbours that are unlikely to have served as export hubs saw an export expansion.

4 A Ricardian Model

I argue that productivity growth is required to explain my empirical findings and propose a Ricardian model. Malthusian models with fixed productivity predict that an adverse labour supply shock should be followed by an export decline as wages increase. If only Heckscher-Ohlin forces were at play, one should observe only a reallocation to capital-intensive production but no overall increase in exports. Finally, such factor theories predict factor price equalisation. As all three are rejected by my findings, I build a Ricardian model with intra-industry variation in productivity, leaning on Eaton and Kortum, 2002, Costinot, Donaldson, and Komunjer, 2011 and Donaldson and Hornbeck, 2016. I first present the model in a general form and relate it to the empirical evidence presented before. I then impose additional assumptions and recover productivity growth to argue that labour scarcity is associated with productivity gains that explain the post-plague export expansion.

There are many regions, i=1,...,I, and three factors of production: labour L_{ik}, capital K_{ik}, and investment capital I_{ik}. There are five sectors indexed by k: labour-intensive agriculture (LA), capital-intensive agriculture (CA), labour-intensive manufacturing (LM), capital-intensive manufacturing (CM), and unclassified goods (U). Throughout, I am dropping the t subscript indicating time for simplicity. I begin by discussing my modelling choices.

Unique Spatial Equilibrium: Population recovery is an indicator of a unique spatial equilibrium (Davis and Weinstein, 2002). I use city population data by Buringh, 2021 to show that by 1750, plagued cities had returned to their pre-plague growth paths (Appendix Table 12), which compares to a 200 year recovery after the Black Death (Jedwab, Johnson, and Koyama, 2024). While for a sufficiently small shock population may also recover in a NEG setting such as Krugman, 1991, I argue that the median mortality rate of 36% is anything but small. Thus, the model has a unique spatial equilibrium.

Factors and Sectors: The model features labour and two types of capital: capital K_{ik}, which contains fixed and working capital used in the production of goods, and investment capital I_{ik}, which entails capital used to innovate and improve production processes. In the general part of this model, I permit each sector to have a different labour share γ_k and capital share η_k. Both types of capital are assumed to be freely mobile across regions and sectors. For each sector k the production function takes the Cobb-Douglas form:

$$P(L_{ik}, K_{ik}, I_{ik}) = A_{ik} L_{ik}^{\gamma_k} K_{ik}^{\eta_k} I_{ik}^{1-\gamma_k-\eta_k}. \tag{3}$$

One might wonder if land ought to be included as a factor. Temin, 1966 shows that arguments relying on relative factor intensities are complicated by the presence of an additional factor such as land. I argue that land was abundant in the Baltics: Raster, 2023 shows that population densities were so low that after the plague entire manors were abandoned; Allen, 2003 proposes that serfdom in the Russian Empire was an institution

Table 2: Spatial Separation & Capital Intensity

		Labour-intensive		Capital-intensive
Region	City	Labour-int. manufacturing (LM)	$\eta_{LM} < \eta_{CM}$	Capital-int. manufacturing (CM)
	Hinterland	Labour-int. agriculture (LA)	$\eta_{LA} < \eta_{CA}$	Capital-int. agriculture (CA)

Notes: Assumptions on spatial separation, sectors, and factor intensities. η_k denotes the capital share in each sector k.

to preserve the power of the owners of abundant land over scarce peasants. Therefore, I argue that land was abundant and labour the constraining factor, keeping land-to-labour ratios fixed. In line with Redding and Venables, 2004, one could therefore view land and labour as constituting a composite immobile factor. Swedish agricultural data support my assumption of land abundance. Had land been a constraining factor, the increased relative supply of land should benefit the production of land-intensive goods. However, Appendix Figure 31 shows that the production of rye and barley drops after the plague, whereas that of calves and foals increases. Finally, Appendix Table 16 and Appendix Figure 18 show that the shift into capital-intensive exports and the larger export expansion in capital-intensive goods occur also within manufacturing, where different land intensities should play almost no role. Therefore, I argue that the crucial comparison is between labour- and capital-intensive goods and do not model land as a factor.

A second differentiation assumes cities to produce manufacturing and hinterlands to produce agricultural goods. This assumption finds historical support in policies that restricted manufacturing to cities and viewed crafts and industrial production as purely urban activities. In Sweden, the textile industry was restricted to cities, with rural producers supplying only the input goods; similarly, urban blast furnaces were to be supplied by rural pig iron (Magnusson, 2007). To ensure this separation, a 'town economic policy' was introduced in the 17th century, which strictly banned rural trade. In a similar vein, Klein and Ogilvie, 2015 describe how urban institutions hindered rural crafts and industrial production in 17th century Bohemia. Therefore, manufacturing is assumed to take place in cities and agriculture in the countryside. Unclassified goods make up a fifth sector assumed to be produced in the countryside.

I define a region as a city and its hinterland. Larger cities on navigable rivers will naturally boast a larger hinterland and I assume that this does not change over the study period. Historical evidence suggests that cities hinterlands were partially exogenously determined. Swedish cities, for example, enjoyed trade monopolies over their surrounding area, which only changed in 1765 when the Commodity Act was withdrawn (Magnusson, 2007). All 1,425 cities in the data are coastal or near a coast, and the average diameter of the hinterland is 25 kilometres. Table 2 summarises these assumptions.

Labour Mobility: Without migration, higher wages increase fertility in a Malthusian model (Cantoni, 2015). With full labour mobility across regions, higher wages attract migrants until wage differentials are eliminated. One would have to observe an almost immediate population recovery under this assumption, which is surely excessive. I find that population recovery was achieved by 1750. The literature on plague outbreaks finds significant wage increases (Jedwab, Johnson, and Koyama, 2022), implying local labour scarcity and the absence of factor price equalisation. The latter is also supported by Davis and Weinstein, 2001. Accordingly, I model labour as immobile across regions but mobile across sectors within a region. Plagued cities, where mortality rates were higher than in the hinterland, can recover via rural-to-urban migration. This is true in areas without serfdom. Under serfdom, however, peasants could not move to cities and thus a wedge between urban and rural persisted. I suggest that such wage differences can be conceptualised as a mobility friction.

In both settings, workers are assumed to freely move within agriculture and within manufacturing in a given region, implying wage equalisation.[13] Let $w_i^{CM} = w_i^{LM} \equiv w_i^M$ and $w_i^{CA} = w_i^{LA} \equiv w_i^A$. Without serfdom, all four sectors pay equal wages in a region. With serfdom, there are equalised wages within agriculture and within manufacturing. The wedge between urban and rural wages, ϕ_i, will be region-specific and depends, in particular, on mortality differences between the two parts of a region. ϕ_i captures both mobility and other frictions, such as the fact that serfs in the Eastern Baltic did not speak the language of city dwellers (German) and were not permitted to learn a craft, leaving them with little outside options to pursue by moving to cities. Equation 4 summarises the assumptions on labour mobility. Appendix Figure 8 shows that a wedge between urban and rural wages appeared in Denmark after the re-introduction of serfdom.

$$w_{iM} = \begin{cases} w_{iA}, & \text{without serfdom,} \\ (1+\phi_i)w_{iA}, & \text{with serfdom.} \end{cases} \tag{4}$$

Productivity: Each sector's output features in an infinite number of varieties, $\omega\epsilon\Omega$, which is exogenously given. Productivity A_{ik} is modelled as a random variable, drawn independently for each (i, k, ω, t) from a Fréchet distribution as in Donaldson and Hornbeck, 2016:

$$F_{ik}(z) = 1 - exp(-A_{ik}z^{-\theta}), \tag{5}$$

where $A_{ik} > 0$ and $\theta > 1$. A_{ik} captures fundamental productivity of region i in sector k, and encompasses productivity-affecting fundamentals that pertain to all producers in that region and sector. θ reflects intra-industry heterogeneity.[14] In this model, productivity is therefore total factor productivity and not factor biased (Acemoglu, 2002). This choice follows Davis and Weinstein, 2001 who argue that a model of Hicks-neutral technical differences is best suited to explain global production structures.

(Investment) Capital Intensity: Producers take the variety-level draw $A_{ik}(\omega)$ as given when allocating labour, capital, and investment capital. Factor prices equal marginal products for each factor, so the production of each variety ω becomes more intensive in both types of capital after a plague-induced wage increase:

$$\frac{I_{ik}(\omega)}{L_{ik}(\omega)} = \frac{(1-\gamma_k-\eta_k)}{\gamma_k i}w_{ik},$$
$$\frac{K_{ik}(\omega)}{L_{ik}(\omega)} = \frac{\eta_k}{\gamma_k r}w_{ik}.$$

[13]While serfs are not paid wages and cannot move between different agricultural employments, the assumption here is that their lords efficiently allocate them to equalise the marginal products of labour between labour-intensive and capital-intensive agriculture.

[14]Costinot, Donaldson, and Komunjer, 2011 elaborate on the implications of assuming $\theta_k = \theta \forall k$.

The (investment) capital-to-labour ratios rise also overall, with $I_{ik} = \int_{\omega \in \Omega} I_{ik}(\omega)$. The model therefore predicts the shift *within* sectors into capital-intensive production.

Marginal Costs: Returns for both types of capital are equalised across regions, $r_i = r \forall i$ and $i_i = i \forall i$. Production uses Cobb-Douglas technology 3, where $A_{ik}(\omega)$ is drawn from probability distribution 5. The marginal cost of production is given by:

$$MC_{ik}(\omega) = \frac{(w_{ik})^{\gamma_k} r^{\eta_k} i^{1-\gamma_k-\eta_k}}{A_{ik}(\omega)}. \tag{6}$$

This is a model of constant marginal costs. My finding relates to the theory of venting out (Almunia et al., 2021), in which a domestic demand slump leading to an export boom is rationalised by non-constant marginal costs of production. In Section 5.2, I discuss how their mechanism fits my empirical results. I argue that one can better rationalise these findings through a mechanism linking factor adjustments to sectoral productivity growth without resorting to assuming non-constant marginal costs.

Trade Costs: I assume the standard iceberg form. Also, $d_{ii,k} = 1$, and no trade costs apply when transporting goods from the hinterland to the city. Trade costs may vary by sector, $d_{ijk} \neq d_{ijk'}$, but are symmetric, $d_{ijk} = d_{ji,k}$. The no-arbitrage condition $d_{il,k} \leq d_{ijk} d_{jl,k}$ is also imposed. Trade costs are allowed to vary by sector and time, thus subsuming any potential tariffs.

Market Structure & Prices: Markets are perfectly competitive, $p_{ijk}(\omega) = c_{ijk}(\omega) = d_{ijk} MC_{ik}(\omega)$. Consumers in region j purchase a variety ω from its cheapest supplier location i:

$p_{jk}(\omega) = \min_{1 \leq i \leq I} c_{ijk}(\omega)$, where $c_{ijk}(\omega)$ is as above and assumed to be strictly positive. Following Redding and Venables, 2004 and Donaldson and Hornbeck, 2016, consumer market access and firm market access are defined as the price indices:[15]

$$CMA_{jk} = (P_{jk})^{-\theta} = \chi_k \Sigma_{i=1}^{I} A_{ik} (w_{ik})^{-\gamma_k \theta} d_{ijk}^{-\theta},^{16} \tag{7}$$

$$FMA_{ik} = \chi_k \alpha_k \Sigma_{j=1}^{J} d_{ijk}^{-\theta} (CMA_{jk})^{-1} Y_j. \tag{8}$$

Wage Rate & Labour Force: Wages are determined sectorally. Combining market clearing conditions and plugging in firm market access yields:

$$w_{ik} = \zeta_k \left(\frac{A_{ik} FMA_{ik}}{L_{ik}} \right)^{\frac{1}{1+\gamma_k \theta}}.^{17} \tag{9}$$

Preferences: The representative consumer in each region has a two-level utility function, where the upper tier is Cobb-Douglas and the lower tier is CES. α_k are the

[15] Note that the existence of these CES price indices requires the assumption $\sigma_k < 1 + \theta$.

[16] $\chi_k = \left(\Gamma(\frac{\theta+1-\sigma_k}{\theta}) \right)^{\frac{-\theta}{1-\sigma_k}} r^{-\eta_k \theta} i^{-(1-\gamma_k-\eta_k)\theta}$

[17] $\zeta_k = \left(r^{\eta_k} i^{1-\gamma_k-\alpha_k} \right)^{\frac{-\theta}{1+\gamma_k \theta}}$

Cobb-Douglas weights in the upper tier and $\sigma_k > 1$ is the elasticity of substitution between differentiated varieties in the lower tier. I assume $\sigma_k < 1 + \theta$. A continuum of these differentiated varieties ω are consumed. I will later follow Fieler, 2011 in introducing non-homotheticity.

Trade Flows: Trade flows take the gravity form:

$$X_{ijk} = \frac{\chi_k A_{ik} (w_{ik})^{-\gamma_k \theta} d_{ijk}^{-\theta}}{CMA_{jk}} \alpha_k Y_j. \tag{10}$$

Equation 10 implies that region i exports more to region j in sector k if it has a higher labour productivity, A_{ik}, lower trade costs, d_{ijk}, or lower wages, w_i, all relative to all other exporter regions i. Region i further exports larger volumes to region j if region j has low consumer market access in a sector, which means low competition for i when exporting to j.

Equation 10 can be used to recover productivity growth. Adding a time dimension to the procedure in Costinot, Donaldson, and Komunjer, 2011, I estimate:

$$X_{ijkt} = exp(\alpha + \delta_{ijt} + \delta_{jkt} + \delta_{ikt}) \times \epsilon_{ijkt}, \tag{11}$$

where all δ parameters are fixed effects and ϵ_{ijkt} is the error term. δ_{ikt} recovers relative productivity growth. I estimate this equation using PPML, which implicitly absorbs multilateral resistance terms (Fally, 2015). All details can be found in Appendix D.1.

5 Mechanisms

In this section, I present the mechanism which I argue to be best suited to explain plagued regions' export success: investment-driven productivity growth. In response to labour scarcity (Step #1), producers increase the amount of investment capital they use relative to labour (Step #2). I suggest that producers respond to labour scarcity at the variety level but do not internalise that a sectorally increased investment capital-to-labour ratio increases productivity growth (Step #3). This step is not an endogenisation of productivity. Indeed, the procedure used in the literature to recover productivities requires the assumption of variety-level productivity draws from a given distribution (Costinot, Donaldson, and Komunjer, 2011) and views the distribution's scale parameters as fundamentals of the model. Rather than endogenising such fundamentals, origin-sector variation in trade data has then been projected on observables to assess the determinants of productivity (Chor, 2010). I suggest a general and a specific functional form that gives economic meaning to the recovered productivities. With sufficiently granular data, these functional forms could be tested precisely by projecting them on sector-region factor data and institutional controls as in Chor, 2010. As I have no data on regional capital stocks and other observables, I will instead regress recovered productivity growth on a plague dummy and mortality rates as a measure of the shock to factor proportions.

I suggest a general and a specific functional form to lend economic meaning to sectoral productivities. While producers take the variety-level draw $A_{ik}(\omega)$ as given, I suggest that the Fréchet distribution's scale parameters A_{ik}, which govern the average sectoral productivity, are a function of the sectoral investment capital-to-labour ratio $\frac{I_{ik}}{L_{ik}}$, a vector permitting permanent effects of shocks, H_{ik}, and sectoral, regional, and region-sector determinants x_i, x_k, x_{ik}:

$$A_{ik} = g\Big((\frac{I_{ik}}{L_{ik}})^{\beta_k}, H_{ik}, x_i, x_k, x_{ik} \Big). \tag{12}$$

The function g(.) is increasing in the investment capital-to-labour ratio, whose impact on productivity is scaled by β_k. Sectors differ in the degree to which increased investments can move productivities and technological barriers present the main hurdle. In the production of wheat, for example, investment in the early 18th century had limited effects on productivity, as no modern farm machinery was available. According to Gallardo and Sauer, 2018 and Coleman, 1956, the scope for capital investment to increase agricultural productivity was severely limited in this period, with most productivity-increasing devices centuries old. Atack, Margo, and Rhode, 2019 concludes that few technologies were available before the 19th century to increase productivities in labour-intensive manufacturing. In capital-intensive iron and steel making, on the other hand, investments into more efficient furnaces more readily translate into productivity improvements.

I account for potentially lasting effects of shocks and policies by introducing a vector H_{ik} at the region-sector level. While my model is static and not dynamic, this vector is supposed to allow for permanent productivity effects of shocks during my study period. Previous shocks, if they were persistent at all, will be absorbed by fixed effects below. While the absence of detailed data does not permit me to differentiate the underlying mechanisms that give rise to permanent productivity changes, this formulation generalises the arguments in Krugman, 1987, Juhász, 2018, and Lane, 2025. Learning-by-doing and scale effects are the likely drivers of my long-run findings.

As there are no sufficiently granular data for this period to test which elements of vectors x_i and x_k have a significant relationship with productivity, I instead absorb this variation with fixed effects. Origin-destination-time and destination-sector-time variation are absorbed when decomposing gravity equation 11. In my analysis below, I include origin-sector fixed effects to absorb the time-invariant part of vector x_{ik}. I also absorb area-sector-time variation with fixed effects, leaving only sector-time variation within areas. Further, I assume that in the short-run there are no effects of recent economic shocks, as learning-by-doing and other underlying mechanisms unobserved to me take time to materialise.

I then relate the remaining origin-sector-time variation to the plague as a proxy for the increased investment capital-to-labour ratio. The specific and short-run functional form I suggest simplifies the general form above by accordingly focusing on origin-sector variation:

$$A_{ik} = \Big(\frac{I_{ik}}{L_{ik}} \Big)^{\beta_k}. \tag{13}$$

This functional form is consistent with the general form above as long as the specified fixed effects indeed absorb the vectors x_i, x_k, and x_{ik} and as long as there are no short-run effects of recent shocks. Whenever I speak of plugging in a functional form for productivities, I will thus plug in this specific short-run functional form to illustrate the proposed mechanism.

Several microfoundations for this relationship can be proposed. Bustos, 2011 is conceptually closest. Relating her framework to mine, firms could choose between a capital-intensive and a labour-intensive technology, with the prior being more expensive such that only the more productive firms would choose it. After the plague, with capital becoming relatively cheaper, productivity growth and the observed shift into capital-intensive production can be rationalised through the lens of a heterogeneous firms model.

Further, learning by doing (Krugman, 1987), learning by exporting (Loecker, 2013), and cost discovery (Hausmann and Rodrik, 2003) can all micro-found my proposed mechanism. Faced with a labour supply shock, plagued regions have to experiment with new factor proportions and new products. In doing so, they may reap the benefits of learning by doing or exporting and may, through forced experimentation, discover their true comparative advantages. These all involve a higher capital-to-labour ratio and predict productivity growth. However, in the absence of more detailed production or firm data, I am unable to differentiate between these competing micro-foundations. I thus choose to work with the more general formulation above. Nonetheless, all of these micro-foundations would correctly be picked up as productivity growth by my approach below. Further, they all imply that comparative advantage patterns are not fully determined by fundamentals. In both senses, these micro-foundations are consistent with my proposed mechanism. Future work may be able to differentiate between these channels. I now introduce the three-step mechanism which I propose to explain the post-plague export boom.

Step #1: The Plague Induces Labour Scarcity

The plague reduced urban populations by 36% on average. I assume an average regional mortality rate of 20%.[18] Theoretically, plague-induced labour scarcity increases the relative price of labour. Equation 9 shows that the elasticity of wages with respect to sectoral employment is $\frac{-1}{1+\gamma_k\theta}$. Supposing $\gamma_k = 0.5$ and $\theta = 5$, a 36% decrease in sectoral employment therefore increases sectoral wages by 5.7%.

Empirical Evidence

Population data by Buringh, 2021 cover urban populations of larger cities every 50 years. I show that plagued cities' populations had recovered by 1750. Additionally, I propose the number of captains reporting to live in a region as a proxy providing annual data.[19] Appendix Figure 29 shows the results of an event study on the number of captains. Considering the pre-plague average of 15 captains per region and year, the point estimates for the plague represent a 50% population drop. Further, the number of captains climbs back to pre-plague levels after 15 years. Thus, this proxy overstates both the population shock and recovery, as captains were highly skilled and mobile. Nonetheless, Appendix Figure 29 confirms the drop in population followed by a gradual recovery.

As to wages, model-based wage rises are low compared to what has been found for the Black Death at a similar mortality rate (Jedwab, Johnson, and Koyama, 2022).

[18] This is in the middle between the upper and lower bound. The mortality estimates in Appendix Table 9 pertain to cities, not regions. As Voigtländer and Voth, 2012, I assume that mortality rates where on average lower in hinterlands. Assuming the median urban mortality rate of 36% to hold for regional population L_i is thus an upper bound. Bairoch, Batou, and Chèvre, 1988 finds a European urbanisation rate of 11.4% in 1700, similar to the 11.9% in Vries, 2013. As a lower bound, if there had been no mortality in the hinterland, regional mortality would lie at 4.3%.

[19] This is a self-reported variable in the Soundtoll data and interpreted as the home port as in Marczinek, Maurer, and Rauch, 2025. To only count captains once, I omit observations in which first name, last name, and region are duplicates in a given year.

While the capital-to-labour ratio rose also after the Black Death, Jedwab, Johnson, and Koyama, 2022 caution against concluding immediate wage increases. From a Smithian perspective, high mortality disrupted trade and increased transaction cost. This process of disintermediation should affect those sectors most whose productivity depends on extensive division of labour. They show that real wages in England and Spain dropped immediately after the Black Death. This very short run response lasted only two years, however. Following Alfani and Murphy, 2017, I suggest that market unravelling would have lasted even shorter after the Great Northern War plague outbreak as institutions were better prepared for a mortality shock. I conclude that increased labour scarcity translated almost immediately into higher wages.

There is evidence from the Black Death that wage increases were real and increased living standards. Broadberry et al., 2014 show that dairy and meat provided a larger share of calories in England after the plague. Galofré-Vilà, Hinde, and Meera Guntupalli, 2018 document an average height increase of 6.59 cm between 1348 and 1400. Both of these findings are consistent with higher real wages after the plague. Pfister, 2017 provides evidence closer to my setting in both time and space: real wages of unskilled urban male labourers in Germany doubled as the Thirty Years' War induced labour scarcity through war and plagues.

Step #2: Production Becomes More Capital-Intensive

Labour scarcity was followed by an increase in capital and investment capital intensity along two margins. First, higher capital-to-labour ratios were used:

$$\frac{K_{ik}}{L_{ik}} = \frac{\eta_k}{\gamma_k r} w_{ik},$$
$$\frac{I_{ik}}{L_{ik}} = \frac{1-\gamma_k-\eta_k}{\gamma_k i} w_{ik}.$$

Second, a shift into capital-intensive sectors occurs. I pick the example of labour-intensive and capital-intensive manufacturing and introduce the specific functional form for sectoral productivities in equation 13. Taking ratios of gravity equation 10 and plugging in equations 13 and factor market clearing yields:

$$\frac{X_{ijCM}}{X_{ijLM}} = \xi w_{iM}^{-\theta(\gamma_{CM}-\gamma_{LM})} w_{iM}^{\beta_{CM}-\beta_{LM}} \frac{CMA_{jLM}}{CMA_{jCM}}.^{20} \tag{14}$$

The second shift is a result of three channels. First, capital-intensive sectors expand as they have smaller labour shares. This is the first term in equation 14, $w_{iM}^{-\theta(\gamma_{CM}-\gamma_{LM})}$, and follows immediately from the fact that the input bundle used in capital-intensive sectors has a smaller labour share. This is the **labour cost channel**, which is switched off when setting $\gamma_k = \gamma \forall k$.

Second, capital-intensive sectors expand as higher wages increase the investment capital-to-labour ratio. This, in turn, increases productivities as per assumption 13. For $\beta_{CM} > \beta_{LM}$, the increased investment capital-to-labour ratio increases productivity in capital-intensive manufacturing more than in labour-intensive manufacturing. This

[20] $\xi = \frac{\left(\frac{1-\gamma_{CM}-\eta_{CM}}{\gamma_{CM} i}\right)^{\beta_{CM}}}{\left(\frac{1-\gamma_{LM}-\eta_{LM}}{\gamma_{LM} i}\right)^{\beta_{LM}}} \frac{\alpha_{CM}}{\alpha_{LM}} \frac{\chi_{CM}}{\chi_{LM}} \left(\frac{d_{ijCM}}{d_{ijLM}}\right)^{-\theta}$

results in the term $w_{iM}^{\beta_{CM}-\beta_{LM}}$ in equation 14. This **productivity channel** will further increase the expansion of capital-intensive sectors.

In general equilibrium, there is a third channel operating on the demand side in unplagued destination j. The ratio $\frac{CMA_{jLM}}{CMA_{jCM}}$ will decrease, counteracting to some extent the shift into capital-intensive exports. The plague-induced manufacturing wage increase weighs more heavily on the contribution an origin makes to a destination's market access in a labour-intensive sector. Beyond that, differences in β may lead to slower productivity growth in labour-intensive sectors. Both work to decrease the ratio $\frac{CMA_{jLM}}{CMA_{jCM}}$. In other words, plagued regions' labour scarcity and productivity advances increase the relative prices of labour-intensive compared to capital-intensive goods. This relative price channel reduces the value of capital-intensive exports to j compared to labour-intensive exports. I control for this channel by estimating equation 2 with destination-time fixed effects.

Capital Stocks

How did capital stocks respond to labour scarcity? Combining market clearing conditions and sectoral wages 9 reveals:

$$K_{ik} = \frac{\eta_k \zeta_k}{\gamma_k r} \Big(A_{ik} FMA_{ik} \Big)^{\frac{1}{1+\gamma_k \theta}} L_{ik}^{\frac{\gamma_k \theta}{1+\gamma_k \theta}}. \tag{15}$$

Equation 15 thus confirms that capital stocks drop with sectoral employment, but less than one for one, as the elasticity is $\frac{\gamma_k \theta}{1+\gamma_k \theta} < 1$. While capital stocks decrease - post-plague capital is so abundant that to earn return rate r some of it freely flows to other regions - this elasticity explains why the capital-to-labour ratio increases. The same result can be established for investment capital.

While no administrative or firm data are available to test this feature, I employ a proxy for regional capital stocks: the number of ships owned in a region.[21] Ships are an expensive infrastructure investment and highly mobile.[22] Appendix Table 26 shows that the plague led to a larger number of ships registered in a region, which I interpret as an indication of capital accumulation. Focussing on the time path, Appendix Figure 30 shows that for two decades during and after the plague, significantly less ships were registered in plagued regions' harbours. 50 years after the plague, there were significantly more ships registered in previously plagued regions' harbours, and this higher capital stock remained in place until the mid 19th century. The model showed that capital stocks decline with population, but with an elasticity of less than 1. Indeed, the number of ships declined less and recovered faster than the number of captains, implying an increased capital-to-labour ratio.

Empirical Evidence

In trade data, the shift *across* sectors is observable: Figure 3 shows that exports of capital-intensive goods rise compared to labour-intensive goods. I find further historical evidence from farm-level data: farms shifted out of labour-intensive agriculture and into capital-intensive agriculture. I present a case study for the province of Scania in Southern

[21] I cannot differentiate this by sector. For expositonal clarity, I present theoretical results for sectoral capital stocks. The channels determining the allocation of regional capital stocks across sectors are again the labour cost and productivity channels.

[22] Note that the export expansion is not mechanically linked to an accumulation of ships. Merchants from other regions could sail to productive locations and ship their goods abroad.

Sweden. In 1712, Ystad and Malmö suffered plague outbreaks, with mortality rates of 38% and 35%, respectively. I draw on micro-data by Olsson and Svensson, 2017. Three products are consistently reported: rye and barley, which are labour-intensive, and calves, which are capital-intensive agriculture. Appendix Figure 31 shows that in the years after the plague, Scania's farms reduced their production of rye and barley and shifted significantly into raising calves.

This underscores that insights from trade data carry over to production data. The same pattern was observed in English agriculture after the Black Death (Clark, 2016). To test the link with labour scarcity, I construct for each farm i a measure of distance, $plaguedist_{it}$, to both Ystad and Malmö:

$$plaguedist_{it} = \Sigma_j Distance_{ij} * Plague_{jt}. \tag{16}$$

Farms located closer to plagued Ystad or Malmö will have lower values of $plaguedist_{it}$ after the plague hits. As the plague spread across space, I expect greater proximity to plagued cities to be associated with higher mortality. Accordingly, the shift into capital-intensive agriculture should be increasing in mortality and thus proximity to plagued cities. In Appendix Table 27, I regress production values of calves, rye, and barley on $plaguedist_{it}$ and find that proximity to plagued cities is associated with higher growth in calves production and lower growth in rye and barley production.[23] Thus, I find that the shift into capital-intensive production correlates positively with the degree of labour scarcity.

Innovation: Exports of new products increase after the plague.

While it is difficult to study increased investment and innovation in this period and at a sufficient level of granularity, I investigate novel export goods as they indicate innovation and investment into new production lines. The extensive margin expansion established in Appendix Figure 14b raises the question whether it is already previously produced or novel goods that are being exported. On the one hand, region may more intensely employ existing knowledge in that they more regularly export goods that previously they would have exported less frequently. On the other hand, regions may create new production knowledge, which I refer to as innovation. Initiating the production of these novel goods requires investment capital I_{ik}. After the plague, a higher investment capital-to-labour ratio may have permitted plagued regions to make precisely these investments. Innovation and investment would thus manifest themselves in an increased number of novel export goods. I partial out trade in goods that regions first exported between 1689, 20 years before the first year of the plague in my study area, and 1732, 20 years after the end of the plague.

Appendix Figure 32 shows that the number of new goods, not exported before the plague, increased significantly faster in plagued regions than in non-plagued ones. This link between innovation and labour scarcity finds empirical support in Andersson, Karadja, and Prawitz, 2020. Novel export goods contribute a quarter to the overall extensive margin expansion shown in Appendix Figure 14b. Crucially, Appendix Figure 24c shows that the novel export goods are significantly more frequent in capital-intensive sectors. By implication, capital-intensive sectors see significantly more innovation. Results at the

[23]Note that the overall regional trend out of rye and barley and into calves is accounted for by Scania-wide time trends.

goods level are shown in Appendix Figure 25. Appendix Tables 17 and 18 show PPML results.

This finding implies that even after 20 years, plagued regions continue to innovate more than non-plagued ones. The time path suggests that plagued regions began to produce and export a large number of new goods but eventually converged to a subset of the most successful ones. This pattern can be rationalised through forced experimentation, with labour scarcity pushing regions to experiment with new goods. Consistent with a time lag in observed novel export goods, Juhász, Squicciarini, and Voigtländer, 2024 find that the reorganisation of production takes time. They argue for a process of trial and error followed by the diffusion of best practices across firms. In my case, one can therefore suppose an immediate push to experiment with new products that became visible in export data only with a time lag as production knowledge takes time to spread.

Step #3: Productivity Grows More in High β_k Sectors

I propose that an increased investment capital-to-labour ratio raises productivity growth. With both the labour cost and the productivity channels active, I am unable to recover productivity growth. Similarly, serfdom complicates the separation of wages from productivities. In the remainder of this section, I therefore make two assumptions to recover productivity growth as detailed in Appendix D.1:

1. All sectors have the same labour share, $\gamma_k = \gamma \forall k$.[24]
2. The labour mobility friction does not vary within but only across areas, such that $\phi_{ikt} = \phi_{jkt} \forall (k, t)$ and i,j within the same area.[25]

My assumption is that sectors differ in the efficiency with which they translate a higher investment capital-to-labour ratio into productivity gains. Above I suggested an economic interpretation of productivities. As discussed there, I do not endogenise productivity but instead propose a formal relationship that determines productivity as a function of factor proportions, where regional, sectoral, time-invariant region-sectoral, and time-varying area-sectoral determinants are absorbed by fixed effects. I also assume that there are no short-run productivity effects of recent shocks. To illustrate the suggested productivity channel, I focus on the specific short-run functional form in equation 13:

$$A_{ik} = \left(\frac{I_{ik}}{L_{ik}}\right)^{\beta_k}.$$

If all sectors were to operate the same production function, proportionate shifts into investment capital would still produce different productivity gains: sectors with higher β_k efficiencies see faster productivity growth. I expect this efficiency to be higher in capital-intensive than in labour-intensive sectors. At the time, few machines and technologies existed in labour-intensive agriculture and labour-intensive manufacturing that could have led to investments increasing productivity growth (Atack, Margo, and Rhode, 2019, Gallardo and Sauer, 2018, Coleman, 1956). To test the impact of the plague on sectoral

[24] An especially strong assumption would be to also let $\eta_k = \eta \forall k$. All sectors would then operate the exact same production function. Capital-intensity as defined above then comes no longer down to different factor shares, but solely to different efficiencies β_k with which sectors turn investment capital-to-labour increases into productivity growth.

[25] An alternative assumption is discussed in Appendix D.1.

productivity growth in the short-run, I estimate equation 17 on data between 1668 and 1749:[26]

$$\text{productivity growth}_{ikt} = \delta_k plague_{it} + \alpha_{ik} + \alpha_{akt} + \epsilon_{ikt}, \tag{17}$$

where productivity growth$_{ikt} = \delta_{ikt}$ are the fixed effects recovered from equation 11.[27] α_{ik} are region-sector fixed effects, absorbing time-invariant region-sector-specific determinants of productivity, such as availability of resources or time-invariant institutions. α_{akt} are area-sector-time fixed effects, absorbing area-wide time variation in sectoral productivity. These absorb sectoral productivity growth across an entire area, such that I compare the plague's effects of productivity growth within an area.[28] Examples of this are area- and country-wide economic and trade policies. Crucially, if there is time variation in the serfdom-induced mobility friction, these are absorbed by α_{akt} as long as they do not vary within areas. The fixed effects α_{ik} and α_{akt} thus absorb the time-invariant and area-level time-varying parts of vector x_{ik} in the general functional form for productivities in equation 12. ϵ_{ikt} are the error terms. δ_k is the coefficient on the plague.

Table 3 shows significant productivity growth in capital-intensive sectors after the plague. There are differences within agriculture and manufacturing depending on their capital-intensities. Capital-intensive agriculture sees significant productivity growth, whereas labour-intensive agriculture stagnates. Labour-intensive manufacturing productivity growth falls significantly, whereas capital-intensive manufacturing productivity growth accelerates.[29]

The difference between labour-intensive and capital-intensive sectors is indicative of different β_k values. Different productivity growth effects come down only to differences in β_k under the assumption that all sectors use the same production function and factor shares. In that case, the shift into investment capital in response to wage increases is symmetric across sectors, and can be expressed in terms of wage increases as follows:

$$log\Big(\frac{A_{ikt}}{A_{ikt'}}\Big) - log\Big(\frac{A_{ik't}}{A_{ik't'}}\Big) = \big(\beta_k - \beta_{k'}\big) log\Big(\frac{w_{it}}{w_{it'}}\Big). \tag{18}$$

Supposing a 50% wage increase, which is what Jedwab, Johnson, and Koyama, 2022 find for England 50 years after the 1348 Black Death, allows to back out:

$$\beta_{CM} - \beta_{LM} = 2.57$$
$$\beta_{CA} - \beta_{LA} = 3.24.$$

Thus, the extent to which capital-intensive agriculture is more efficient than labour-intensive agriculture at turning an increased investment capital-to-labour ratio into productivity gains is more than twice as large as the same comparison in manufacturing.

[26] By 1750, populations had recovered from the plague. In the short-run, I assume that recent shocks have no effect on productivities.

[27] As described in Appendix D.1, I pick unclassified goods, London, and the year 1668 as the reference sector, region, and time, such that $\delta_{ikt} = \frac{A_{ikt} A_{LON,k,1668} A_{i,U,1668} A_{LON,U,t}}{A_{i,k,1668} A_{LON,k,t} A_{i,U,t} A_{LON,U,1668}}$.

[28] 57 areas with 12 regions on average: provinces of Belgium, Finland, Ireland; regions of Denmark, England, France, Norway; states of Germany, each Baltic state, Scotland, and Wales, oblasts of Russia, autonomous communities of Spain, national areas of Sweden, and voivodeships of Poland. Details in Appendix B.

[29] As for all values, this is a statement of growth relative to the reference sector of unclassified goods. While productivity in levels is not identified, I suggest that labour-intensive manufacturing saw no overall productivity drop, as its investment capital-to-labour ratio also rose.

Table 3: Impact of plague on sectoral productivity growth, by sector and factor intensity

	Agriculture				Manufacturing			
	Labour-intensive		Capital-intensive		Labour-intensive		Capital-intensive	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Plague Dummy	-0.078		0.805***		-1.502***		0.236	
	(0.226)		(0.265)		(0.209)		(0.215)	
Mortality Rate		0.156		2.064***		-3.093***		0.898*
		(0.547)		(0.642)		(0.507)		(0.520)
Fixed Effects:								
– Region	✓	✓	✓	✓	✓	✓	✓	✓
– Area x Year	✓	✓	✓	✓	✓	✓	✓	✓
Observations	36,152	36,152	36,162	36,162	36,162	36,162	36,162	36,162

Notes: Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is log sectoral productivity growth. The independent variable is first a plague dummy that equals 1 for plagued regions after the plague hit. The second independent variable is the mortality rate, which for half of regions is imputed as the predicted value from regression results presented in Appendix Table 11. Denmark and Norway have been dropped from the sample as they reintroduced serfdom in 1733.

This may come down to technological barriers that are hard to overcome in manufacturing before the Industrial Revolution, limiting how capital-intensive manufacturing could use investment.

I find similar results when accounting for spatial correlation in productivity following Conley, 1999. In Appendix Figure 33, I repeat the regressions underlying Table 3 for distance cut-offs between 10 and 200 km in steps of 10 km. The negative effect on productivity in labour-intensive manufacturing is significant for the entire range, as is the positive effect for capital-intensive agriculture. Labour-intensive agriculture sees no significant productivity effect for any distance cut-off. Capital-intensive manufacturing, consistent with Table 3, sees weakly significant positive effects for small distance cut-offs only.

The assumption on the time-invariance of serfdom implies that Denmark and Norway are excluded in these results as they reintroduced serfdom in 1733. Appendix D.1 details how wage data by Gary et al., 2022 can be used to adjust manufacturing productivities in these areas for this change in serfdom. With this adjustment applied, Denmark and Norway can be included in the sample. Appendix Table 28 adjusts for the urban-rural wage wedge that appeared after the reintroduction of serfdom and finds very similar results to Table 3 above.

How did productivities respond once the adverse labour supply shock had been overcome? As shown in Appendix Table 12, plagued cities' populations had recovered by 1750, or about 40 years after the plague. I argue that the same is true for regional populations. I show in Appendix Figure 13 that the shift into capital-intensive exports persists for 90 years and in Appendix Figures 20a and 20b that the export expansion persists for 70 to 80 years. In Appendix Table 29, I expand this analysis to the recovered sectoral productivity growth figures. For both agriculture and manufacturing, there is an immediate significant productivity growth gap already in the first post-plague decade, with capital-intensive manufacturing (agriculture) seeing faster productivity growth than labour-intensive manufacturing (agriculture). While this gap never closes in manufacturing within a century of the plague, productivity growth in labour-intensive agriculture has caught up with capital-intensive agriculture after 90 years. Therefore, the plague-induced productivity changes persist for half a century longer than the underlying changes in factor proportions. This suggests that temporary shocks to factor proportions, captured by H_{ik} in the general interpretation of sectoral productivities, can produce persistent productivity changes.

Empirical Evidence

I now discuss historical evidence for productivity growth after the plague. The association between population loss and productivity increases relates to Clark, 2016, who shows in English wage and price data that the Black Death was followed by substantial efficiency gains. Broadberry et al., 2014, too, find that agricultural productivity rose significantly after the Black Death.

For this particular plague outbreak, Appendix Figure 34 shows a brief drop in total agricultural output per farm, adjusting for size, based on Scanian farm-level data by Olsson and Svensson, 2017. However, agricultural production surpasses pre-plague levels after a few years. Given that fewer workers are producing more agricultural products and that the size of farms is accounted for, this is consistent with a productivity effect. In Sweden overall, agricultural output per capita began a sustained increase only in the 1720s, a few years after the plague (Magnusson, 2007). There is evidence of increased adoption of machinery in this period, suggesting an increased investment capital-to-labour ratio. The post-plague decades in Sweden saw the adoption of metal ploughs, early threshing machines and modern farm building designs that improved the efficiency of raising live stock. Further, Swedish agriculture departed from strip farming in an overtly labour saving methodological shift.[30] While the historical literature does not permit to decompose this important shift by region, it is noticeable that plagued Scania stands out as an early adopter.

An important role is played by land reclamations. Magnusson, 2007 notes that historically, it was not the most fertile land that was farmed in Sweden, but the land that was most easily farmed. In the decades after the plague, historians observe land reclamations but no overall increase in the amount of cultivated land. Costly drainage systems were put in place to make fertile, yet inaccessible land suitable for farming. This required heavy investments that were not previously possible and may be reflective of a higher investment capital-to-labour ratio. Reclamations of fertile land imply that labour input was shifted onto on average more fertile farm land. The literature believes that this adjustment accounts for a large part of Sweden's observed post-plague productivity increases.

Sweden's industry, too, experienced growth. Textile factories became the biggest employers in Stockholm in the mid-18th century and Norrköping rose to be Sweden's Manchester. Textile schools spread throughout the land, increasing human capital levels in industrially relevant matters. One particular industry that saw important changes was ship building. Using data on ships from the Swedish East India company, I show in Appendix Figure 35 that the vast majority of ship yards built in Sweden after the plague years was built in previously plagued regions, indicating high relative amounts of investment capital.[31] These also accounted for the production of the largest and most

[30] Previously, farmers had to sustain long commutes to individual strips of land that were intentionally scattered across the land so as to provide insurance to individuals by giving access to different soil types.

[31] Construction of the Polhemsdockan in Karlskrona began in 1717, five years after the plague hit the

productive ships, as measured by the number of successful trips to East Asia.

5.1 Factor Adjustments & Serfdom

How do factor mobility frictions affect the relationship between labour scarcity and productivity growth? History provides us with an institution that severely limited the mobility of labour between cities and their hinterlands: serfdom. In this section, I analyse how the proposed mechanism differs for regions with serfdom. I classify regions by their serfdom status as described in Section 2.3. Appendix Figure 9 displays this classification.

While serfdom had many facets, I focus on the fact that rural-to-urban migration was severely limited. This came down to several aspects. On the one hand, serfs were usually bound to their lords' lands, either explicitly or implicitly through expected labour contributions. Additionally, serfs were usually not permitted to learn a trade, limiting their outside options as moving to cities was relatively unattractive for unskilled farm workers. Finally, many areas that traditionally featured serfdom, such as modern-day Estonia and Latvia were divided along ethnic lines between cities and their hinterlands. Most cities in this area were founded and populated by German-speaking urbanites, whereas Latvian and Estonian were spoken in the hinterlands. Accordingly, formal institutions and cultural barriers limited the number of rural dwellers that would move to cities.

Full labour mobility between a region's rural and urban area implies wage equalisation. However, under mobility restrictions, higher mortality in cities leads to higher urban wages that are no longer equalised to those in the hinterland as peasants cannot move. Denmark and Norway present a testing ground for this hypothesis of wage equalisation as serfdom was re-introduced in 1733. I use data by Gary et al., 2022 to show that there was no wage gap between unskilled urban and rural workers before the re-introduction of serfdom in Denmark in 1733, consistent with free movement between these areas. After serfdom was brought back, a wage gap appears, with scarcer urban unskilled labour compensated significantly higher. Appendix Figure 8 compares nominal day wages in Danish skilling for farmhands and unskilled workers in Copenhagen. Specifically, this figure displays the ratio $wage_{ratio} = \frac{wage_{urban} - wage_{farm}}{wage_{farm}}$. While few observations are available before 1733, the picture that emerges is one of a significant post-serfdom urban wage premium, averaging 0.7 farm day wages. With full labour mobility, peasants would have moved to Copenhagen to benefit from these higher wages. Therefore, restricted labour mobility translates into an urban-rural wage wedge. I conceptualise this by assuming a wedge of ϕ_i between urban and rural wages: $w_{iM} = (1 + \phi_i)w_{iA}$.

While mortality rates were higher in cities (Voigtländer and Voth, 2012), labour mobility within a region would equalise labour scarcity across sectors. I refer to this form of labour scarcity as *absolute* labour scarcity, as for all sectors, labour has become scarce. With serfdom, however, labour mobility does not equalise labour scarcity. Beyond absolute labour scarcity, cities suffer from *relative* labour scarcity as workers from the hinterland cannot move to benefit from higher urban wages. Thus, labour is artificially scarce in cities and artificially abundant in rural areas. This *relative* labour scarcity manifests itself in a wage wedge.

Comparing two regions, one with and one without serfdom, with the same mortality rate, I therefore expect the share of workers in agriculture to be higher in the region with serfdom and the share of workers in manufacturing to be higher in the region without

city. This dry dock used pumps rather than tides and is considered by some the Eighth Wonder of the World.

serfdom. Plagued cities in regions with serfdom remain relatively scarcer in labour, whereas their rural counterparts become relatively abundant in labour. The strength of the shift into capital-intensive exports therefore depends on the presence of serfdom. I revisit the result from Step #3 above for both sectors:

$$\frac{X_{ijCM}}{X_{ijLM}} = \xi w_{iM}^{-\theta(\gamma_{CM}-\gamma_{LM})} w_{iM}^{\beta_{CM}-\beta_{LM}} \frac{CMA_{jLM}}{CMA_{jCM}},$$
$$\frac{X_{ijCA}}{X_{ijLA}} = \xi w_{iA}^{-\theta(\gamma_{CA}-\gamma_{LA})} w_{iA}^{\beta_{CA}-\beta_{LA}} \frac{CMA_{jLA}}{CMA_{jCA}}.$$

With urban wages increasing more with serfdom than without, the ratio $\frac{X_{ijCM}}{X_{ijLM}}$ should increase more in regions with serfdom. Agriculture becomes relatively abundant in labour, leading to lower agricultural wage increases in areas with serfdom than in those without. Accordingly, the ratio $\frac{X_{ijCA}}{X_{ijLA}}$ should increase less in regions with serfdom. I put this prediction to the test and estimate:

$$\begin{aligned} T_{ift} = {} & \delta_p plague_{it} + \delta_{ps} serfdom_i \text{ x } plague_{it} + \delta_{pf} factor_f \text{ x } plague_{it} \\ & + \delta_{pfs} serfdom_i \text{ x } plague_{it} \text{ x } factor_f + \alpha_{if} + \alpha_{ft} + \gamma x_{it} + \epsilon_{ijkt}, \end{aligned}$$

where T_{ift} are exports by factor intensity, α_{if} are origin-factor fixed effects and α_{ft} are factor-time fixed effects. ϵ_{ift} denotes the error term. δ are the coefficients of interest displayed in Appendix Table 30. δ_{pfs} is the most interesting coefficient as it measures how the effects of labour scarcity on capital-intensive exports vary by the presence of second serfdom. The results in Appendix Table 30 confirm this expectation. The plague's effect on the capital intensity of exports is significantly higher in manufacturing under serfdom. This reflects *relative* labour scarcity.

Both manufacturing sectors should see faster productivity growth under serfdom, as they are artificially labour-constrained and see larger increases in the investment capital-to-labour ratio. The opposite is true for agriculture, where the incentives for employing more (investment) capital are smaller under serfdom as labour is artificially abundant. Appendix Tables 31 and 32 test this prediction and find no evidence supporting this conjecture. As the shift into higher capital intensity takes place, I speculate that the missing element are learning and scale effects, hampered by insufficient population mobility.

Historical evidence confirms that agricultural productivities evolved differently under serfdom. In particular, the recovery of Russia and the Baltics shows different patterns from Sweden. Broadberry and Korchmina, 2024 note that Russian agricultural output per capita was no different in 1800 than it was in 1700. There is no evidence that strip farming was abandoned in Russia, unlike in Sweden, where this change was made to save labour. Relative labour abundance in serfdom-dominated areas simply may not have necessitated changes to production methods. Crop rotation and new farming machinery also only show up towards the end of the 18th century in Russia, far later than in Sweden. Magnusson, 2007 suggests that this is not driven by the availability of tools through trade, as he shows that all of Sweden could have had access to modern tools but not all areas adopted it. This suggests that for Russia, too, this was a choice. The agricultural history of Prussia, which also had serfdom, paints a similar picture of no change after the plague.

5.2 Alternative Mechanisms

This section discusses three alternative mechanisms that could produce the observed export boom after the plague. I argue that directed technical change (Acemoglu, 2002) is theoretically compatible with my findings, but present historical evidence against the presence of a factor bias in technical change. I also discuss the phenomenon of "venting out" and conclude that it is unlikely to have been present after the plague. Relatedly, I show that plagued ports' export prices dropped, suggesting that increased market power does not contribute to my findings. Finally, I test for the presence of non-homotheticity (Fieler, 2011).

Directed Technical Change

Acemoglu, 2002 shows that the factor bias of technical change is governed by the relative strength of two effects: a price and a market size effect. In my model, these channels cancel out and technology is not factor biased. Acemoglu, 2010 shows that labour scarcity increases the rate of technological progress if technological change reduces the marginal product of labour. In recent work, Alfaro et al., 2024 study a policy-induced scarcity of rare earths in downstream industries. They find that affected industries see faster TFP growth as a result of directed innovation to save rare earths.

Under these frameworks, labour scarcity could lead to directed technical change and productivity growth. Thus, conceptually their findings are consistent with the mechanism proposed in my paper. However, I argue that history does not support the presence of a labour-saving factor bias in the period studied. Gallardo and Sauer, 2018 argue that labour-saving mechanisation in crop agriculture began succeeding only in the 19th century. An early example of a crop harvesting machine that explicitly substituted labour for capital was the cotton gin by American inventor Eli Whitney, patented only in 1794. Focusing on the 17th century in England, Coleman, 1956 argues that labour-saving technologies in agriculture were practically non-existent. Those that existed, such as mills, spinning wheels, and water-powered blast furnaces, were centuries old and not a testament to a changed factor bias in technological improvements. In manufacturing, Atack, Margo, and Rhode, 2019 document how innovative machinery consolidated multiple hand tasks into a single machine task. They consider this the most labour-saving type of technological transition, which, however, only came to bear during the 19th century. Coleman, 1956 further argues for a political determination to absorb rather than substitute labour in this period, resulting in opposition to the development of labour-saving devices in agriculture and manufacturing alike. Thus, I consider the historical evidence to point towards unbiased technical change.

Venting Out & Market Power

Almunia et al., 2021 find that a domestic demand slump during the Great Recession was accompanied by increased exports. They show in Spanish firm-level data that the larger a firm's domestic sales decline, the larger was their increase in exports. They term this phenomenon "venting out". Under constant marginal costs, venting out cannot be explained. Instead, the authors suggest a model with flexible inputs, whose usage was reduced as domestic demand fell. Using less flexible inputs reduced short-run marginal costs, permitting an increase in exports.

This historical setting provides an ideal testing ground for venting out: while the Black

Death hit all of Europe, the 1708-1714 plague outbreak left most of Europe as unperturbed export markets to counteract the local demand shock of the plague. Under venting out, regions would reduce their short-run marginal costs. This increases competitiveness and exports in line with my findings.

I suggest the time dimension as a crucial difference, however. Almunia et al., 2021 find an almost immediate response of exports to domestic demand, this paper documents a five year gap between the plague and the export expansion. Further, while Almunia et al., 2021 track Spanish exports for four years, this paper studies trade for decades after the plague. Short-run marginal costs are unlikely to explain this persistent export boom.

Market power may reconcile short-run marginal cost changes with long-run market share gains. If plagued regions capture market shares through lower marginal costs, a combination of market power and switching costs could explain persistent market share gains. However, I present evidence in Appendix Table 35 that export prices of plagued origins drop significantly. While in the short-run this may be explained through venting out, export prices of capital-intensive goods continue to fall for 30 years. This pattern is incompatible with increased market power.

Thus, over the long-run, an additional force is required to keep marginal costs from rising again. I postulate that productivity growth is precisely this force. The shift into capital-intensive exports, unlike the export expansion, indeed appears in the data almost immediately after the plague struck.

Non-Homotheticity

The leading alternative driver of post-plague economic adjustments is non-homothetic demand. Under non-homothetic demand, demand can shift relatively into more income-elastic goods after labour scarcity led to real wage gains. The model I work with has Cobb-Douglas upper tier demand shares and is, as such, one of homothetic demand.

Voigtländer and Voth, 2012 place non-homothetic demand at the centre of their argument. The authors study the much earlier Black Death of 1346, which encompassed all of Europe. Therefore, my paper is not a test of Voigtländer and Voth, 2012. However, as non-homothetic demand is frequently discussed in this context, I gather evidence that it played no role for this outbreak. In Voigtländer and Voth, 2012, wage increases represent a positive demand shock for income-elastic goods. In my setting, it seems reasonable to assume that capital-intensive agriculture (manufacturing) is more income-elastic than labour-intensive agriculture (manufacturing).

First, I show that my finding on productivity growth is robust to permitting non-homothetic demand. Fieler, 2011 provides a trade model with non-homotheticity which allows a neat mapping onto my model under the assumption that $\theta_k = \theta \forall k$, i.e. a fixed intra-industry heterogeneity in the Fréchet distribution. Even under non-homothetic preferences, her model then breaks down to an Eaton and Kortum, 2002 model:

$$X_{ijk} = \frac{\chi_k A_{ik} (w_{ik})^{-\gamma_k \theta} d_{ijk}^{-\theta}}{CMA_{jk}} X_{jk}, \tag{19}$$

where I no longer assume $X_{jk} = \alpha_k Y_j$. Note that δ_{jkt} in equation 11 still absorbs the demand side under non-homotheticity. Therefore, my findings on productivity growth are unaffected. The question is therefore not whether there is one or the other but whether there is both productivity growth and non-homotheticity.

Next, I analyse prices, as non-homothetic demand has tractable implications for relative prices of capital-intensive and labour-intensive goods. The prior should become more expensive compared to the latter. Crucially, the productivity channel advocated for in this paper produces the opposite relative price effect. Forming the ratio of the price indices for capital-intensive and labour-intensive (agricultural) goods in equation 7, I find:

$$\frac{P_{jCA}}{P_{jLA}} = \left(\frac{\chi_{CA} \Sigma_i A_{iCA} (w_{iA})^{-\gamma_{CA}\theta} d_{ij}^{-\theta}}{\chi_{LA} \Sigma_i A_{iLA} (w_{iA})^{-\gamma_{LA}\theta} d_{ij}^{-\theta}} \right)^{-\frac{1}{\theta}}, \tag{20}$$

where I impose $w_{iCA} = w_{iLA} = w_{iA}$ due to labour mobility in the agricultural sector and $d_{ijCA} = d_{ijLA} \forall (i,j)$. This ratio takes the same form in a general model of non-homothetic demand (Fieler, 2011) as in my model. I will differentiate between three types of prices. First, the price index at the regional level, which incorporates productivities, wages, and trade costs in all exporting regions. Trade costs and productivities in unplagued exporting regions do not change, but wages may as firm market access changes given productivity growth in plagued Baltic regions. I assume these changes to be small and scaled down by trade costs to North Sea regions. Productivities in plagued exporting regions change, but their trade with Baltic importers is not observed in my data. Unobserved trade within the Baltic will unequivocally lower the relative price of capital-intensive goods: certainly via the productivity channel and additionally via the labour cost channel if labour shares differ. Price data at the regional level should therefore show a relative decline in the price of capital-intensive goods. Note, however, that this confounds demand- and supply-side factors, limiting the ability of regional prices to speak for or against non-homotheticity.

I assemble price data at the regional level from Allen and Unger, 2018.[32] For plagued Danzig and unplagued Amsterdam, their dataset holds annual prices on 77 products, which I classify according to Appendix Table 4.[33] I show in Appendix Table 33 that labour-intensive agricultural and manufacturing prices rise in Danzig compared to Amsterdam and capital-intensive agricultural prices fall. This may reflect both the labour cost and productivity channels.

Voigtländer and Voth, 2012 make precisely the opposite prediction: a hump-shaped pattern of prices for plagued regions, with prices of capital-intensive goods increasing relative to those of labour-intensive goods. My results reject this prediction. If demand shifted relatively into capital-intensive agriculture, this should have increased its relative price. Instead, the relative price decline of capital-intensive goods supports a supply-driven explanation. These price results also reconcile the evidence that after the plague consumers received a higher share of their calories from meat and dairy (Broadberry et al., 2014) with my assumption of homothetic demand. As capital-intensive agricultural prices drop under constant consumption shares, consumers mechanically demand higher quantities of meat and dairy. Accordingly, non-homotheticity is not required to make sense of this finding.

Owing to the exceptional granularity of the Soundtoll data, I can also analyse export and import prices, which are the other two types of prices analysed. I construct prices at

[32] No data on goods I classify as capital-intensive manufacturing are containted in the data set and few for labour-intensive manufacturing.

[33] While the effects of labour scarcity were passed on to Amsterdam through trade, Amsterdam itself was not affected by the plague and faced higher trade costs to the regions that were plagued.

the bilateral level by unifying historical measures of account and dividing duty amounts by the recorded weight (available for 46% of passages), thus creating a comparable price per kilogram. I will refer to prices of goods sent to ports as import prices and to prices of goods sent from ports as export prices.

Import prices are only indirectly affected: productivities and trade costs in North Sea regions do not change; the indirect effects of firm market access changes on wages are small and weighted down by trade costs. In Appendix Table 34, I control for the supply side and show that relative prices of capital-intensive goods are unaffected by the importer's plague status. These importing prices are the relevant metric in my test for non-homotheticity below as they show no demand-driven relative price changes.

Export prices are directly affected by both the productivity and labour channels. If wages rise in plagued ports i and $\gamma_k < \gamma_{k'}$, the ratio $\frac{P_{jk}}{P_{jk'}}$ falls. Even if $\gamma_k = \gamma_{k'}$, the productivity channel will still produce a relative drop of capital-intensive export prices. In Appendix Table 35, this prediction is confirmed: the (relative) export prices of capital-intensive goods shipped from plagued origins decline significantly. When analysing the time path of this price diversion, I find that the relative drop in prices of capital-intensive goods intensifies over time.

Comparing import prices and export prices allows me to disentangle supply-side from demand-side factors. The null finding for import prices supports my claim that there is no evidence for non-homothetic demand; the significant findings on export prices support my claim of supply-side changes after the plague.[34]

Finally, I directly test for a demand shift in plagued regions. Instead of absorbing non-homothetic demand structures or comparing implied price changes, I test for the presence of non-homothetic demand. I form the ratio of equation 19 between any two sectors k and k', where I need to asssume $w_{ik} = w_{ik'}$ and $\gamma_k = \gamma_{k'}$, and take the ratio of this fraction between a pre-period p, 1700-1710, and any year t after the plague:

$$\frac{X_{ijkt}X_{ijk'p}}{X_{ijk't}X_{ijkp}} = \frac{A_{ikt}A_{ik'p}}{A_{ik't}A_{ikp}} \frac{X_{jkt}X_{jk'p}}{X_{jk't}X_{jkp}} \frac{CMA_{jk't}CMA_{jkp}}{CMA_{jkt}CMA_{jk'p}}. \tag{21}$$

Relative export volumes evolve as a function of relative productivity changes in the exporting region and two demand-side factors: relative demand and relative market access. In my analysis, I form the left-hand side based on trade data and absorb relative productivity changes with exporter-time fixed effects. The argument made above about the behaviour of relative import prices under non-homotheticity simplifies the demand side further. As consumer market access is a price index, the finding that for equal labour shares and wages in a region relative (import) prices do not change carries over to the ratio of consumer market access. This is true for import prices coming from unplagued North Sea ports, which is sufficient here as that is the only trade I observe. Thus, equation 21 simplifies as the final fraction drops out. In this case, I can directly test for the presence of non-homothetic demand while controlling for the supply side.

While the assumption on constant relative prices simplifies the demand side of equation 21, it actually works against me in that any changes in relative demand will be seen as evidence for non-homotheticity, even if they arise from relative market access changes.

[34]In this specification, I am unable to disentangle the productivity and labour cost channels. However, the decline of relative prices of capital-intensive goods intensifies over time. This is consistent with dynamic productivity gains, especially since populations recovered over time, lowering the relative contribution of the labour cost channel.

The only possibility for this ratio to obscure underlying relative demand shifts is a change in relative demand that is offset by a change in relative consumer market access.

I define the baseline period p as the years 1700 to 1710 and let t be any year after 1710. In essence, the variable I regress on is a double ratio: relative exports to j compared between any post-plague year t and the pre-plague period. To capture changes in the import ratio indicative of non-homotheticity, I present event study results in Appendix Figure 36 where I regress on the log of the left-hand side of equation 21. The independent variable is a dummy for a plague outbreak in the importing region. I absorb the productivity ratio by origin-time fixed effects and the time-invariant component in relative demand by destination fixed effects. I find no evidence of plague-related changes in relative demand. I conclude that there is no evidence supporting non-homotheticity in either price or trade data. Instead, both kinds of data support the supply-side changes advanced in this paper.

6 Counterfactual

In this counterfactual analysis, I shut down the productivity channel. I find that market shares of plagued regions would have contracted rather than expanded. As only Malthusian forces are at play, wages rise and competitiveness falls. I abstract from factor adjustments *across* sectors by focusing on one sector.

The outcome are market shares, where I plug in gravity equation 10, equation 9 for wages and equations 7 for firm and consumer market access to arrive at an equation defining market shares as a function of productivities, sectoral employment, trade costs, wages, and total income. I shut down the productivity channel, so A_{ik} is fixed.[35] Counterfactual market shares t years after the plague can then be decomposed into a time-invariant term, s_{ijkPRE}, that contains productivities, trade costs, and incomes, and a time-varying component reflecting sectoral employment changes:

$$s^c_{ijkt} = \frac{L_{ikt}}{L_{ikPRE}}^{\frac{\gamma_k\theta}{1+\gamma_k\theta}} s_{ijkPRE}. \tag{22}$$

As no annual population estimates are available, I suppose an upper bound for population recovery and impose exponential population growth.[36]

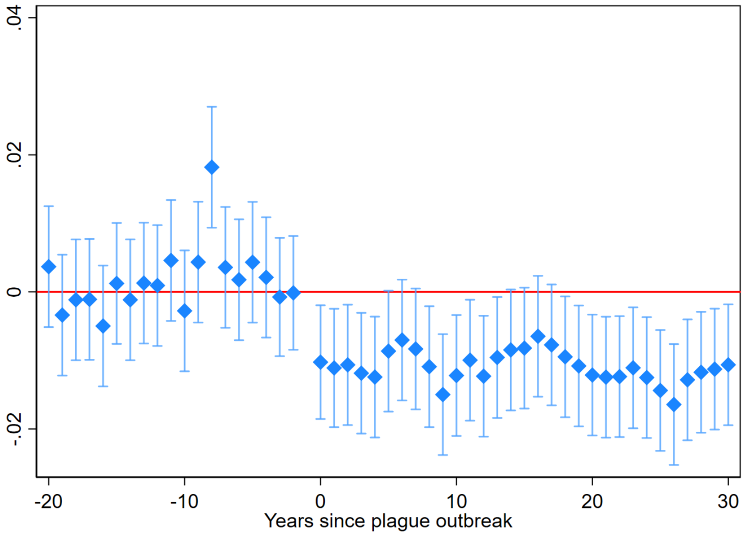
In Figure 5, I repeat the event study in equation 2 but replace post-plague export shares of plagued regions by the counterfactual shares calculated above. I find significantly lower export shares as a smaller population led to labour scarcity, higher wages, and lower competitiveness in destination markets. This stands in a stark contrast to my empirical findings and supports the prediction of Malthusian models.

[35] All other assumptions and justifications are in Appendix F.

[36] I show in Appendix F that for mortality rate m_i and 40 years as the upper bound:

$$s^c_{ijkt} = (1-m_i)^{\frac{\gamma_k\theta}{1+\gamma_k\theta}} \left(\frac{1}{1-m_i}\right)^{\frac{\frac{\gamma_k\theta t}{1+\gamma_k\theta}}{40}} s_{ijkPRE}. \tag{23}$$

Figure 5: Counterfactual market shares without productivity channel



Notes: Counterfactual export shares, shutting down productivity channel. Estimate equation 2 on counterfactual export shares after the plague and observed export shares before the plague.

7 Conclusion

This paper studies the relationship between labour scarcity and productivity growth. I establish novel empirical facts: First, capital-intensive exports expand relative to labour-intensive exports. Second, plagued regions expand their market shares in destination markets.

To conceptualise my findings, I build a Ricardian model. I suggest that productivity is a function of factor proportions, where other determinants are absorbed by fixed effects. From this model, I back out productivity and show that productivity growth in capital-intensive sectors accelerates. These productivity changes are in place for almost a century, even though populations had recovered after 40 years.

I also discuss alternative mechanisms and present arguments against them. In counterfactual analysis, I shut down the productivity channel and find that exports decline. The difference between this counterfactual export contraction and the observed export expansion adds plausibility to the proposed channel: productivity growth driven by capital deepening.

The findings of this paper suggest several take aways. Many industrialised economies grapple with persistently low productivity growth rates. At the same time, their societies are aging and preferences on working hours appear to be changing. Further, long-term health conditions are reducing labour force participation rates in several large economies (Di Meo and Eryilmaz, 2025). Thus, labour scarcity in industrialised economies reflects both declines in the working age population and in labour force participation. I argue that this labour scarcity can lead to productivity growth if agents adjust to factor price and comparative advantage changes.

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A Data Appendix

A.1 Commodities

This Appendix details how goods are constructed and classified. The Soundtoll data do not provide researchers with cleaned information on commodities. Instead, the variable ‘soort’ denotes the type of commodity simply in words, and specifically in the words of the custom official at the time. 143,855 separate goods descriptions are reported. The data are documented in Danish, which is further changing over time. I am using two sources to translate goods: first, the Soundtoll Project provides researchers with a list of proudcts, which holds 44 pages of (theoretically appearing) goods translated into English, Dutch, French, and Frisian. Many of them are very specific and do not actually exist in that spelling in the data. This document forms the basis of good classification, and the second source consulted are etymological dictionaries for Danish to ensure, as much as possible, that correct classifications are made. However, the list of products only classifies a small fraction of goods due to the variety in spelling and unstructured nature of the goods variable. Standard text analysis is not suitable for this cleaning task, as these data are in a time-varying version of Danish and a lot of similar sounding words introduce complexity and require intuition, as closest neighbour matching can be highly misleading. I now explain how I approach the manual classification of goods. I clean spellings and create unified ‘goods’ as outlined below.

There are a couple of general issues with these text data, which lead me to specific approaches when cleaning the data and classifying goods:

1. The Danish special characters ‘ø’ and ‘æ’ are more often than not coded incorrectly. **Cleaning needs to take account of special characters.**

2. The data are unstructured and not concise. While sometimes ‘wheat’ is denoted, usually it is something like ‘wheat from Livland’ or ‘two tons of wheat’. **Cleaning cannot use just perfect matches, but needs to look for matching substrings.**

3. Goods names are contained within each other. For example, I can distinguish iron ore from iron and iron works. The more general category should be searched for first, therefore, so that iron works are not accidentally classified as iron. **The order of substring matching matters.**

4. Goods vary greatly in their specificity. While sometimes just ‘goods’ or ‘fish’ is denoted, I also regularly find ‘goods from Greenland’ and specific types of fish. When the distinction carries meaning, I distinguish these. **Some goods are bundled and others are highly specific.**

5. Goods are spelled in a great variety of ways. This concerns similar vowels, double or single consonants, and also language-specific terms. **A variety of close matches needs to be considered.**

6. Goods sometimes cannot be distinguished. Plums, ‘pruneller’, are very close to a type of textile, ‘prynellen’. **Discretion needs to be applied at points.**

Following these approaches, I arrive at 227 goods, 8 out of which only exist in the early trade data without bilateral coverage, and which therefore are never part of the analysis. In total, 143,855 goods descriptions are mapped onto 219 goods, so the average commodity appears in 9,000 variations. An example of different spellings is sturgeon, appearing in four variations: Stor, Større, Støre, and Stører. Another example of varieties of goods and spellings is iron, of which there are six variations: jerren, jeern, jern, jeren, osmundt jern, and osmunds jern, where the latter two denote specifically Swedish iron. Many variations in fact contain information on value or amounts: lead oxide appears in 15 variations, six of which specify value, e.g. 'gleide 3 ort' and 'gleide a 6 skilling'.

Sometimes, a number of goods is reported, e.g. 'wheat and chestnuts'. This is surprising, as usually a tax official would note goods line by line. In fact, it only applies to 104,132 out of over 3.66 million shipments, so about 2.8%.[37] These shipments capture 2.5% of shipped value. The issue this introduces is, like in the case where several cities are reported, that the researcher cannot discern which value accrues to either of the goods. Besides the relative uncommonness of this, there are two more reasons not to worry: for one, these two goods are usually within the same category. This may have been one of the reasons for simply reporting them at once. The other reason is that these goods were regarded as substitutes by tax officials, that is, they carried the same relative duties, and only for this reason were reported together in one line rather than separately.

There are some goods which appear both in an aggregated and in a disaggregated form in the data: there are both 'textiles' and 'woollen textiles'. Rather than aggregating them up, I code goods as granularly as I can. Evidently, when aggregating into agricultural or manufacturing goods, both textiles and woollen textiles will be in the same category. The most important bundled categories in the original data are textiles, fish, and goods. The latter is simply not further specified, and thus distinguishing English goods from French goods captures the only difference, and I accordingly code these as different goods, even though I will later aggregate them into a group of unspecified goods. For fish, I find that often the data just speak of fish, and on occasion they are very specific, e.g. 'lings'. The approach I follow is to code as specific as I can, so individual types of fish are their own good, and the compound category of fish contains all types that are not further specified in the original data.

For textiles, I distinguish raw materials (cotton, linen, wool) from processed textiles (band, gaze, ribbon, yarn, tissue, stockings), luxury textiles (flannel, satin, silk, velours, velvet) and naval textiles (sail/canvas, flag cloth). In cases where the data are insufficiently specific, I use compound categories (cloth, cotton textile, woollen textile). The compound categories distinguish, if possible, at least by cotton and wool. The good 'clothes' contains all types of fabric, textile, and clothes which are not further distinguishable, either by material or by degree of processing.

As mentioned above, the order of partial matching matters: as one example, 'haardug' is a woollen textile. For this specific case, 'haardug' contains 'haar' and is thus first classified as hair. I then classify all goods containing 'dug' into the compound category of cloth, so 'haardug' moves from hair to cloth. Then, when a perfect match of 'haardug' is encountered, the good is instead classified as a woollen textile, which is the correct match.

I then construct five sectors: labour-intensive agriculture, capital-intensive agriculture, labour-intensive manufacturing, capital-intensive manufacturing, and the remaining sector of unclassified goods. I distinguish agricultural from manufacturing goods based on their likely location of production, namely the countryside rather than the city. Capital-intensive goods require a high amount of capital that cannot be swapped for labour. This

[37] Counting as double whenever 'og' (also) or 'etc' are contained in a goods description.

capital may consist of factories, furnaces, machinery, or tools necessary to produce the good. Labour-intensive goods are limited in the degree to which labour can be saved in their production. Labour-intensive agriculture is all of arable farming, whereas pastoral farming, mining, and processed foods including alcohols are capital-intensive agriculture. Labour-intensive manufacturing are largely textiles. Capital-intensive manufacturing produces goods such as processed metals, tools, and ship building materials. All 227 goods, accompanied by an assignment into the four sectors, are reported in Table 4. 2% of traded value is in unclassified goods, 99% of which are generic goods and mercery. This implies that 98% of traded value is assigned into goods.

Table 5 ranks the 30 most common goods traded between 1668 and 1750, which together make up 90% of the value of trade.

Table 4: Goods Classification

Animals	Capital-int. ag.	Rhine Wine	Capital-int. ag.	Ship Nails	Capital-int. man.	Tea	Labour-int. ag.
Arrack	Capital-int. ag.	Rum	Capital-int. ag.	Soda	Capital-int. man.	Tobacco	Labour-int. ag.
Beef	Capital-int. ag.	Salmon	Capital-int. ag.	Staves	Capital-int. man.	Trees	Labour-int. ag.
Beer	Capital-int. ag.	Salpeter	Capital-int. ag.	Steel	Capital-int. man.	Wheat	Labour-int. ag.
Bones	Capital-int. ag.	Salt	Capital-int. ag.	Swords	Capital-int. man.	Wood	Labour-int. ag.
Brandy	Capital-int. ag.	Seed	Capital-int. ag.	Tar	Capital-int. man.	Baize	Labour-int. man.
Bread	Capital-int. ag.	Sekt	Capital-int. ag.	Tiles	Capital-int. man.	Band	Labour-int. man.
Bristles	Capital-int. ag.	Soap	Capital-int. ag.	Tools	Capital-int. man.	Bay	Labour-int. man.
Buckling	Capital-int. ag.	Sprat	Capital-int. ag.	Turpentine	Capital-int. man.	Bowls	Labour-int. man.
Butter	Capital-int. ag.	Starch	Capital-int. ag.	Almonds	Labour-int. ag.	Chests	Labour-int. man.
Caviare	Capital-int. ag.	Stockfish	Capital-int. ag.	Amber	Labour-int. ag.	Cloth	Labour-int. man.
Chalk	Capital-int. ag.	Stones	Capital-int. ag.	Anise	Labour-int. ag.	Confectionaries	Labour-int. man.
Cheese	Capital-int. ag.	Sturgeon	Capital-int. ag.	Apples	Labour-int. ag.	Cotton Textile	Labour-int. man.
Cidre	Capital-int. ag.	Sulphur	Capital-int. ag.	Barley	Labour-int. ag.	Flag Cloth	Labour-int. man.
Coal	Capital-int. ag.	Talcum	Capital-int. ag.	Beans	Labour-int. ag.	Flannel	Labour-int. man.
Codfish	Capital-int. ag.	Tartar	Capital-int. ag.	Bushel	Labour-int. ag.	Folio	Labour-int. man.
Copper	Capital-int. ag.	Tin	Capital-int. ag.	Capers	Labour-int. ag.	Furniture	Labour-int. man.
Downs	Capital-int. ag.	Tow	Capital-int. ag.	Cardamon	Labour-int. ag.	Gaze	Labour-int. man.
Dye	Capital-int. ag.	Train Oil	Capital-int. ag.	Chestnuts	Labour-int. ag.	Gloves	Labour-int. man.
Eal	Capital-int. ag.	Treacle	Capital-int. ag.	Cinnamon	Labour-int. ag.	Hat	Labour-int. man.
Feather	Capital-int. ag.	Vetch	Capital-int. ag.	Cloves	Labour-int. ag.	Lace	Labour-int. man.
Fish	Capital-int. ag.	Vinegar	Capital-int. ag.	Cocoa	Labour-int. ag.	Lamps	Labour-int. man.
Flounders	Capital-int. ag.	Vitriol	Capital-int. ag.	Coffee	Labour-int. ag.	Linnen	Labour-int. man.
Flour	Capital-int. ag.	Wax	Capital-int. ag.	Cork	Labour-int. ag.	Mats	Labour-int. man.
Fur And Skin	Capital-int. ag.	Wine	Capital-int. ag.	Cotton	Labour-int. ag.	Paper	Labour-int. man.
Gin	Capital-int. ag.	Wool	Capital-int. ag.	Cucumbers	Labour-int. ag.	Ribbon	Labour-int. man.
Grass	Capital-int. ag.	Zinc	Capital-int. ag.	Dates	Labour-int. ag.	Ropes	Labour-int. man.
Gymsum	Capital-int. ag.	Alkali	Capital-int. man.	Dodder	Labour-int. ag.	Sail	Labour-int. man.
Haddock	Capital-int. ag.	Anchors	Capital-int. man.	Figs	Labour-int. ag.	Satin	Labour-int. man.
Hair	Capital-int. ag.	Ash	Capital-int. man.	Flax	Labour-int. ag.	Silk	Labour-int. man.
Ham	Capital-int. ag.	Barrels	Capital-int. man.	Frankincense	Labour-int. ag.	Spears	Labour-int. man.
Herring	Capital-int. ag.	Bells	Capital-int. man.	Fruit	Labour-int. ag.	Spokes	Labour-int. man.
Honey	Capital-int. ag.	Black Powder	Capital-int. man.	Ginger	Labour-int. ag.	Stockings	Labour-int. man.
Horn	Capital-int. ag.	Bottles	Capital-int. man.	Grapes	Labour-int. ag.	Tissue	Labour-int. man.
Horses And Horse Products	Capital-int. ag.	Bowsprits	Capital-int. man.	Groats	Labour-int. ag.	Trousers	Labour-int. man.
Iron	Capital-int. ag.	Brass	Capital-int. man.	Hemp And Hemp Products	Labour-int. ag.	Velours	Labour-int. man.
Lead	Capital-int. ag.	Brass Works	Capital-int. man.	Hops	Labour-int. ag.	Velvet	Labour-int. man.
Leadoxide	Capital-int. ag.	Bullets	Capital-int. man.	Ivory	Labour-int. ag.	Woollen Textile	Labour-int. man.
Leather	Capital-int. ag.	Cannons	Capital-int. man.	Juniper	Labour-int. ag.	Yarn	Labour-int. man.
Lings	Capital-int. ag.	Caps And Helmets	Capital-int. man.	Lemons	Labour-int. ag.	Ballast	Unclassified
Liquorice	Capital-int. ag.	Cement	Capital-int. man.	Linseed	Labour-int. ag.	Chinese Goods	Unclassified
Mackarel	Capital-int. ag.	China	Capital-int. man.	Millet	Labour-int. ag.	Comm	Unclassified
Malt	Capital-int. ag.	Glass	Capital-int. man.	Muscade	Labour-int. ag.	English Goods	Unclassified
Marble	Capital-int. ag.	Glue	Capital-int. man.	Nuts	Labour-int. ag.	Faroer Goods	Unclassified
Mead	Capital-int. ag.	Hoes And Shovles	Capital-int. man.	Oats	Labour-int. ag.	French Goods	Unclassified
Meat	Capital-int. ag.	Iron Works	Capital-int. man.	Olives	Labour-int. ag.	Goods	Unclassified
Mineral	Capital-int. ag.	Masts	Capital-int. man.	Peas	Labour-int. ag.	Icelandic Goods	Unclassified
Mustard	Capital-int. ag.	Medicine	Capital-int. man.	Pepper	Labour-int. ag.	Luggage	Unclassified
Oil	Capital-int. ag.	Nails	Capital-int. man.	Plums	Labour-int. ag.	Mercery	Unclassified
Ox Products	Capital-int. ag.	Oars	Capital-int. man.	Potatoes	Labour-int. ag.	Norwegian Goods	Unclassified
Oysters	Capital-int. ag.	Pipe Tools	Capital-int. man.	Resin	Labour-int. ag.	Provisions	Unclassified
Paint	Capital-int. ag.	Pipes	Capital-int. man.	Rice	Labour-int. ag.	Sailors	Unclassified
Pimento	Capital-int. ag.	Pistols	Capital-int. man.	Rubber	Labour-int. ag.	Ship Sully	Unclassified
Pollock	Capital-int. ag.	Pitch	Capital-int. man.	Rye	Labour-int. ag.	Soldiers	Unclassified
Quicksilver	Capital-int. ag.	Planks	Capital-int. man.	Safran	Labour-int. ag.	Swedish Goods	Unclassified
Raisins	Capital-int. ag.	Powder	Capital-int. man.	Spices	Labour-int. ag.	Waste	Unclassified
Rays	Capital-int. ag.	Sheet Metal	Capital-int. man.	Sugar	Labour-int. ag.		

Notes: List of 227 goods and classification into capital-intensive and labour-intensive agriculture and manufacturing, and unclassified goods.

Table 5: Top 30 goods by value

Good	Sector	Share of traded value	Cumulative share of traded value	Rank
Hemp	Labour-int. Agriculture	11.25	11.25	1
Rye	Labour-int. Agriculture	10.57	21.82	2
Salt	Capital-int. Agriculture	9.75	31.57	3
Wine	Capital-int. Agriculture	8.84	40.42	4
Wheat	Labour-int. Agriculture	8.63	49.05	5
Flax	Labour-int. Agriculture	6.1	55.15	6
Iron Works	Capital-int. Manufacturing	4.31	59.46	7
Iron	Capital-int. Agriculture	3.9	63.36	8
Tobacco	Labour-int. Agriculture	3.68	67.04	9
Planks	Capital-int. Manufacturing	3.22	70.27	10
Leather	Capital-int. Agriculture	2.81	73.07	11
Sugar	Labour-int. Agriculture	2.05	75.13	12
Unclassified	Unclassified	1.32	76.44	13
Ash	Capital-int. Manufacturing	1.22	77.67	14
Goods	Unclassified	1.22	78.88	15
Linnen	Labour-int. Manufacturing	1.14	80.03	16
Cloth	Labour-int. Manufacturing	1.12	81.14	17
Herring	Capital-int. Agriculture	1	82.14	18
Wax	Capital-int. Agriculture	.97	83.12	19
Brandy	Capital-int. Agriculture	.97	84.09	20
Barley	Labour-int. Agriculture	.8	84.89	21
Tow	Capital-int. Agriculture	.69	85.58	22
Wool	Capital-int. Agriculture	.68	86.26	23
Dye	Capital-int. Agriculture	.63	86.88	24
Tools	Capital-int. Manufacturing	.61	87.49	25
Silk	Labour-int. Manufacturing	.58	88.07	26
Wood	Labour-int. Agriculture	.56	88.62	27
Pepper	Labour-int. Agriculture	.55	89.17	28
Cotton	Labour-int. Agriculture	.48	89.65	29
Train Oil	Capital-int. Agriculture	.45	90.1	30

Notes: This table shows the top 30 goods by value of trade between 1668 and 1750.

A.2 Currencies

In principle, the Soundtoll Data contain a variety of coins in which toll transactions are recorded. Over all recorded passages, there are 40 types of coins, out of which 48.88% are Daler and 50.88% Skilling. These two are Danish coins, leaving only 0.24% of transactions to non-Danish currency. The use of non-Danish currency is, reassuringly, focused on earlier years, for which I lack destination information and which are therefore not included in the analysis. My data of bilateral trade flows start in 1668 and cover 4.38 million coin transactions, as an individual passage usually requires payment of an amount in full Daler and in fractions of a Daler, calculated in Skilling. From 1668 onwards, 48.8% of coin transactions are recorded in Daler and 51.2% are in Skilling. Out of 4.38 million transactions, 347 use the Ort and one uses the Rosenobel. An Ort is a quarter Daler, so 24 Skilling, and a Rosenobel is an English gold coin. When converting it based on its gold content compared to the Danish daler, I find that one Rosenobel corresponds to roughly 3.94 Daler or 378 Skilling. Given that only 0.008% of transactions in my data are recorded in non-Danish currencies, it is safe to declare foreign currency a non-issue in this data set. Table 6 records the conversion rates across the four currencies actually in use in these data.

Table 6: Currency conversion rates

	Daler	Skilling	Ort	Rosenobel
Daler	1	0.0104	0.25	3.94
Skilling		1	24	378
Ort			1	15.76
Rosenobel				1

A.3 Units

Table 7 lists the conversion of historical units of account into kilograms, liters, meters, and counts.

Table 7: Conversion of units of account

Amount	Unit	Commodity	Value
Kilogram	Boeter	Butter	3.96
Kilogram	Centner		50
Kilogram	Skippund		159
Kilogram	Quarter Skippund		39.75
Kilogram	Drompt		35.6
Kilogram	Faad		950
Kilogram	Half Faad		475
Kilogram	Quarter Faad		237.5
Kilogram	Sacker		165
Kilogram	Half Sacker		82.5
Kilogram	Tonder	Wheat, Rye, Barley	100
Kilogram	Tonder	Butter	112
Kilogram	Half Tonder	Wheat, Rye, Barley	50
Kilogram	Half Tonder	Butter	56
Kilogram	Kister	Tea	25
Kilogram	Half Kister	Tea	12.5
Kilogram	Quarter Kister	Tea	6.25
Kilogram	Pund		0.5
Kilogram	Lispund		8
Kilogram	Last		1905
Kilogram	Last	Hemp, Hops	952
Kilogram	Skaeppe	Rye, Wheat, Barley	12.5
Kilogram	Steen		15
Kilogram	Woger		17.856
Liter	Ahmer		150
Liter	Ancker		38.5
Liter	Boeter	Wine	585
Liter	Boeter	Oil	1225
Liter	Korff		24.8
Liter	Drompt		431
Liter	Faad		930
Liter	Half Faad		465
Liter	Quarter Faad		232.5
Liter	Flaske		0.7245
Liter	Tonder	Beer	131
Liter	Tonder	Salt	170
Liter	Tonder	Herring	108
Liter	Half Tonder	Beer	65.5
Liter	Half Tonder	Salt	85
Liter	Half Tonder	Herring	54
Liter	Oxehoffde		232
Liter	Oxehoffde	Beer Vinegar	197
Liter	Moyer		876
Liter	Ottinger		16.945
Liter	Piber		464
Liter	Quarter Piber		116
Liter	Skaeppe		17.39
Meter	Allen		0.63
Unit	Bale		1
Unit	Ladning		1
Unit	Ries		0.1
Unit	Quarter Bale		0.25
Unit	Double Bale		2
Unit	Daler		1
Unit	Gulden		1
Unit	Deger		10
Unit	Dosin		12
Unit	Fierdinger		0.25
Unit	Kister	Glass	120
Unit	Kister	Tin	225
Unit	Half Kister	Glass	60
Unit	Half Kister	Tin	112.5
Unit	Quarter Kister	Glass	30
Unit	Quarter Kister	Tin	56.25
Unit	Stocker		1
Unit	Half Stocker		0.5
Unit	Hundred		100
Unit	Ort		1
Unit	Paar		2
Unit	Ring		240
Unit	Skilling		1
Unit	Schock		60
Unit	Thilther		12
Unit	Thommer		40
Unit	Tylvt		12
Unit	Thussend		1000

A.4 Duties

I now turn to explaining the way in which duties are recorded in the data. For every passage, the type and amount of duty is recorded, and usually there are several duties payable, some fixed and some proportional. As an example, I picked passage number 304. This ship paid 4 Daler of fire money ('fyrpenge', a fixed fee for the maintenance of the lighthouse) and passed the Sound on April 27, 1790. Its captain, Daniel Wendlandt, citizen of Windau, received a captain's compensation of 1.5 Daler, which was deducted from the total duty payable. This is a proportional tax free allowance. The first sub-total is 37.5 Daler and a function only of proportional duties. I therefore call it proportional duty from now on. When subtracting the captain's allowance, the second sub-total comes to 36 Daler, and the total duty payable is 40 Daler, which is the net proportional duty plus the fire money of 4 Daler. The ship is going from Windau to Rotterdam with 75 last of rye; the recorded tax amount is 37.5 Daler, which equals the proportional duties, rather than the payable duties which account for the allowance and the fixed fee, and which is the basis for my value calculations. Table 8 shows the summation exercise.

Table 8: An example from the Soundtoll Data to show the different duties and sub-totals

Proportional duty	37.5 Daler
First sub-total	37.5 Daler
Captain's allowance	-1.5 Daler
Second sub-total	36 Daler
Fixed duty (fire money)	+4 Daler
Total payable duty	40 Daler

I now turn to describing the way in which the duty data are recorded. The Soundtoll team digitised the toll books in setting up three separate files.

1. The first one, called 'belastingen' or duties, records for each passage and good the name of the applied duty and the amount payable. This captures fixed duties that vary at most by the number of goods, but not by their value. The most common fixed duty is the fire money, or 'fyrpenge', at about 80% of all fixed duties. 64% of fire duty payments amount to 4 Daler and 24% to 2 Daler.

2. The second file, called 'ladingen' or carriage, records for each passage and good the origin and destination, the goods transported, and the overall amount of duty paid per good. The amount of duty given here corresponds to a sub-total of all duties, to be explained below. Importantly, I am using this sub-total for my value calculations, as it captures the cleanest function of true value, abstracting from fixed duties, which are by nature uninformative about shipped value, and from allowances and reductions.

3. The third data set is called 'doorvaarten', or passages. For every passage, it records the day of passage through the Sound, information on the captain, discounts (or 'korting') applied to the duty, and two sub-totals and a total. A 'korting' is a discount, 87% of which are 'føring', a compensation for the captain in terms of a tax free allowance at their disposal.

The duty amount I use as a proxy for value is the proportional duty, or the first sub-total. Waldinger, 2022, using the same data, focuses on the same proportional duty. It corresponds to the duty amount recorded in 'ladingen' and forms the basis of my value calculations, abstracting from both fixed duties and the 'korting'. The latter should not be taken off the sum as it reflects goods' value. When subtracting it from the proportional duty, however, we arrive at the second sub-total recorded in the books. The recorded total, on the other hand, equals this second sub-total plus the fixed duties, usually the fire money. This is the least suitable measure of value and captures the actual financial transaction in terms of paid duty. For the above arguments, the proportional duty (first sub-total) will be used for all value calculations. Gøbel, 2010 elaborates on the mechanics of the proportionality of this duty, which is summarised in Waldinger, 2022 as a duty of 1-2% of cargo value. In order to discourage understating cargo value, a truth-telling mechanism was put in place: the toll official could purchase the cargo at the total value indicated in the customs forms. As outlined in Section 2 and detailed in Section A.5 below, I use the information on duty variation in Gøbel, 2010 to back out underlying values from toll data by specifying a functional form for duty rates. This exercise produces virtually identical results, suggesting that it is appropriate to focus on the proportional duty, here the first sub-total.

A.5 Recovering underlying value

In this section, I will lay out how I recover underlying value from duty data. Underyling value, rather than the amount of duties paid, is a measure of value which I use as a robustness check. Gøbel, 2010 notes that the rate at which proportional duties were applied varied by flag, with Danish ships paying lower tax rates, by good, with e.g. salt facing an additional duty, and also by time, with Swedish cargoes taxed at a lower rate only until 1720. Importantly, the origin and destination were not important for the determination of the proportional duty rate.

Motivated by this finding, I assume that taxed value, $\phi_{ijo,kt}$ is the product of a proportional duty $\psi_{o,kt}$, varying by flag o, sector k and time t, and underlying value $v_{ijo,kt}$. In particular, I assume the following relationship:

$$\phi_{ijo,kt} = \psi_{o,kt} v_{ijo,kt} = \psi_{o,kt} p_{ijkt} q_{ijo,kt}, \tag{24}$$

such that the duty rate paid for shipping sector k goods from i to j under the flag of o in time t depend on the value of these goods multiplied by a proportional duty, $\psi_{o,kt}$, which varies only by flag o, sector k, and time t.

Turning equation 24 into logs and absorbing log proportional duties by $d_{o,kt}$, I can recover proportional duties by estimating:

$$ln\phi_{ijo,kt} = d_{o,kt} + lnv_{ijo,kt}. \tag{25}$$

I let flag o be the country in which a ship is registered as recorded in the Soundtoll records and code a ship's country in accordance with these data.[38] Sectors k are the five sectors used throughout, where again I use unclassified goods as the reference sector. While I estimate the following on annual data, I let the time dimension of fixed effects be decades.

This estimation recovers differences-in-differences-in-differences. I set Denmark as the reference flag o, unclassified goods as the reference sector k, and the 1670s as the reference decade in order to turn these triple differences into levels of proportional duties.[39]

[38]The main countries are Sweden, Russia, the German states, Denmark, the Netherlands, France, and Britain. Within these larger states, I also allow Norway, Belgium, Estonia, Lithuania, Latvia and Finland to potentially have different duty rates.

[39]Using $d_{o,kt} = ln\psi_{o,kt}$ and writing in terms of $\psi_{o,kt}$, estimating equation 25 recovers:

$$\frac{\psi_{ikt}\psi_{i'kt'}\psi_{ik't'}\psi_{i'k't}}{\psi_{ikt'}\psi_{i'kt}\psi_{ik't}\psi_{i'k't'}}.$$

This procedure imposes that there are no time trends in the proportional duty rate of unclassified goods shipped under Danish flags, but similarly one could fit the recovered differences around a historical time series of duties for Danish merchants at the Sound. Choosing Denmark as the reference is motivated by the fact that Danish merchants paid on average the lowest rates. While the differences contain economically meaningful relations, levels allow a more intuitive understanding of underlying value. With these estimated tariff rates, I turn the observed tariff amounts into underlying value by dividing taxed value by the normalised duty rate, in line with equation 24. For the reference sector and decade and a Danish merchant, underlying value thus equals duty value, whereas for a merchant paying a higher duty rate, underlying value will be proportionately higher. The normalisation of duty rates implies that underlying value is, in fact, proportional to true underlying value, as it sets underlying value equal to taxed value for the reference observation. However, the proportionality constant is now the same across observations and absorbed by fixed effects in all regression.

B History and Geography Appendix

Observing a ship in the data depends on it passing through the Oresund. Thus, trade flows between cities on either side of the Sound will not be observed: trade between Danzig and Stockholm or London and Amsterdam will not be observed in this dataset. For these flows, I do not impose zero trade, but rather will not include these. It is highly unlikely that any trade between Danzig and London occurred other than through the Sound. Other straits, such as the Little Belt between Jutland and Funen, were difficult and dangerous to navigate for larger ships such as the ones used for trading with the West. Note further that trade over land faced a high number of tolls, too, in that many more borders would have to be crossed when compared to simply passing through the Sound.

The main alternative to passing the Sound, between Sweden and Denmark's main island Zealand, was sailing through the Great Belt, between Zealand and Funen. Degn, 2017 makes a number of arguments against this being an issue for these data. The Danish king introduced a prohibition on sailing through the Belt, directed specifically against the Prussian towns, extending this prohibition later on to all foreign nations. This was precisely because the Great Belt potentially allowed merchants to circumvent the Sound Toll. Only expert skippers possessed the specific knowledge required to pass through the Great Belt, a route usually taken in case of storms. Degn, 2017 concludes that skippers only reluctantly avoided the Sound. Finally, toll records from the Great Belt reveal that the number of passages was small. This implies only a small number of unobserved vessels in my data. Importantly, there is no reason to believe that these would be high value trade flows I am missing: according to Gøbel, 2010, the toll revenue from the Great Belt and the Little Belt combined equalled but a few percent of the Sound Toll revenues.

My source for identifying cities in the trade data are two files provided by the Soundtoll team: one maps every mentioning of a city, for all spellings and versions appearing in the toll records, to a unique identifier, the "soundcoding", and the other one links these unique identifiers to a unified way of naming the city. (So 'Dantzig', 'Dannzig', and 'Danzig' all become 'Danzig'.) This converts 90,737 original city names to 3,085 unified city names. My sample are coastal cities (less than 25 kilometres distance to the coast, or those along a major river up to 100 kilometres from the coast) between Ireland to the West, Saint Petersburg to the East, the Arctic Circle to the North, and Bayonne to the South. 1,425 cities are in this sample, though only 676 will be actively trading during the main period I study.

In order to find the lowest cost route connection two cities, I compute cost distances for each city pair in the dataset using a raster approach and the CostDistance tool in ArcGIS similar to Bakker et al., 2021 or Nunn and Puga, 2012. As in the latter paper, my pixel resolution is 30 arc-seconds, corresponding to square cells of about 1 km side length (in fact, the longitudinal dimension is even less than that given the latitude of Northern Europe). I compute bilateral distances over sea between all cities. Including land transport is motivated by some large ports slightly inland, such as Thorn or Bordeaux.

The trade regressions in Section 3 include area-time fixed effects. These areas are different from European NUTS regions as their granularity is not suitable for my purposes. NUTS 1, for example, is far too aggregate for Northern Europe, with Finland and Denmark as each only one region. NUTS 2 is sufficiently granular in Northern Europe, but far too granular in Western Europe, prompting most areas to only contain one city. Therefore, I construct similarly sized areas from current country's administrative borders. When aggregating areas below, this is always to ensure that no area has only one city. The United Kingdom is disaggregated into Scotland, Wales, and the Channel Islands, with England disaggregated into her nine regions, where I pool the East Midlands with the East of England, London with the South East, and the Isle of Man with the North West. Ireland's four provinces are aggregated to three together with Northern Ireland, with Connacht pooled with Ulster. The Netherlands are made up of their 5 provinces by the North Sea. Belgium's areas are her three provinces by the North Sea, where Antwerpen is grouped with East Flanders. Denmark has 5 regions and the Faroe Islands are pooled with the main country. For Finland, I pick the provinces of Finland as of 1997, pooling Oulu and Lapland as Northern Finland and Aland with Western Finland. France's areas are the five regions on the Atlantic Coast and Channel. For Germany, I pick the current states. The three Baltic states are separate areas. Norway is disaggregated into five traditional regions, though Nord Norge never shows up in the data. For Russia, I choose oblasts, pooling Arkhangelsk with Leningradskaya Oblast. Eight national areas are chosen in Sweden, corresponding to the NUTS 2 areas, though I pool Northern Sweden. The few ports in Northern Spain, specifically in Asturias and Galicia, are pooled as one area. Finally, the areas in modern-day Poland are the three voivodeships on the Baltic Sea.

B.1 Additional Plague Results

Figure 6 shows digitised army marching routes. As armies spread the plague across Europe, regions' proximity to these routes is used in Table 11 to predict mortality rates when this information is not known. Table 9 shows information on plague outbreaks in my sample and provides an overview of timing and mortality rates. For plagued cities whose mortality rates were not observed, I form predicted mortality rates from regressing geographical covariates, the timing of the plague, and the proximity of army marching routes on observed mortality routes. These results are shown in Table 11 and used to form predicted mortality rates. Army marching are digitised based on maps by Spruner and Menke, 1880 and Barraclough, 1997. Table 11 regresses geographical controls, the timing of the plague, and proximity to army marching routes on observed mortality rates for the subset of plagued cities. For half of these cities, I form predicted mortality rates based on the results presented in this table, as no mortality estimates are available.

Figure 6: Army marching routes, 1706-1714

Notes: Map of army marching routes between 1706 and 1714, when the plague was recorded to have spread across Eastern and later Northern and Central Europe. No distinction is made between armies, as both allied and Russian troops are known to have spread the plague. I base these routes on maps by Spruner and Menke, 1880 and Barraclough, 1997 which I digitised.

Table 9: List of plagued cities and mortality estimates

City	Modern Country	Plague	Time	Population	Mortality	Source
København/Copenhagen	Denmark	1	1711	60000	.283	Kroll and Grabinsky, 2007, Kroll, 2006
Helsingør	Denmark	1	1710 - 1711	4000	.408	Frandsen, 2009
Flensburg	Germany	1	not specified			Ulbricht, 2004
Frederiksort	Germany	1	1712			Ulbricht, 2004
Kiel	Germany	1	1712			Frandsen, 2009
Rendsburg	Germany	1	1712			Ulbricht, 2004
Altona	Germany	1	1712			Frandsen, 2009, Winkle, 1983
Glückstadt	Germany	1	1712			Frandsen, 2009
Pinneberg	Germany	1	1712			Winkle, 1983
Itzehoe	Germany	1	1712			Frandsen, 2009
Schleswig	Germany	1	1712			Ulbricht, 2004
Helsinki	Finland	1	1710		.66	Engström, 1994
Rauma	Finland	1	1710 - 1711			Vourinen, 2007
Turku	Finland	1	1710 - 1711	6000	.33	Vourinen, 2007
Raseborg	Finland	1	1710			Kroll and Grabinsky, 2007, Kroll, 2006
Pori	Finland	1	1710 - 1711			Vourinen, 2007
Oulu	Finland	1	1710 - 1711			Vourinen, 2007
Borgå	Finland	1	1710			Vourinen, 2007
Pietarsaari	Finland	1	1710 - 1711			Vourinen, 2007
Kokkola	Finland	1	1710 - 1711			Vourinen, 2007
Uusikaupunki	Finland	1	1710 - 1711			Vourinen, 2007
Enköping	Sweden	1	1710			Frandsen, 2009
Stockholm	Sweden	1	1710 - 1711	53750	.378	Kroll and Grabinsky, 2007, Kroll, 2006
Visby	Sweden	1	1710 - 1711	2375	.233	Kroll and Grabinsky, 2007, Kroll, 2006
Karlskrona	Sweden	1	1710 - 1712			Persson, 2011
Karlshamn	Sweden	1	1710 - 1712			Persson, 2011
Jönköping	Sweden	1	1710 - 1711	2500	.374	Kroll and Grabinsky, 2007, Kroll, 2006
Ystad	Sweden	1	1712	1950	.385	Kroll and Grabinsky, 2007, Kroll, 2006
Blekinge	Sweden	1	1710			Persson, 2011
Malmö	Sweden	1	1712	5000	.35	Kroll and Grabinsky, 2007, Kroll, 2006
Linköping	Sweden	1	1710 - 1711	1500	.295	Kroll and Grabinsky, 2007, Kroll, 2006
Domsten	Sweden	1	1711			Kroll and Grabinsky, 2007, Kroll, 2006
Narva	Estonia	1	1710 - 1711	3000		Kroll and Grabinsky, 2007, Kroll, 2006
Tallinn/Reval	Estonia	1	1710	9900	.661	Kroll and Grabinsky, 2007, Kroll, 2006
Kuressaare	Estonia	1	1710			Frandsen, 2009
Saaremaa	Estonia	1	1710			Frandsen, 2009
Riga	Latvia	1	1710 - 1711	10477	.651	Kroll and Grabinsky, 2007, Kroll, 2006
Pärnu	Estonia	1	1710	2350	.529	Kroll and Grabinsky, 2007, Kroll, 2006
Kaliningrad/Königsberg	Russia	1	1709 - 1710	36250	.239	Kroll and Grabinsky, 2007, Kroll, 2006
Klaipeda/Memel	Lithuania	1	1709 - 1710			Kroll and Grabinsky, 2007, Kroll, 2006
Sovjetsk/Tilsit	Russia	1	1709 - 1710			Kroll and Grabinsky, 2007, Kroll, 2006
Gdansk/Danzig	Poland	1	1709	50000	.533	Kroll and Grabinsky, 2007, Kroll, 2006
Elblag/Elbing	Poland	1	1709 - 1710		.3	Frandsen, 2009
Kamien Pomorski/Cammin	Poland	1	not specified			Wieden, 1999
Stargard	Poland	1	1710 - 1711	7000	.041	Kroll and Grabinsky, 2007, Kroll, 2006
Szczecin/Stettin	Poland	1	1709 - 1711	11250	.171	Kroll and Grabinsky, 2007, Kroll, 2006
Wolin	Poland	1	1710 - 1711			Wieden, 1999
Anklam	Germany	1	not specified			Wieden, 1999
Greifswald	Germany	1	1711			Wieden, 1999
Wolgast	Germany	1	1710 - 1711		.4	Wieden, 1999
Stralsund	Germany	1	1710 - 1711	7250	.314	Kroll and Grabinsky, 2007, Kroll, 2006
Goleniow/Gollnow	Poland	1	1709			Schöning, 1837
Hamburg	Germany	1	1712 - 1714	70000	.130	Kroll and Grabinsky, 2007, Kroll, 2006
Stade	Germany	1	1712			Frandsen, 2009, Winkle, 1983
Bremen	Germany	1	1712 - 1713	28000	.007	Frandsen, 2009

Notes: Sources are indicated in the last column. Population and mortality estimates, in the case of several available sources, denote the mean estimate. The modern names and countries of cities are used here.

Table 10: List of besieged cities

City	Modern Country	Siege
København	Denmark	1
Tönning	Germany	1
Hamburg	Germany	1
Halden	Norway	1
Gävle	Sweden	1
Härnösand	Sweden	1
Hudiksvall	Sweden	1
Piteå	Sweden	1
Söderhamn	Sweden	1
Umeå	Sweden	1
Södertälje	Sweden	1
Norrköping	Sweden	1
Nyköping	Sweden	1
Trosa	Sweden	1
Sundsvall	Sweden	1
Vyborg	Russia	1
Narva	Estonia	1
Riga	Latvia	1
Szczecin	Poland	1
Wolgast	Germany	1
Stralsund	Germany	1
Wismar	Germany	1

Notes: Six cities are both besieged and plagued. The six cities are Copenhagen (København), Narva, Riga, Stettin (Szczecin), Stralsund, and Wolgast. For Copenhagen and the first siege of Riga, there was no association with the plague, as these sieges occurred at the very beginning of the war in 1700 before the plague spread.

Table 11: Determinants of urban mortality

	Mortality rate
	(1)
Year of plague outbreak	-0.000
	(0.001)
Latitude	0.010
	(0.022)
Longitude	0.017**
	(0.007)
Distance to closest army	-0.062**
	(0.023)
East of the Sound	0.160**
	(0.055)
Observations	19

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is the median urban mortality estimate. The independent variables are the year of the plague outbreak, latitude, longitude, distance to the closest army route between 1706 and 1714, and a dummy for the city being to the East of the Sound. The rationale for including army marching routes is that armies spread the plague.

B.2 Demography

Table 12 shows that plagued cities were not larger or smaller than other cities, taking into account time trends and locational fundamentals by including time (or country x time) and city fixed effects. The source for these city-level populations is Buringh, 2021. As the closest data point after the plague is in 1750, I conclude that cities' populations had recovered to the common trend after about four decades. While these are city-level data, the plague afflicted also their hinterlands, for which no consistent population data are available. Given that urbanisation rates were low, the required rural-to-urban migration was quite small, and I therefore consider urban population recovery sufficient for regional population recovery.

Table 12: Impact of plague on city population

	Population		Log Population	
	(1)	(2)	(3)	(4)
Plague x Year=800	0.0749	-0.0242	0.224	0.154
	(11.86)	(10.77)	(0.811)	(0.584)
Plague x Year=900	0.0715	-0.0998	0.141	0.0493
	(11.86)	(10.77)	(0.810)	(0.625)
Plague x Year=1000	0.251	-0.0178	0.0817	0.0286
	(11.86)	(10.76)	(0.737)	(0.531)
Plague x Year=1100	0.161	-0.232	0.112	0.0373
	(11.84)	(10.74)	(0.710)	(0.479)
Plague x Year=1200	0.424	-0.163	0.130	0.0898
	(11.82)	(10.72)	(0.697)	(0.469)
Plague x Year=1300	1.339	0.352	0.366	0.282
	(11.78)	(10.68)	(0.691)	(0.460)
Plague x Year=1400	1.772	1.043	0.460	0.468
	(11.74)	(10.64)	(0.690)	(0.458)
Plague x Year=1500	3.816	2.709	0.597	0.592
	(11.35)	(10.34)	(0.688)	(0.455)
Plague x Year=1550	4.758	3.489	0.622	0.637
	(11.24)	(10.23)	(0.686)	(0.454)
Plague x Year=1600	6.464	4.798	0.684	0.704
	(11.05)	(10.02)	(0.686)	(0.455)
Plague x Year=1650	7.789	5.332	0.783	0.747*
	(10.81)	(9.784)	(0.685)	(0.453)
Plague x Year=1700	9.645	6.381	0.800	0.737
	(10.52)	(9.499)	(0.687)	(0.455)
Plague x Year=1750	11.20	7.018	0.840	0.668
	(10.29)	(9.271)	(0.686)	(0.454)
Plague x Year=1800	14.78	8.766	0.954	0.697
	(9.583)	(8.657)	(0.687)	(0.454)
Plague x Year=1850	21.37**	10.64	0.844	0.692
	(8.999)	(8.147)	(0.687)	(0.454)
Plague x Year=1900	63.51***	44.93**	0.767	0.948**
	(19.85)	(18.64)	(0.691)	(0.460)
Plague x Year=1950	107.4**	87.99**	0.548	0.907*
	(42.88)	(38.62)	(0.695)	(0.465)
Plague x Year=2000	162.9***	153.2***	0.438	0.999**
	(59.85)	(54.14)	(0.694)	(0.467)
Constant	19.54***	19.69***	1.640***	1.637***
	(0.940)	(0.947)	(0.0266)	(0.0181)
Fixed Effects:				
– City	✓		✓	
– Country x Year	✓	✓	✓	✓
– Year		✓		✓
Observations	22,470	22,489	17,027	17,059

Notes: Robust standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is (log) city population. The independent variable is a plague dummy interacted with year dummies. The area is restricted to the Baltic Sea and North Sea areas, specifically to cities between the tip of Norway, the Northern end of the Alps, the Irish West Coast and Arkhangelsk.

Demographic Response

What was the demographic response to this plague outbreak? Theoretically, three main channels could contribute to the recovery of cities. First, an increase in fertility. Guinnane, 2011 argues for a positive elasticity of fertility with respect to income, implying that higher post-plague wages would increase fertility. However, there is reason to doubt the strength and direction of this relationship in the particular area studied here. There is evidence for increased human capital acquisition (Zanden, 2009) and delayed marriage (De Moor and Zanden, 2009) after the Black Death for the North Sea region, both of which may suggest falling fertility. While there is no direct evidence on Baltic cities, this area falls under the European Marriage Pattern in the classification of Hajnal, 1965.

While the effect on fertility is thus debatable, it appears reasonable that population growth accelerated nonetheless due to lowered mortality, the second channel. Waldinger, 2022 shows that higher agricultural productivity was associated with lower mortality in this region. Migration is the third channel through which urban populations may have recovered. Waldinger, 2022 also shows for England that warming increased agricultural productivity and drew in more migrants. While there is limited evidence for such migration across regions, I argue that rural-to-urban migration within regions may be sufficient to produce urban population recovery.

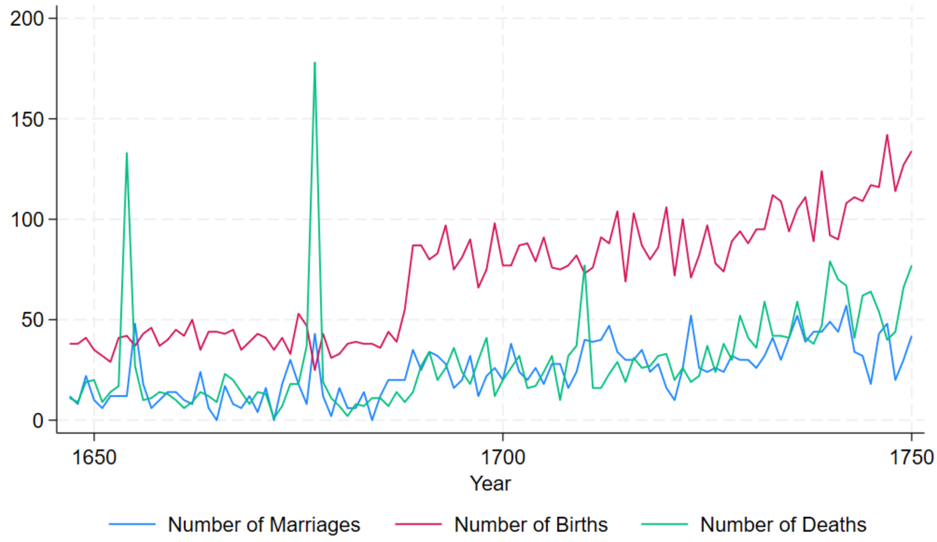
Through rural-to-urban migration, plagued regions' urbanisation rates may have increased. This is a prediction of Voigtländer and Voth, 2012 and explored empirically in Jedwab, Johnson, and Koyama, 2022. They find a range of 0.16-0.24 for the elasticity of the urbanisation rate with respect to mortality after the Black Death. This implies a 5.8-8.6 pp increase in the urbanisation rate in the long run. With median regional (urban) mortality of 20.15% (36%), urban population recovery only through rural-to-urban migration requires a 25% increase in the urbanisation rate.[40] Considering the European urbanisation rate of 11.9% in 1700 (Vries, 2013), the range based on estimates in Jedwab, Johnson, and Koyama, 2022 is far higher than a 25% increase. This suggests that rural-to-urban migration may be enough to explain urban population recovery.

The Scanian Economic Demographic Database provides a uniquely granular source to answer this question (Bengtsson et al., 2014). Figure 7 shows annual births, deaths, and marriages for all of Scania. The 1710 peak in deaths is the plague outbreak studied in this paper. It was followed by a slight increase in marriages and births. This suggests a positive fertility response as less inhabitants gave birth to a larger number of children.

I also present results on the fertility channel at the parish level in Table 13. Births are the only variable in this dataset that is recorded at the parish-level going back to the 17th century. I analyse whether plagued parishes saw changes in the number of births after the plague. While not all parishes' plague status can be ascertained beyond doubt, I conservatively code the five urban parishes of Ystad, Malmö and Domsten as plagued, as their plague outbreaks are established (Kroll, 2006, Kroll and Grabinsky, 2007). I estimate a two-way fixed effects regression and find no significant fertility response at the parish level. As about a third of inhabitants of these parishes vanished, this implies a positive fertility response. However, this result is based on 59 parishes in one particular region of Sweden, limiting the external validity of this finding.

[40] The median regional mortality rate sits in the middle between two extremes: assuming no rural mortality would imply a 4.3% regional mortality rates given prevailing urbanisation rates; assuming identical rural mortality rates situates regional mortality rates at 36%. As in Voigtländer and Voth, 2012, I choose urban mortality rates as an upper bound to rural ones.

Figure 7: Number of births, deaths, and marriages in Scania, 1647-1750



Notes: The 1650s peak in deaths marks the Second Northern War and the 1670s peak the Scanian War.

Table 13: Impact of plague on number of births in 59 Scania parishes

	Births		Log Births	
	(1)	(2)	(3)	(4)
Post Plague	0.174	-0.376	-0.065	-0.104
	(0.725)	(0.735)	(0.068)	(0.083)
Fixed Effects:				
– Origin	✓	✓	✓	✓
– Year	✓	✓	✓	✓
Years	All	1647-1750	All	1647-1750
Observations	1,015	591	973	578

Notes: Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is a the (log) number of births per year and parish. The independent variable is a plague dummy, equal to one after the parish suffered a plague outbreak.

Insights from Other Plague Outbreaks

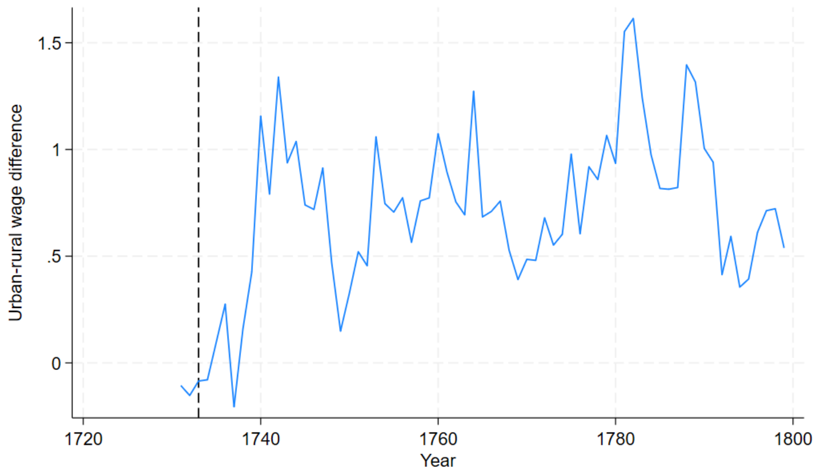
I conclude the exposition of this plague outbreak by comparing it to the Black Death outbreak of the 14th century. The Great Northern War plague outbreak's mortality rate of 36% is similar to the 40% mortality rate of the Black Death (Jedwab, Johnson, and Koyama, 2022). A crucial difference is the geographical dimension of these outbreaks. While the Black Death affected most of Europe, the Great Northern War plague outbreak was geographically very concentrated. This is a feature of later plague outbreaks also in Southern Europe (Alfani, 2023). Several reasons may have contributed to this, most importantly environmental and epidemiological changes affecting both immunity and transmissibility, and institutional responses (Alfani and Murphy, 2017). Alfani, 2022 stresses that later plague outbreaks did not bring about the sizeable reduction in inequality seen after the Black Death. He argues that local elites shaped institutions such that the distribution of income would be less responsive to mortality shocks. This may also have limited the geographic spread of later plague outbreaks, in particular through the erection of extramural plague houses. It is therefore not atypical for such a late plague outbreak to be geographically concentrated.

The economic consequences of plague outbreaks further depend crucially on how mortality interacts with sex, age, and socioeconomic status. While less is known about the Great Northern War plague outbreak, Alfani and Murphy, 2017 summarises the existing literature on other plague outbreaks. There is no evidence that mortality differed by sex and ambiguous evidence on age. Some studies find that the youngest and oldest were relatively spared, with higher mortality rates for (young) adults. Undoubtedly, crowding and lack of hygiene in poor neighbourhoods will have contributed to higher mortality rates there. For truly large mortality shocks, however, such as the original Black Death and some later plague outbreaks, there is clear evidence that elites, too, suffered high mortality. Pullan, 1992 describes that 17% of the members of the Great Council were killed in the 1630 Venice plague and that 40% of the members of the Great and Low Councils died in the 1656-57 Genoa plague outbreak. Considering the high mortality rates associated with the Great Northern War plague outbreak, I take this summary evidence as suggesting higher mortality rates for working age adults, with no consistent differences by sex or socioeconomic status. Raster, 2023 analyses plague mortality by age, sex, and social status for the Great Northern War plague outbreak. While geographically constrained to Estonia, he finds no significant differences in mortality rates. Frandsen, 2009 shows qualitative evidence confirming this finding. Thus, the compositional effects of the plague outbreak should have been very limited.

B.3 Other Results

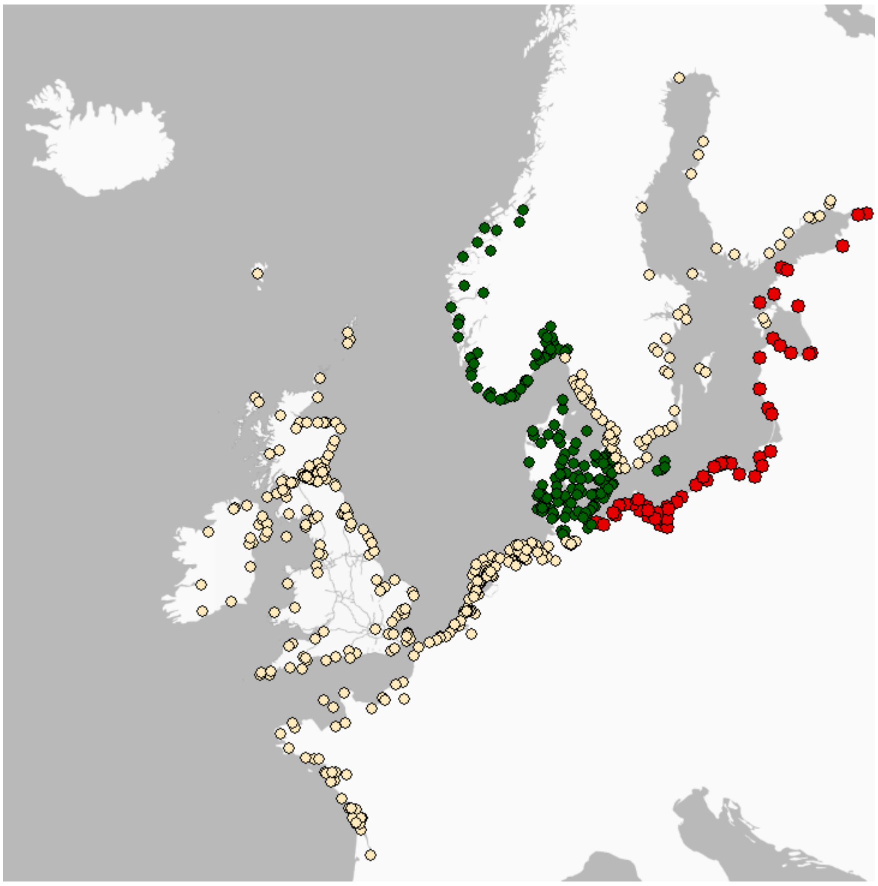
Figure 8 shows that the re-introduction of serfdom in Denmark was associated with a wedge in wages between urban and rural areas that had previously not existed. Figure 9 shows regions by their serfdom status.

Figure 8: Urban-rural wage differential in Copenhagen



Notes: Difference between urban and farm day wages divided by farm day wages. Data by Gary et al., 2022. The dotted line signifies the 1733 re-introduction of serfdom.

Figure 9: Regions by serfdom status



Notes: This map classifies regions by their serfdom status according to the above discussion. Yellow regions did not feature serfdom before and after the plague, whereas red regions did. Green areas re-introduced serfdom in 1733.

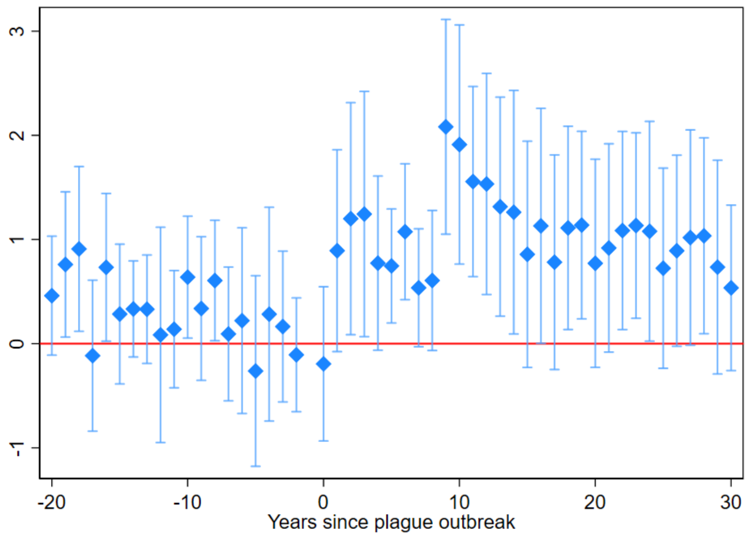
C Trade Appendix

This Appendix holds all additional and robustness results for trade. The structure of this Appendix follows the structure of the trade results in the main paper.

C.1 Fact #1: Capital-intensive exports increase more than labour-intensive exports.

Figure 10 shows that reassigning four debatable goods (wine, tow, ash, and planks) as labour-intensive produces virtually identical results. Table 14 shows PPML and OLS results for Fact #1 in a difference-in-difference-in-difference set up. Table 15 repeats the specification while including army proximities and sieges. Figure 11 shows findings by factor intensity using the imputation estimator in Borusyak, Jaravel, and Spiess, 2021. Table 16 corroborates the increase in capital-intensive exports over labour-intensive exports by sector. Figure 12 shows the result by goods. Finally, Figure 13 shows that the shift into capital-intensive exports lasts for almost 90 years.

Figure 10: Alternative assignment as capital-intensive: Fact #1



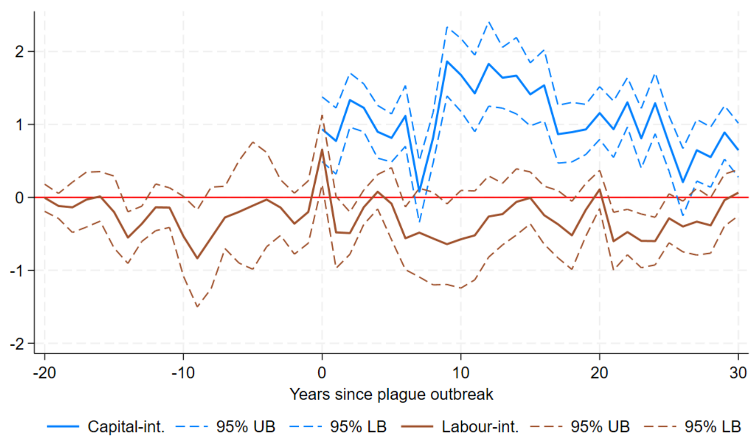
Notes: Among the top 30 goods (see Table 5), I have reassigned four debatable goods (wine and tow from CA to LA, planks and ash from CM to LM) and find almost identical results.

Table 14: Plague increases capital-intensive exports more than labour-intensive exports

	PPML		OLS	
	(1)	(2)	(3)	(4)
Post Plague	-0.980**	-1.151***	-0.471**	-0.563***
	(0.416)	(0.357)	(0.190)	(0.160)
Post Plague x Capital-Int.	0.970*	1.302***	0.451	0.840***
	(0.522)	(0.266)	(0.317)	(0.187)
Fixed Effects:				
– Origin x Sector	✓	✓	✓	✓
– Sector x Year	✓		✓	
– Year		✓		✓
Estimator	PPML	PPML	OLS	OLS
Observations	102,636	105,908	17,545	17,560

Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is annual exports by sector in levels (columns 1-2) and logs (columns 3-4). The independent variable is a post plague dummy, equal to one after the origin suffered a plague outbreak, and a dummy interacting the post plague dummy with a dummy for capital-intensive exports. Columns 1-2 show unweighted results, whereas in columns 3-4 the weight are exports in levels. Annual growing season temperatures are an additional control in all specifications.

Figure 11: Fact #1 using imputation estimator in Borusyak, Jaravel, and Spiess, 2021



Notes: I estimate equation 1 by factor intensity using the imputation estimator in Borusyak, Jaravel, and Spiess, 2021. The package does not permit the estimation of pretrend heterogeneity, so these estimates are pooled across both factor intensities.

Table 15: Shift into capital-intensive exports by army proximity and siege

	PPML		OLS		PPML		OLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Army Distance x Post War	-0.060	-0.061	0.015	0.006				
	(0.071)	(0.057)	(0.031)	(0.025)				
Army Distance x Post War x Capital-Int.	0.061	0.047**	0.008	-0.002				
	(0.043)	(0.023)	(0.028)	(0.016)				
Siege x Post War					0.715***	0.750***	0.579***	0.607***
					(0.098)	(0.083)	(0.090)	(0.092)
Siege x Post War x Capital-Int.					0.335	0.309	0.007	0.007
					(0.273)	(0.315)	(0.229)	(0.239)
Post Plague	-1.136**	-1.256***	-0.424**	-0.545***	-1.156***	-1.321***	-0.615***	-0.709***
	(0.510)	(0.419)	(0.177)	(0.119)	(0.385)	(0.324)	(0.131)	(0.103)
Post Plague x Capital-Int.	1.132**	1.265***	0.514*	0.842***	1.109**	1.345***	0.573*	0.923***
	(0.530)	(0.270)	(0.308)	(0.193)	(0.563)	(0.340)	(0.329)	(0.216)
Fixed Effects:								
– Origin x Sector	✓	✓	✓	✓	✓	✓	✓	✓
– Sector x Year	✓		✓		✓		✓	
– Year		✓		✓		✓		✓
Estimator	PPML	PPML	OLS	OLS	PPML	PPML	OLS	OLS
Observations	100,530	103,750	17,353	17,368	102,636	105,908	17,545	17,560

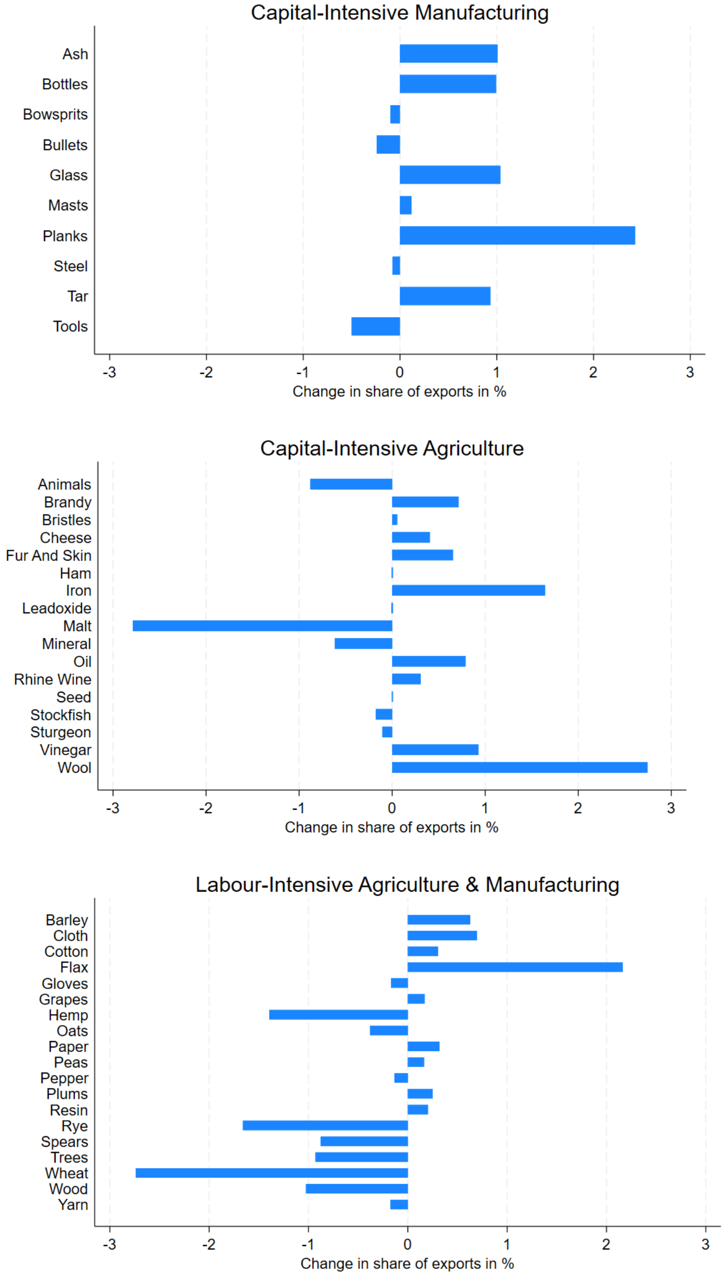
Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is annual exports by sector in levels (PPML) or logs (OLS). The independent variable is a post plague dummy, equal to one after the origin suffered a plague outbreak, and a dummy interacting the post plague dummy with a dummy for capital-intensive exports. Additionally, in columns 1-4 I include the smallest distance any army had to a region during the Great Northern War, interacted with a post-war dummy (equal to 1 after 1721), and this interactions interaction with a capital-intensity dummy. The PPML columns show unweighted results, whereas in the OLS columns the weight are exports in levels. Annual growing season temperatures are an additional control in all specifications. Table 10 shows besieged cities and Figure 6 shows army routes.

Table 16: Plague increases capital-intensive exports more than labour-intensive exports in both sectors

	Manufacturing		Agriculture	
	(1)	(2)	(3)	(4)
Post Plague	-1.491***	-0.547***	-1.136***	-0.566***
	(0.498)	(0.121)	(0.355)	(0.183)
Post Plague x Capital-Int.	1.267***	0.787***	1.507**	0.740*
	(0.235)	(0.142)	(0.647)	(0.379)
Fixed Effects:				
– Origin x Sector	✓	✓	✓	✓
– Year	✓	✓	✓	✓
Estimator	PPML	OLS	PPML	OLS
Observations	31,023	5,043	53,369	9,578

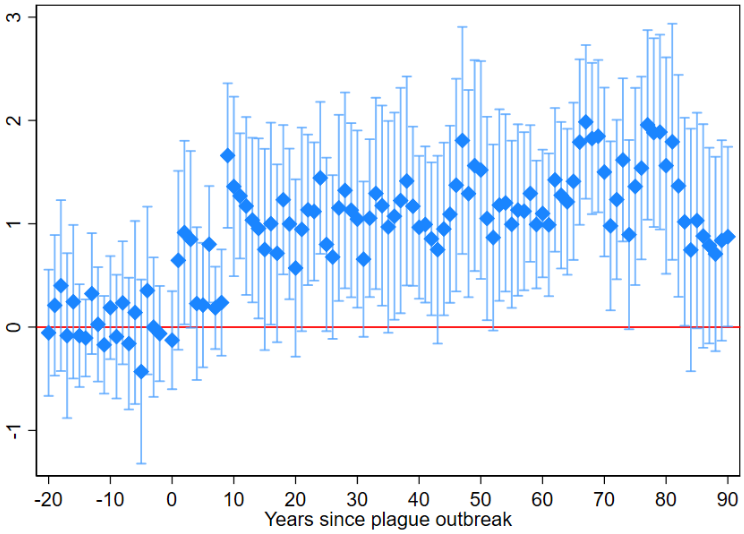
Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is annual exports by sector in levels (columns 2 and 4) and logs (columns 1 and 3). The independent variable is a post plague dummy, equal to one after the origin suffered a plague outbreak, and a dummy interacting the post plague dummy with a dummy for capital-intensive exports. Columns 1 and 3 show unweighted results, whereas in columns 2 and 4 the weight are exports in levels. Annual growing season temperatures are an additional control in all specifications.

Figure 12: Fact #1: Shift into capital-intensive exports by good



Notes: Results from regressing a plague dummy on the share a good constitutes among origin-time exports, including origin and time fixed effects. Shown is a selection of point estimates that are significant at the 10% level.

Figure 13: Capital-intensive exports expand relative to labour-intensive exports also in the long run

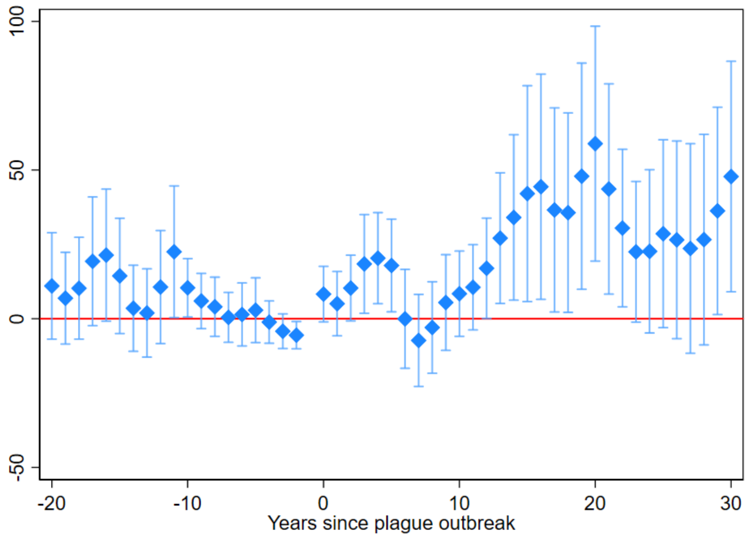


Notes: Estimation of equation 1 in the long run. Standard errors clustered at the origin level.

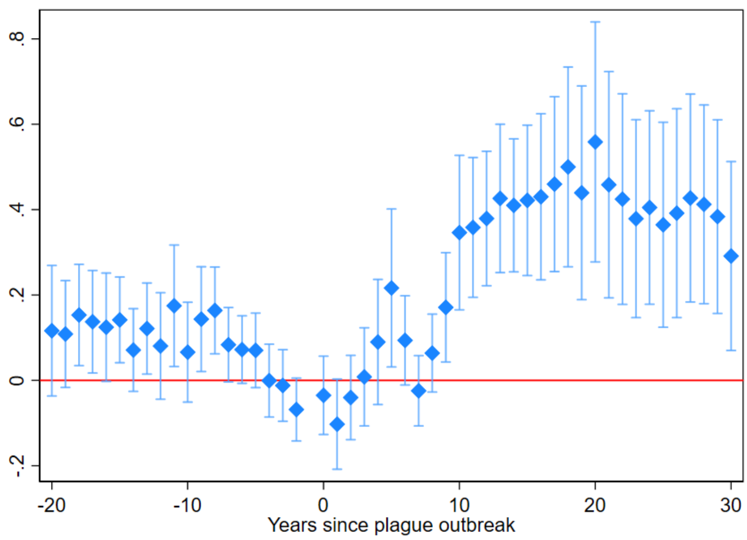
C.2 Fact #2: Plagued regions capture larger shares of destination markets.

I now present robustness results for the post-plague export expansion. Figure 14a shows that export volumes expand and Figure 14b shows the extensive margin expansion. Figure 15a extends the pre-period to 30 years and again finds no pre-trends. I also show results from cleaned values following the decomposition of duty records into underlying value as outlined in Section A.5 in Figure 15b. Figure 16 repeats the main analysis on trade shares using the imputation estimator by Borusyak, Jaravel, and Spiess, 2021. Figure 17 decomposes the intensive margin expansion by sector and Figure 18 by factor intensity. Figure 19 shows the export volume expansion by good. Finaly, Figures 20a and 20b show the export expansion in the long run.

Figure 14: Robustness results for Fact #2: Export volumes and the extensive margin expand



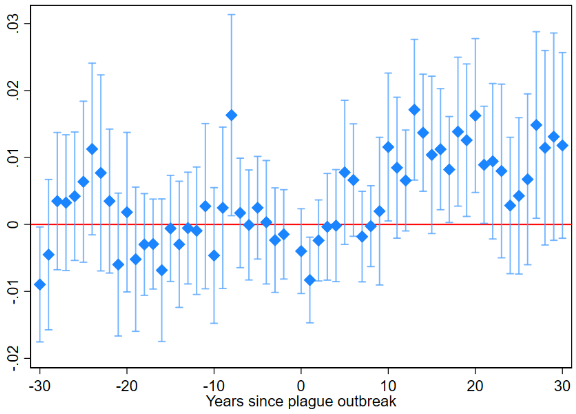
(a) Export volumes



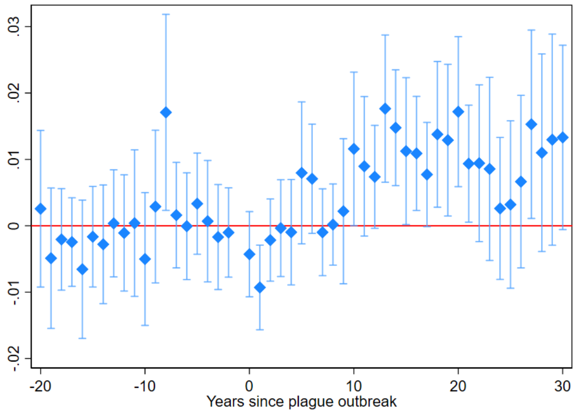
(b) Number of exported goods

Notes: In Figure 14a, estimation of equation 2 on $T_{ijt} = x_{ijt}$. Standard errors clustered at the origin level. In Figure 14b, estimation of equation 2, where T_{ijt} is the number of exported goods.

Figure 15: Robustness results for Fact #2: Thirty pre periods and underlying value



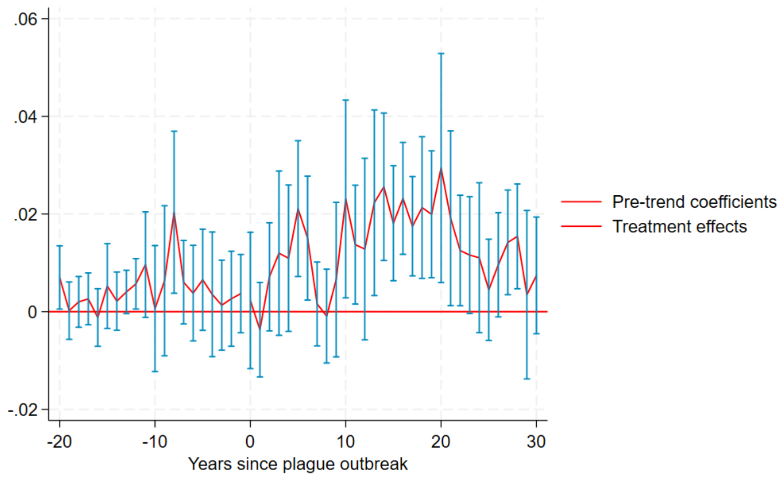
(a) Market shares with 30 pre periods



(b) Market shares, underlying value

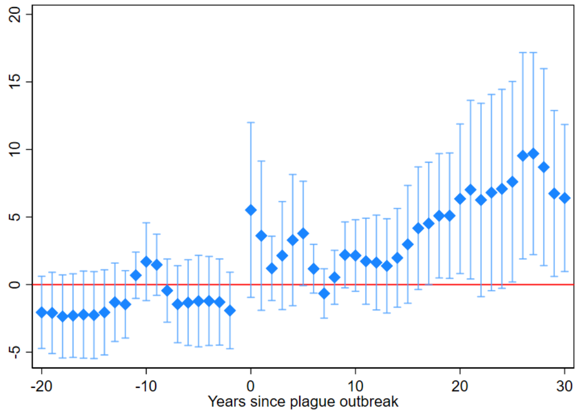
Notes: Figure 15a estimates equation 2 on shares, extending the pre-period to 30 years. Figure 15b shows regression results based on underlying value, as recovered in Appendix A.5. Standard errors clustered at the origin level.

Figure 16: Market shares, using imputation estimator in Borusyak, Jaravel, and Spiess, 2021

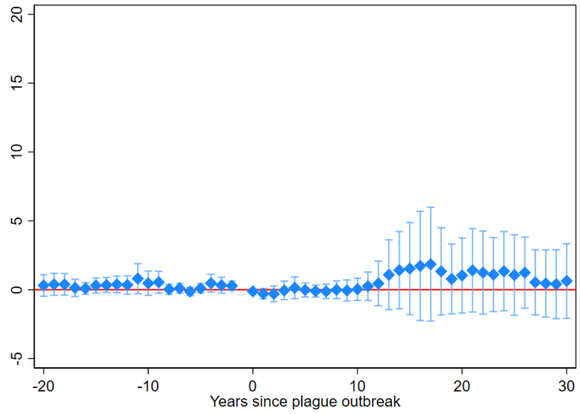


Notes: This Figure shows results from estimating equation 2 with 20 pre-trends and 30 post periods using the imputation estimator by Borusyak, Jaravel, and Spiess, 2021. Standard errors clustered at the origin level.

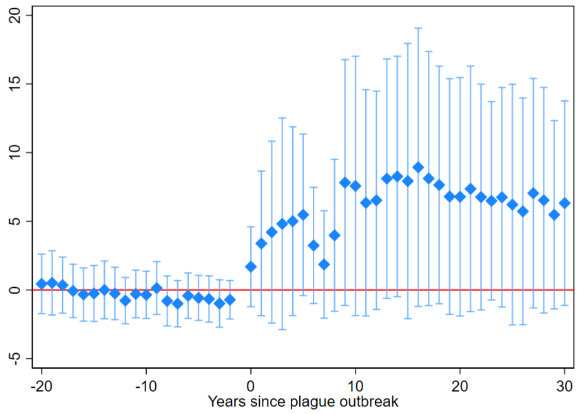
Figure 17: Intensive margin expansion, volumes by sector



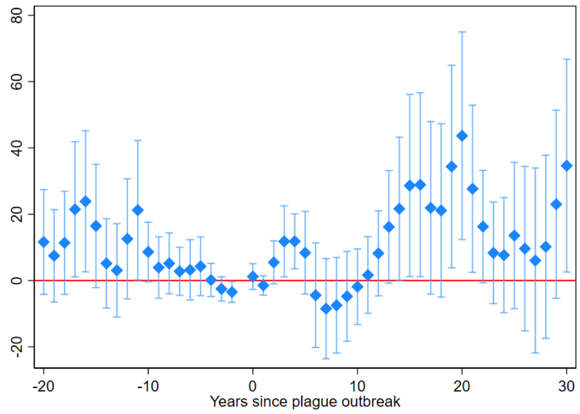
(a) Capital-int. manufacturing



(b) Labour-int. manufacturing



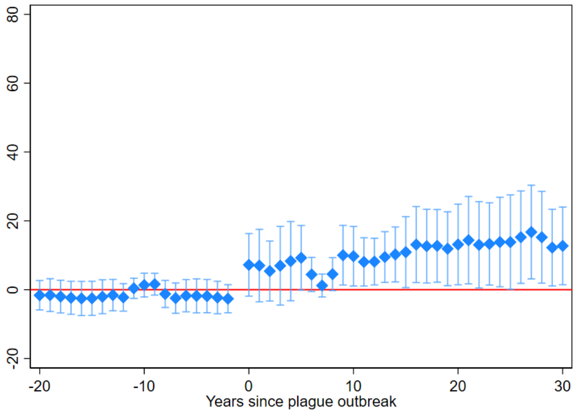
(c) Capital-int. agriculture



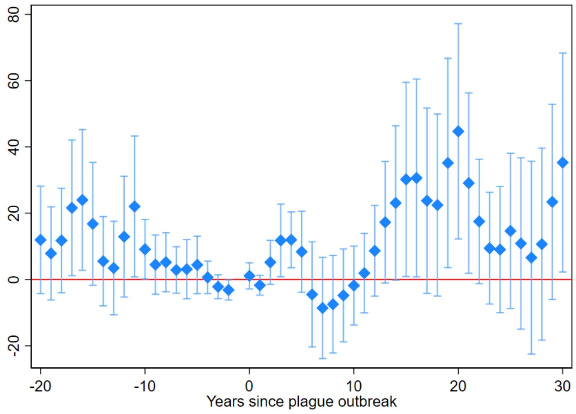
(d) Labour-int. agriculture

Notes: Estimation of equation 2 on volumes. The y-axis differs in Figure 17d to preserve the legibility of the other Figures. Between 1668-1750, 55% of traded value was in labour-intensive agriculture, 27% in capital-intensive agriculture, 3% in labour-intensive manufacturing and 13 % in capital-intensive manufacturing. Standard errors clustered at the origin level.

Figure 18: Intensive margin expansion, volumes by factor intensity



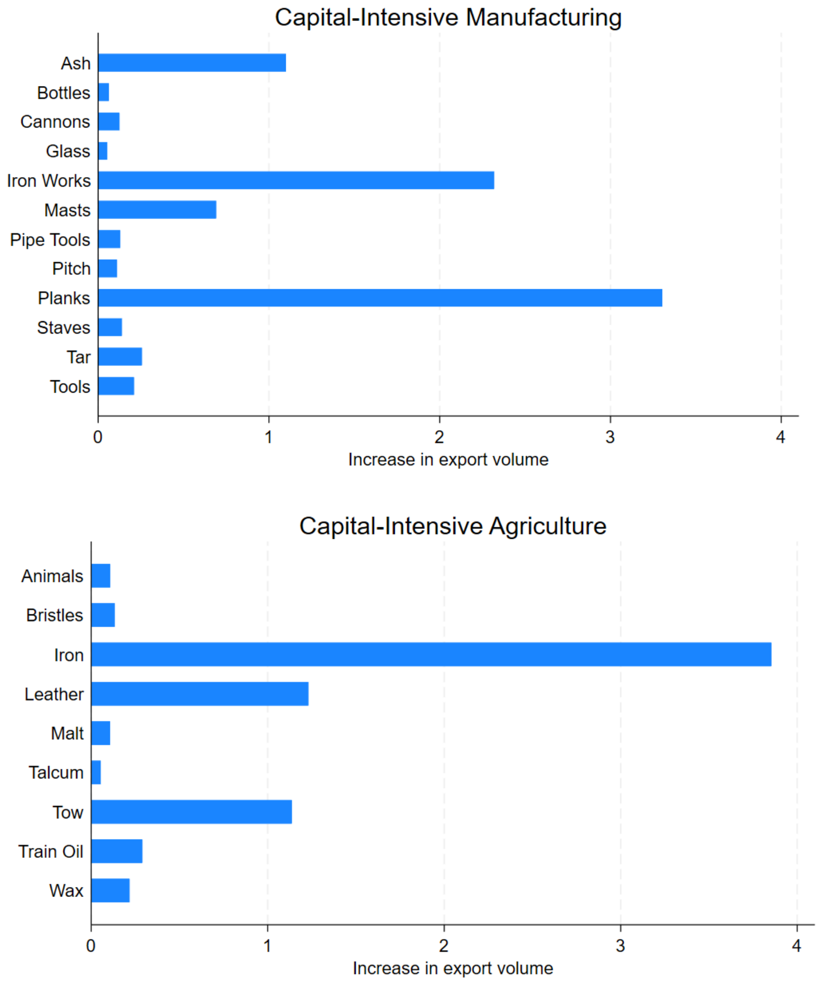
(a) Capital-intensive sectors



(b) Labour-intensive sectors

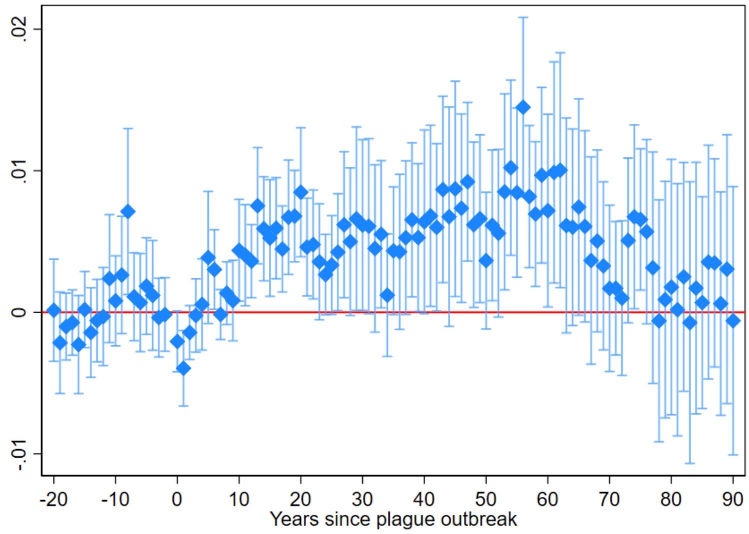
Notes: Estimation of equation 2 on volumes. Between 1668-1750, 58% of traded value was in labour-intensive sectors and 40% in capital-intensive sectors. Standard errors clustered at the origin level.

Figure 19: Fact #2: Volume expansion by good, capital-intensive sectors

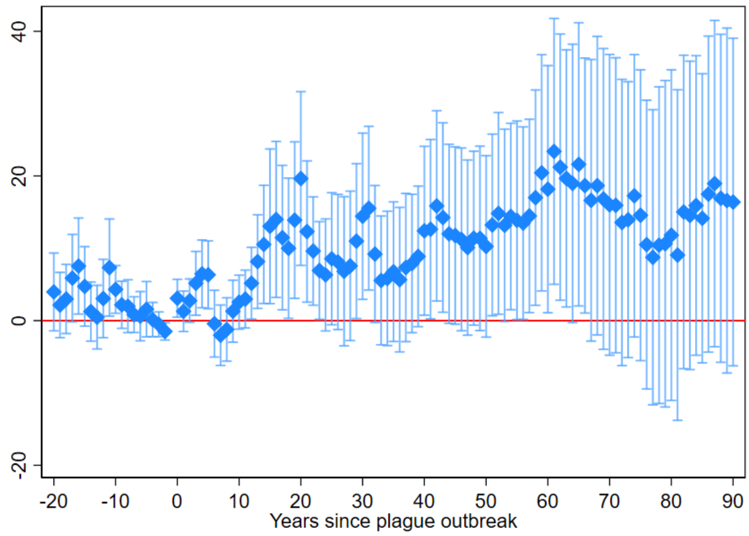


Notes: Results from regressing a plague dummy on i's exports to j in good g in annual data, controlling for area x year, origin x destination, and destination x year fixed effects. Shown are only point estimates that are significant at the 5% level.

Figure 20: Market shares and export volumes expand in the long run



(a) Market shares



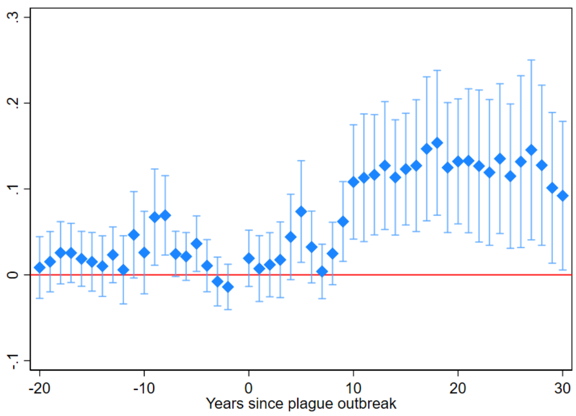
(b) Export volumes

Notes: In Figure 20a, estimation of equation 2 on i's share of j's imports, $T_{ijt} = \frac{x_{ijt}}{\Sigma_{i \in I} x_{ijt}}$. In Figure 20b, estimation of equation 2 on $T_{ijt} = x_{ijt}$. Standard errors clustered at the origin level.

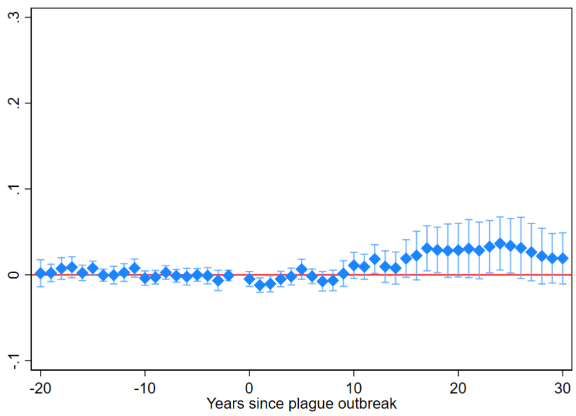
C.3 Extensive Margin: Plagued regions export a larger variety of goods.

Robustness results for the extensive margin expansion follow. Figure 21 shows that all four sectors participated in the expansion, with labour-intensive manufacturing contributing the least. Figure 22 separates the extensive margin expansion by factor intensity. Figure 23 shows results at the goods level.

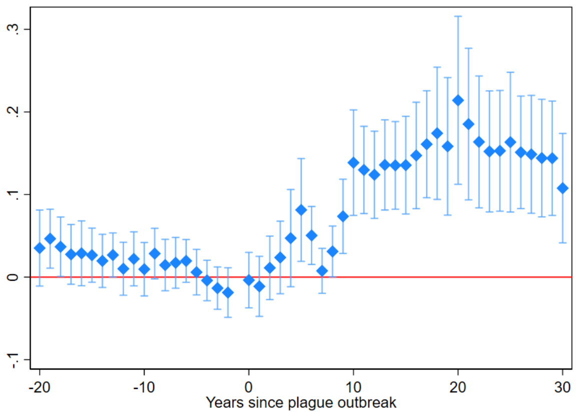
Figure 21: Extensive margin expansion, by sector



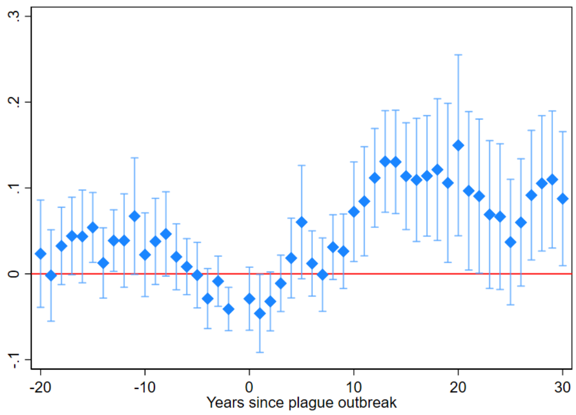
(a) # exported capital-int. man. goods



(b) # exported labour-int. man. goods



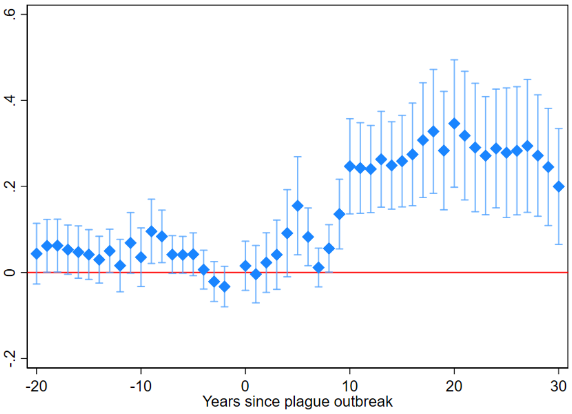
(c) # exported capital-int. ag. goods



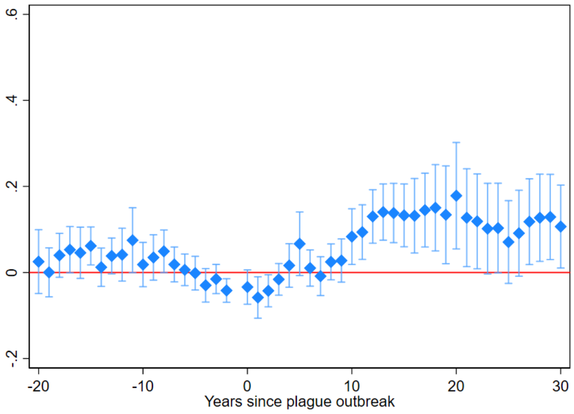
(d) # exported labour-int. ag. goods

Notes: Estimation of equation 2 on the number of exported goods by sector and factor intensity. Between 1668-1750, 55% of traded value was in labour-intensive agriculture, 27% in capital-intensive agriculture, 3% in labour-intensive manufacturing and 13 % in capital-intensive manufacturing. Standard errors clustered at the origin level.

Figure 22: Extensive margin expansion, by factor intensity



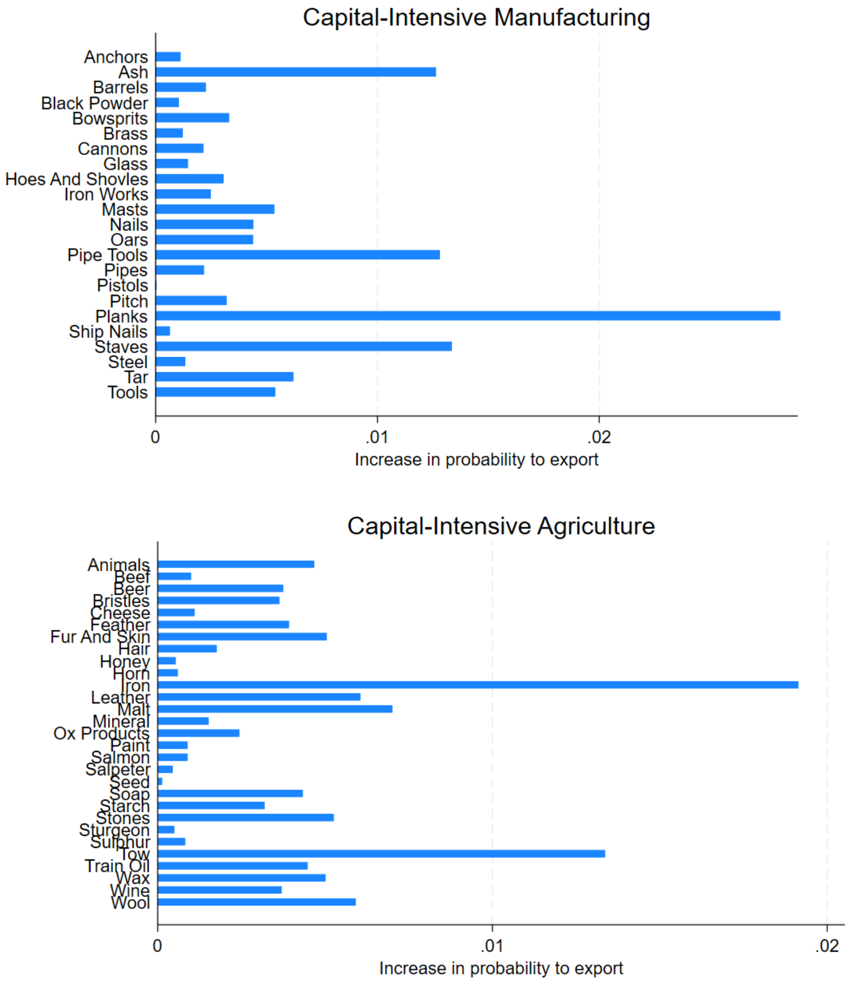
(a) # exported capital-intensive goods



(b) # exported labour-intensive goods

Notes: Estimation of equation 2 on the number of exported goods by factor intensity. Between 1668-1750, 58% of traded value was in labour-intensive sectors and 40% in capital-intensive sectors. Standard errors clustered at the origin level.

Figure 23: Fact #3: Extensive margin expansion by good, capital-intensive sectors

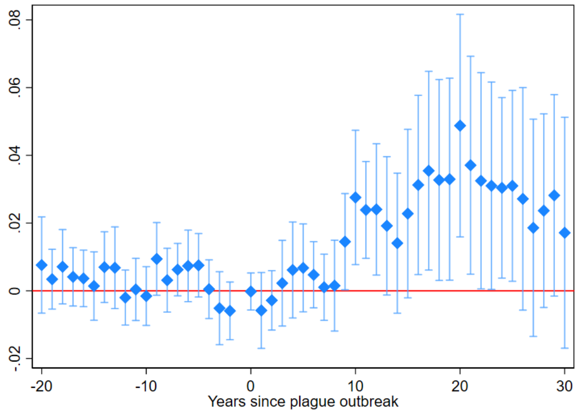


Notes: Results from regressing a plague dummy on a dummy for positive exports of good g from i to j in annual data, controlling for area x year, origin x destination, and destination x year fixed effects. Shown are only point estimates that are significant at the 5% level.

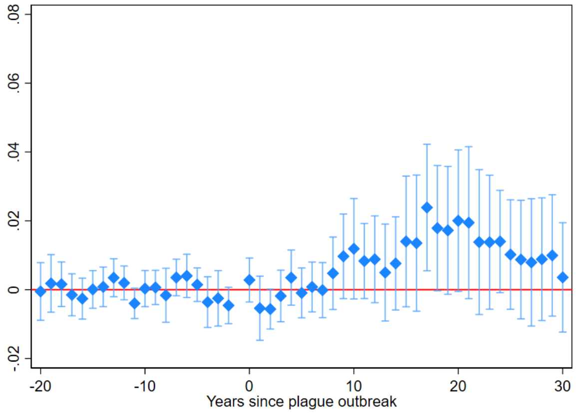
Innovation: Exports of new products increase after the plague.

Figure 24 shows the extensive margin of new goods by factor intensity, while Figure 25 shows these results by good. Table 17 shows results from PPML panel regressions of a post plague dummy on the number of goods never exported before for each of the four sectors. Table 18 shows these results for the volume of goods never exported before, thus illustrating the contribution of new exports to the intensive margin results.

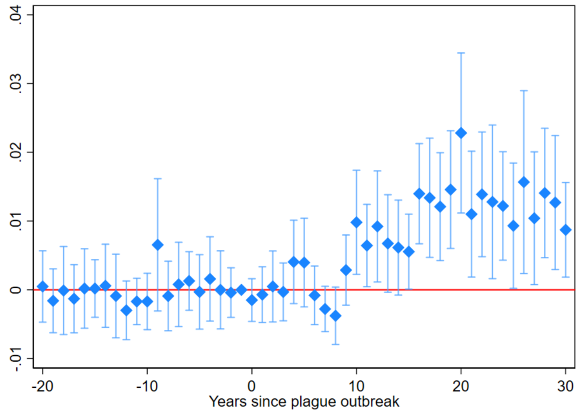
Figure 24: New exports at the extensive margin, by factor intensity



(a) # new goods, capital-intensive sectors



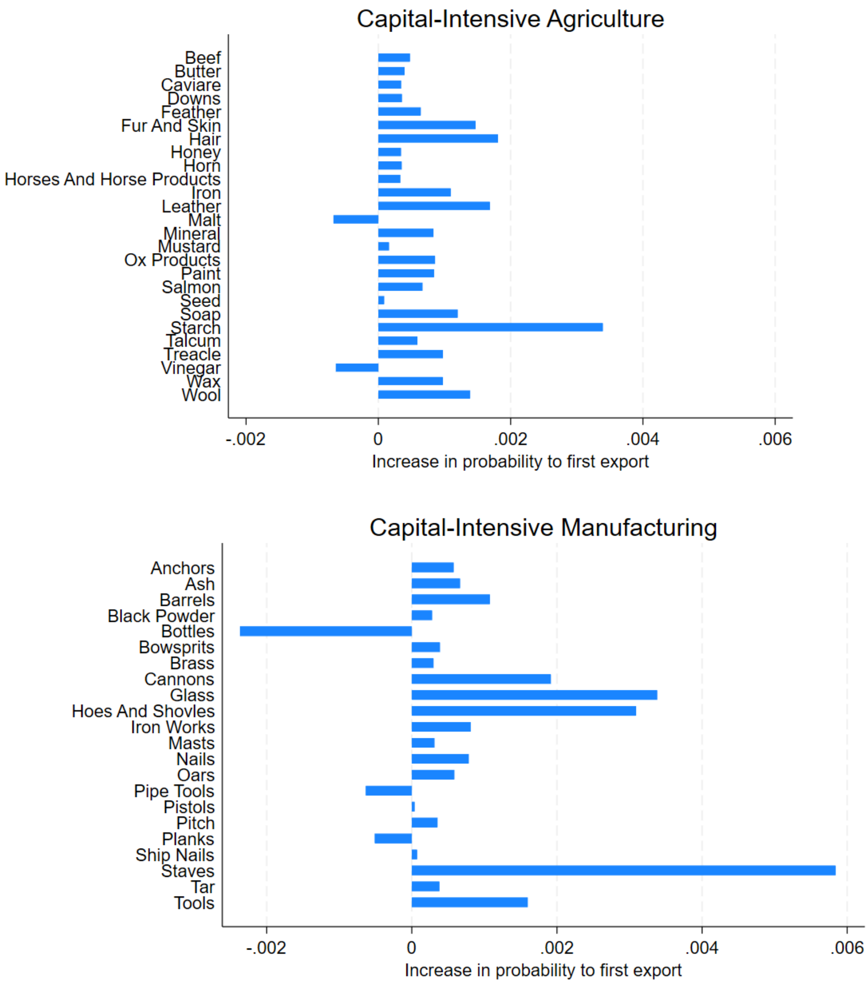
(b) # new goods, labour-intensive sectors



(c) Difference between capital- and labour-intensive sectors

Notes: Estimation of equation 2 on the number of exported goods, by factor intensity. A new export is defined as a good first exported by a city between 1709, the onset of the plague in my study area, and 1732, 20 years after the last plague year in this region. Standard errors clustered at the origin level.

Figure 25: Fact #4: Increased probability of exporting a good for the first time, capital-intensive sectors



Notes: Results from regressing a plague dummy on a dummy for a new export of good g from i to j in annual data, controlling for area x year, origin x destination, and destination x year fixed effects. A new export is a good not exported before the plague. Shown are only point estimates that are significant at the 5% level.

Table 17: Impact of plague on number of goods never exported before, by factor intensity

	Overall	Labour-intensive ag.	Capital-intensive ag.	Labour-intensive man.	Capital-intensive man.
	(1)	(2)	(3)	(4)	(5)
Post Plague	0.962***	1.011***	0.413	1.349***	0.919***
	(0.242)	(0.325)	(0.280)	(0.266)	(0.321)
Fixed Effects:					
– Area x Year	✓	✓	✓	✓	✓
– Origin x Destination	✓	✓	✓	✓	✓
– Destination x Year	✓	✓	✓	✓	✓
– Controls	✓	✓	✓	✓	✓
Estimator	PPML	PPML	PPML	PPML	PPML
Observations	74,452	17,270	40,554	4,140	14,185

Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is the number of goods that a region has never exported before. The independent variable is a plague dummy, equal to one after the origin suffered a plague outbreak. The first 20 years of the data are dropped, as mechanically initially every good is new. Annual growing season temperatures are an additional control.

Table 18: Impact of plague on volume of goods never exported before, by factor intensity

	Overall	Labour-intensive ag.	Capital-intensive ag.	Labour-intensive man.	Capital-intensive man.
	(1)	(2)	(3)	(4)	(5)
Post Plague	1.583***	2.106***	1.260*	1.038**	1.217
	(0.467)	(0.624)	(0.749)	(0.522)	(0.853)
Fixed Effects:					
– Area x Year	✓	✓	✓	✓	✓
– Origin x Destination	✓	✓	✓	✓	✓
– Destination x Year	✓	✓	✓	✓	✓
– Controls	✓	✓	✓	✓	✓
Estimator	PPML	PPML	PPML	PPML	PPML
Observations	50,472	13,365	30,255	3,284	12,149

Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is the volume of goods that a region has never exported before. The independent variable is a plague dummy, equal to one after the origin suffered a plague outbreak. The first 20 years of the data are dropped, as mechanically initially every good is new. Annual growing season temperatures are an additional control.

C.4 Other Robustness Results

Results from gravity regressions with origin-time, destination-time, and origin-destination fixed effects are displayed in Table 19. Table 20 shows that the plague increased regions' probability to export. For all four facts, I present heterogeneity results in Table 21. Table 22 shows heterogeneity results by plagued regions' siege status. Figure 26 presents evidence that my finding is not driven by export hubs whose reduced local consumption pushed more goods into exports. I show that plagued regions expanded their imports, speaking against a local demand contraction.

Table 19: Gravity analysis of plague shock on bilateral trade

	Overall	Agriculture		Manufacturing	
		Labour-intensive	Capital-intensive	Labour-intensive	Capital-intensive
	(1)	(2)	(3)	(4)	(5)
Post Plague	0.674*	0.718**	0.470*	1.232***	-0.602
	(0.372)	(0.356)	(0.279)	(0.454)	(0.682)
Fixed Effects:					
– Origin x Year	✓	✓	✓	✓	✓
– Destination x Year	✓	✓	✓	✓	✓
– Origin x Destination	✓	✓	✓	✓	✓
Estimator	PPML	PPML	PPML	PPML	PPML
Observations	505,415	49,887	69,106	26,141	40,514

Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is annual bilateral trade. The independent variable is a bilateral plague dummy, equal to one after either the origin, the destination, or both cities suffered a plague outbreak.

Table 20: Impact of plague on probability to export

	Marginal Effect		Average Marginal Effect			
	(1)	(2)	(3)	(4)	(5)	(6)
Post Plague	0.035***	0.007	0.032***	0.154***	0.057***	0.003
	(0.010)	(0.008)	(0.008)	(0.025)	(0.015)	(0.004)
Fixed Effects:						
– Origin		✓		✓		✓
– Year		✓		✓		✓
Estimator	OLS	OLS	Logit	Logit	Tobit	Tobit
Observations	502,980	502,980	502,980	502,980	502,980	502,980

Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is a dummy for whether a region exports in a given year. The independent variable is a plague dummy, equal to one after the origin suffered a plague outbreak. For Tobit, I model the exporter dummy as left truncated at 0. For Logit and Tobit, average marginal effects are displayed. In the balanced trade panel, the share of active exporters in a given year averages 10.4%.

Table 21: Heterogeneity of trade findings by pre-plague export levels

	Export Volume		Export Share		# Exported Goods		# New Exported Goods	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Plague	-0.98035050**	-0.57260670	0.01024532***	0.00405861	0.19697625***	0.11466535**	0.06830435**	0.02939703
	(0.41571542)	(0.44376456)	(0.00274101)	(0.00311360)	(0.05694356)	(0.05151306)	(0.03415583)	(0.02897934)
Post Plague x Cap-Int.	0.96971886*	1.14320257***						
	(0.52203372)	(0.41610229)						
Post Plague x Pre-Plague Exports		-0.00000115***		0.00000006***		0.00004342*		0.00002052**
		(0.00000037)		(0.00000001)		(0.00002343)		(0.00000889)
Post Plague x Cap-Int. x Pre-Plague Exports		-0.00000154***						
		(0.00000042)						
Fixed Effects:								
– Origin x Sector	✓	✓						
– Sector x Time	✓	✓						
– Area x Year			✓	✓	✓	✓	✓	✓
– Origin x Destination			✓	✓	✓	✓	✓	✓
– Destination x Year			✓	✓	✓	✓	✓	✓
Estimator	PPML	PPML	OLS	OLS	OLS	OLS	OLS	OLS
Observations	102,636	102,636	491,277	491,277	491,277	491,277	491,277	491,277

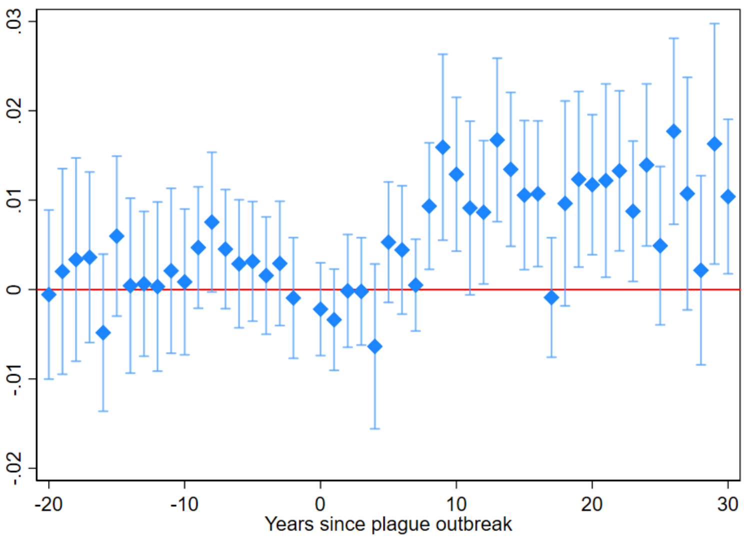
Notes: Standard errors clustered at the origin level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in columns 1-2 is the volume of exports by capital intensity. In columns 3-4, it is the market share origin i captures in j. In columns 5-6, it is the number of exported goods. In columns 7-8, it is the number of new exported goods. The independent variables for all four dependent variables are first a post plague dummy and then additionally its interaction with the level of exports before 1709 (number of exported goods) for columns 1-4 (5-8). In columns 1-2, the independent variables also include a post-plague x capint dummy and its interaction with pre-plague exports.

Table 22: Heterogeneity of trade findings by siege

	Export Volume	Export Share	# Exported Goods	# New Exported Goods
	(1)	(2)	(3)	(4)
Post Plague	-0.948**	0.004	0.128**	0.027
	(0.442)	(0.003)	(0.054)	(0.026)
Post Plague x Pre-Plague Exports	-0.000	0.000***	0.000*	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Post Plague x Cap-Int.	1.436***			
	(0.434)			
Post Plague x Cap-Int. x Pre-Plague Exports	-0.000***			
	(0.000)			
Post Plague x Siege	0.471***	0.000	-0.061	0.010
	(0.147)	(0.003)	(0.087)	(0.026)
Post Plague x Cap-Int. x Siege	-0.085			
	(0.228)			
Fixed Effects:				
– Origin x Sector	✓			
– Sector x Time	✓			
– Area x Year		✓	✓	✓
– Origin x Destination		✓	✓	✓
– Destination x Year		✓	✓	✓
Estimator	PPML	OLS	OLS	OLS
Observations	102,636	491,277	491,277	491,277

Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable in column 1 is the volume of exports by capital intensity. In column 2 it is the market share origin i captures in j. In column 3 it is the number of exported goods. In column 4 it is the number of new exported goods. The independent variables for all four dependent variables are a post plague dummy, its interaction with the level of exports before 1709 (or number of exported goods), and its interaction with a siege dummy. In column 1, the independent variables also includes a post-plague x capint dummy, its interaction with pre-plague exports, and its interaction with a siege dummy. Table 10 shows besieged cities.

Figure 26: Plagued regions also expanded their imports



Notes: Results arguing against mechanical explanations. Standard errors clustered at the level of destinations (as these are import results).

C.5 Continuous Plague Treatment

The main plague treatment used in this paper is a dummy indicating a region's own plague status. Alternatively, I construct a continuous plague treatment variable, incorporating plague outbreaks across all of Europe and drawing on additional sources for 106 recorded plague outbreaks. All recorded outbreaks of the Great Northern War plague across all of Europe are presented in Table 23 and Figure 27. A NUTS 3 region j is counted as plagued at time t if there is at least one town or region within region j that had a recorded plague outbreak by time t. In instances where a region, not a town, is mentioned in the source, I use the coordinates of the historical capital to compute distances.

Closer by and larger regions affect a region's continuous plague treatment by more. To be precise, the continuous plague treatment is constructed as

$$plague_{it}^{cont} = plague_{it}^{own} + \Sigma_j \frac{Population_j}{Distance_{ij}} plague_{jt},$$

where i are ports, j are regions in Europe at the NUTS 3 level, $_{it}^{own}$ denotes a region's own plague status at time t, and $_{jt}$ is a NUTS 3 region's plague status at time t. In the absence of population data at this resolution, I assume a constant population density and proxy with the size of a NUTS 3 region. Distances are computed as straight lines. As a robustness check, I also construct a second continuous plague treatment that weighs all regions j the same by dropping the population (or area) variable:

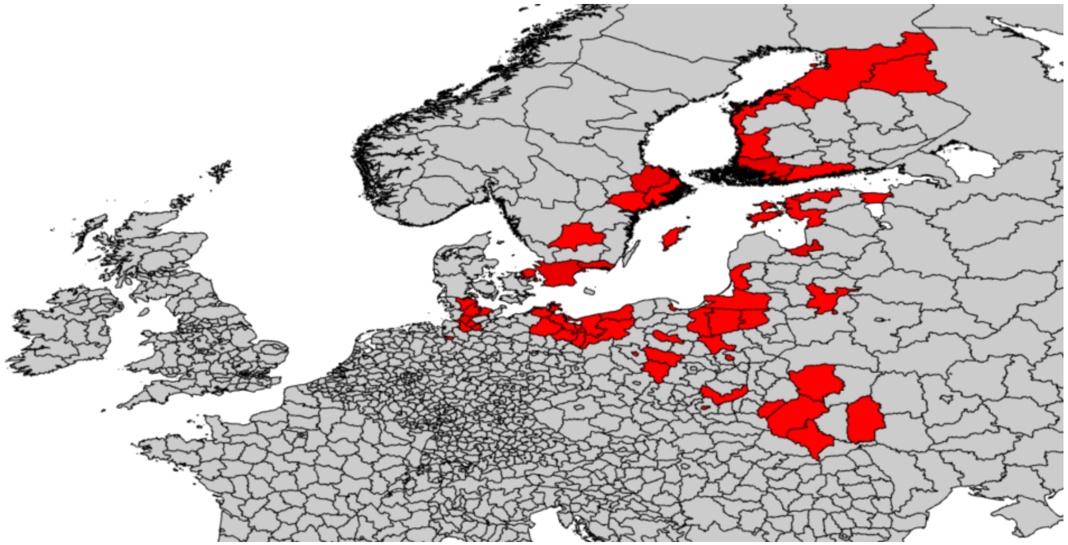
$$plague_{it}^{cont} = plague_{it}^{own} + \Sigma_j \frac{1}{Distance_{ij}} plague_{jt}.$$

I show in Table 24 that all results hold when regressing on a continuous plague treatment variable. The positive coefficients for the shift into capital-intensive exports after an own plague outbreak is no longer significant, however. The first four columns use the continuous plague treatment incorporating both area and distance, whereas the last four columns use the plague treatment that only incorporates distances, thus assigning the same weights to regions.

Table 23: List of plagued cities and regions across all of Europe

Town or Region	Modern Country	Time	Historical Capital	Source
Pińczów	Poland	1702		Frandsen, 2009
Ruthenia	Ukraine	1703–1706	Lwow	Frandsen, 2009
Podolia	Ukraine	1703–1706	Kamianets-Podilskyi	Frandsen, 2009
Volhynia	Ukraine	1703–1706	Lutsk	Frandsen, 2009
Lviv (Lemberg)	Ukraine	1704–1705		Frandsen, 2009
Kołomyja	Ukraine	1705–1706		Jarosław Burchardt, Meissner, and Burchardt, 2009
Stanisławów	Ukraine	1705–1706		Jarosław Burchardt, Meissner, and Burchardt, 2009
Stryj	Ukraine	1705–1706		Jarosław Burchardt, Meissner, and Burchardt, 2009
Sambor	Ukraine	1705–1706		Jarosław Burchardt, Meissner, and Burchardt, 2009
Przemyśl	Poland	1705–1706		Jarosław Burchardt, Meissner, and Burchardt, 2009
Jarosław	Poland	1705–1706		Jarosław Burchardt, Meissner, and Burchardt, 2009
Kraków	Poland	1707		Frandsen, 2009
Lesser Poland	Poland	1707–1710	Krakow	Frandsen, 2009
Mazovia	Poland	1707–1710	Warsaw	Frandsen, 2009
Warsaw	Poland	1707–1710		Frandsen, 2009
Great Poland	Poland	1707–1709	Gniezno	Frandsen, 2009
Ostrów	Poland	1707–1709		Frandsen, 2009
Kalisz	Poland	1707–1709		Frandsen, 2009
Poznań	Poland	1707–1709		Frandsen, 2009
Toruń	Poland	1708		Frandsen, 2009
Piekielko	Poland	1708		Frandsen, 2009
Bialutten	Poland	1708		Frandsen, 2009
Hohenstein	Poland	1708		Sahm, 1905
Masuria	Poland	1708–1710	Elk	Kossert, 2005
Königsberg	Russia	1709–1710		Frandsen, 2009
Danzig (Gdańsk)	Poland	1709		Kroll and Grabinsky, 2007
Elbing (Elblag)	Poland	1709–1710		Frandsen, 2009
Insterburg	Prussia	1708-1711		Kossert, 2005
Memel	Prussia	1708-1711		Kossert, 2005
Ragnit	Prussia	1708-1711		Kossert, 2005
Tilsit	Prussia	1708-1711		Kossert, 2005
Pillupönen (Nevskoye)	Russia	1709		Frandsen, 2009
Stettin (Szczecin)	Poland	1709–1711		Thiede, 1849
Damm (Dabie)	Poland	1709		Wieden, 1999
Pasewalk	Germany	1709–1710		Wieden, 1999
Anklam	Germany	1709–1710		Wieden, 1999
Kammin (Kamień Pomorski)	Poland	1709–1710		Wieden, 1999
Belgard (Białogard)	Poland	1709–1710		Wieden, 1999
Stralsund	Germany	1710–1711		Wieden, 1999
Altentreptow	Germany	1710–1711		Wieden, 1999
Wolgast	Germany	1710–1711		Wieden, 1999
Wollin (Wolin)	Poland	1710–1711		Wieden, 1999
Stargard	Poland	1710–1711		Wieden, 1999
Bahn (Banie)	Poland	1710		Wieden, 1999
Neumark	Poland	1710	Soldin	Schwartz, 1901
Uckermark	Poland	1710	Prenzlau	Wieden, 1999
Prenzlau	Germany	1710		Wieden, 1999
Greifswald	Germany	1711		Wieden, 1999
Lithuania	Lithuania	1709–1713	Vilnius	Frandsen, 2009
Vilnius	Lithuania	1709–1713		Frandsen, 2009
Livonia	Latvia	1709–1711	Riga	Kroll, 2006
Riga	Latvia	1710–1711		Kroll, 2006
Dünamünde (Daugavgrīva)	Latvia	1710		Frandsen, 2009
Estonia	Estonia	1709–1711	Reval	Frandsen, 2009
Reval (Tallinn)	Estonia	1710		Frandsen, 2009
Narva	Estonia	1710–1711		Kroll and Grabinsky, 2007
Pernau (Pärnu)	Estonia	1710		Kroll, 2006
Arensburg (Kuressaare)	Estonia	1710		Frandsen, 2009
Gotland	Sweden	1710–1712	Visby	Bohn, 1989
Visby	Sweden	1710–1712		Bohn, 1989
Stockholm	Sweden	1710–1711		Kroll, 2006
Uppland	Sweden	1710	Stockholm	Persson, 2011
Uppsala	Sweden	1710		Persson, 2011
Södermanland	Sweden	1710	Stockholm	Persson, 2011
Enköping	Sweden	1710		Persson, 2011
Jönköping	Sweden	1710–1711		Kroll and Grabinsky, 2007
Värmdö	Sweden	1711		Frandsen, 2009
Tillinge	Sweden	1711		Frandsen, 2009
Danmark parish	Sweden	1711		Frandsen, 2009
Helsingfors (Helsinki)	Finland	1710		Vourinen, 2007
Borgå (Porvoo)	Finland	1710		Vourinen, 2007
Ekenäs (Tammisaari)	Finland	1710		Vourinen, 2007
Åbo (Turku)	Finland	1710–1711		Vourinen, 2007
Nystad (Uusikaupunki)	Finland	1710–1711		Vourinen, 2007
Raumo (Rauma)	Finland	1710–1711		Vourinen, 2007
Björneborg (Pori)	Finland	1710–1711		Vourinen, 2007
Nådendal (Naantali)	Finland	1710–1711		Vourinen, 2007
Jakobstad (Pietarsaari)	Finland	1710–1711		Vourinen, 2007
Gamlakarleby (Kokkola)	Finland	1710–1711		Vourinen, 2007
Uleåborg (Oulu)	Finland	1710–1711		Vourinen, 2007
Kajana (Kajaani)	Finland	1710–1711		Engström, 1994
Helsingør	Denmark	1710–1711		Frandsen, 2009
Copenhagen	Denmark	1711		Frandsen, 2009
Västana	Sweden	1711		Frandsen, 2009
Karlskrona	Sweden	1710		Persson, 2011
Karlshamn	Sweden	1710		Persson, 2011
Blekinge	Sweden	1710	Karlskrona	Persson, 2011
Domsten	Sweden	1711		Frandsen, 2009
Ystad	Sweden	1712		Frandsen, 2009
Malmö	Sweden	1712		Frandsen, 2009
Hamburg	Germany	1712–1714		Kroll, 2006
Altona	Germany	1713		Frandsen, 2009
Bremen	Germany	1712–1713		Frandsen, 2009
Stade	Germany	1712		Frandsen, 2009
Itzehoe	Germany	1712		Frandsen, 2009
Kropp	Germany	1712		Frandsen, 2009
Glückstadt	Germany	1712		Frandsen, 2009
Rendsburg	Germany	1712		Ulbricht, 2004
Laboe	Germany	1712		Ulbricht, 2004
Holstein	Germany	1712	Glückstadt	Frandsen, 2009
Schleswig	Germany	1712		Ulbricht, 2004
Flensburg	Germany	1712		Ulbricht, 2004
Friedrichsort	Germany	1712		Ulbricht, 2004
Pinneberg	Germany	1712		Winkle, 1983
Rellingen	Germany	1712		Winkle, 1983
Gröpelingen	Germany	1712		Frandsen, 2009

Figure 27: Map of Plagued NUTS 3 Regions



Notes: A map of plagued hinterlands based on Table 23. Red colour indicates 1 or more plagued locations within a NUTS 3 region.

Table 24: Impact of Plague on Trade, Accounting for Outbreaks in the Hinterland

	Plague (continuous treatment)				Plague (only accounting for distance)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Own Plague	70.19260	0.01037***	0.19819***	0.07497**	68.78410	0.01087***	0.20180***	0.07387**
	(48.95880)	(0.00285)	(0.05970)	(0.03609)	(53.02448)	(0.00295)	(0.06222)	(0.03699)
Plague in Hinterland	-0.02843	-0.00000	-0.00002	-0.00006				
	(0.02638)	(0.00000)	(0.00010)	(0.00004)				
Own Plague x Capital-Int.	1.3e+02				1.6e+02			
	(1.2e+02)				(1.4e+02)			
Plague in Hinterland x Capital-Int.	0.01858*							
	(0.01089)							
Plague in Hinterland, Only Distance					-5.6e+01*	-0.00387**	-0.03760	-0.03447
					(31.34625)	(0.00196)	(0.09991)	(0.02659)
Plague in Hinterland, Only Distance x Capital-Int.					-3.4e+01			
					(49.50306)			
Fixed Effects:								
– Origin x Sector	✓				✓			
– Year	✓				✓			
– Area x Year		✓	✓	✓		✓	✓	✓
– Origin x Destination		✓	✓	✓		✓	✓	✓
– Destination x Year		✓	✓	✓		✓	✓	✓
Estimator	246,095	489,617	489,617	489,617	246,095	489,617	489,617	489,617

Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is sectoral exports in columns 1 and 5, trade between i and j in columns 2 and 6, a dummy for positive trade between i and j in columns 3 and 7, and the volume of new export between i and j in columns 4 and 8. The independent variables are an own plague dummy, a continuous plague variable accounting for the size and proximity of other Europe-wide plagued regions, a second such dummy accounting only for proximity of other plagued regions, and their interactions with a capital intensity dummy (only in columns 1 and 5). Annual growing season temperatures are an additional control in all specifications.

D Model Appendix

This Appendix holds results supplementing the model. The first subsection describes how productivity growth is recovered from the model and the second subsection provides additional results on simulations and counterfactuals.

D.1 Recovering Sectoral Productivities

In this Section, I lay out my procedure for recovering sectoral productivities from the gravity equation. First, note that my setting compares to the approach chosen by Costinot, Donaldson, and Komunjer, 2011 in that I have an additional time dimension. Costinot, Donaldson, and Komunjer, 2011 show that the following relationship between trade flows, sectoral productivities, and trade costs is true in their model:

$$\frac{X_{ijk}X_{i'jk'}}{X_{ijk'}X_{i'jk}} = \left(\frac{A_{ik}A_{i'k'}}{A_{ik'}A_{i'k}}\right)^{\theta}\left(\frac{d_{ijk}d_{i'jk'}}{d_{ijk'}d_{i'jk}}\right)^{-\theta}. \tag{26}$$

This equation takes two ratios: one with respect to a reference sector k in i to eliminate wages in i, and another with respect to a reference region i' to eliminate the demand side for sector k. In my setting, I will additionally need to take time into account and form a third ratio. Thus, I will recover relative sectoral productivity growth. Time variation will be introduced into gravity equation 10 as follows:

$$X_{ijkt} = \frac{\chi_k A_{ikt}(w_{ikt})^{-\gamma_k\theta}d_{ijkt}^{-\theta}}{CMA_{jkt}}\alpha_k Y_{jt}. \tag{27}$$

The following result can be established from equation 27:

$$\frac{X_{ijkt}X_{ijk't'}X_{i'jkt'}X_{i'jk't}}{X_{i'jkt}X_{i'jk't'}X_{ijkt'}X_{ijk't}} = \frac{A_{ikt}A_{i'kt'}A_{ik't'}A_{i'k't}}{A_{ikt'}A_{i'kt}A_{ik't}A_{i'k't'}}\left(\frac{w_{ikt}w_{i'kt'}}{w_{i'kt}w_{ikt'}}\right)^{-\gamma_k\theta}\left(\frac{w_{ik't'}w_{i'k't}}{w_{i'k't'}w_{ik't}}\right)^{-\gamma_{k'}\theta}. \tag{28}$$

If one is willing to assume that $d_{ijkt} = d_{ijkt'}\forall(ij,kt)$ or at least that $\frac{d_{ijkt}}{d_{i'jkt}} = \frac{d_{ijkt'}}{d_{i'jkt'}}$, trade costs cancel out when forming this ratio. Therefore, an orthogonality assumption for trade costs is no longer required. As I am studying a relatively short period of time before the introduction of the steamship and it seems reasonable to further assume that trade costs were not changed by the plague, I am willing to make this assumption.

Three ratios are formed in equation 28. First, a ratio with respect to a reference sector k' in the same origin and time period. This allows to separate sectoral productivities from regional wages in period t, up to the wage equalisation condition induced by serfdom, which will be discussed below. Under appropriate assumption, the wage ratios will drop out. Second, a ratio with respect to a reference origin i' is formed, which leads to the demand side cancelling out in that equation 27 for both i and i' contains the same total expenditure and sectoral market access for destination j in period t. Third, a ratio with respect to a reference period t' is formed. This leads to the identification of growth relative to a reference period. Evidently, this three way differencing is precisely what a three-way fixed model delivers (Olden and Møen, 2022). I regress trade flows as follows:

$$X_{ijkt} = exp(\alpha + \delta_{ijt} + \delta_{jkt} + \delta_{ikt}) \times \epsilon_{ijkt}, \tag{29}$$

where i is the exporter, j the importer, k the sector, t the time, δ_{ijt} an importer-exporter-time fixed effect, δ_{ikt} an exporter-sector-time fixed effect and δ_{jkt} an importer-sector-time fixed effect. ϵ_{ijkt} is the error term. Note, first of all, that this specification nests all interaction terms of fixed effects and the model is therefore saturated (Angrist and Pischke, 2009). Second, note that the three-way fixed effect δ_{ikt} recovers differences-in-differences-in-differences (Olden and Møen, 2022):

$$\frac{\delta_{ikt}\delta_{i'kt'}\delta_{ik't'}\delta_{i'k't}}{\delta_{ikt'}\delta_{i'kt}\delta_{ik't}\delta_{i'k't'}} = \frac{\frac{\delta_{ikt}\delta_{i'k't}}{\delta_{ik't}\delta_{i'kt}}}{\frac{\delta_{ikt'}\delta_{i'k't'}}{\delta_{ik't'}\delta_{i'kt'}}}. \tag{30}$$

This is to say, δ_{ikt} recovers a time difference of what δ_{ik} recovered in Costinot, Donaldson, and Komunjer, 2011. Computing equation 28 confirms this finding, such that indeed δ_{ikt} captures the right hand side of equation 28:

$$\frac{A_{ikt}A_{i'kt'}A_{ik't'}A_{i'k't}}{A_{ikt'}A_{i'kt}A_{ik't}A_{i'k't'}}\left(\frac{w_{ikt}w_{i'kt'}}{w_{i'kt}w_{ikt'}}\right)^{-\gamma_k\theta}\left(\frac{w_{ik't'}w_{i'k't}}{w_{i'k't'}w_{ik't}}\right)^{-\gamma_{k'}\theta}. \tag{31}$$

Below, I will detail how equation 31 can be simplified in order to recover a productivity ratio from equation 29. Two assumptions are required:

1. All sectors have the same labour share, $\gamma_k = \gamma \forall k$.
2. **Either:** There is no time variation in the labour mobility friction, $\phi_{it} = \phi_{it'}$ and $\phi_{i't} = \phi_{i't'}$.
3. **Or:** The labour mobility friction does not vary within areas, such that $\phi_{ikt} = \phi_{jkt} \forall (k,t)$ and i,j within the same area.

To make progress in separating wages from productivities, I assume $\gamma_k = \gamma \forall k$. This permits to summarise both wage ratios. I then impose wage equalisation as assumed above. Allowing wages and the serfdom-induced labour mobility friction to vary over time, I assume:

$$w_{iMt} = \begin{cases} w_{iAt}, & \text{without serfdom,} \\ (1+\phi_{it})w_{iAt}, & \text{with serfdom.} \end{cases} \tag{32}$$

Unclassified goods will be the reference sector k', which I assume to produce in the hinterland, paying wage w_{iAt}. Accordingly, for k=LA,CA, I can set $w_{ikt} = w_{ik't} \forall (i,t)$, such that the wage ratio drops out. Thus, δ_{ikt} identifies sectoral productivity growth compared to a reference region and sector, here unclassified goods, for both agricultural sectors.

For manufacturing, k=LM,CM, I plug in wage equalisation assumption 32 to obtain:

$$\delta_{ikt} = \frac{A_{ikt}A_{i'kt'}A_{ik't'}A_{i'k't}}{A_{ikt'}A_{i'kt}A_{ik't}A_{i'k't'}}\left(\frac{(1+\phi_{it})(1+\phi_{i't'})}{(1+\phi_{i't})(1+\phi_{it'})}\right)^{-\gamma\theta}. \tag{33}$$

The ratio of ϕ parameters simplifies to 1 under one of two conditions. First, if $\phi_{it} = \phi_{i't}$ and $\phi_{i't'} = \phi_{it'}$. At all points in time, the labour mobility friction would thus have to be of the same level, which I refuse to assume. Instead, I opt for the second condition:

if $\phi_{it} = \phi_{it'}$ and $\phi_{i't} = \phi_{i't'}$, the ϕ ratio equals 1 and δ_{ikt} in equation 29 recovers a productivity ratio. This assumption implies the absence of time variation in the labour mobility friction. While Raster, 2023 argues for increased serfdom after the plague in Northern Estonia, this finding is compatible with the assumption as long as the degree to which this limits labour mobility is unchanged. I consider this a realistic assumption as serfdom restricted moving to urban areas before and after the plague. Further, the fundamental hurdle of moving to a German-speaking city while not having been allowed to learn a trade remained in place.

Alternatively, one can permit time variation in the serfdom-induced labour mobility friction, as long as the ϕ parameters do not vary within areas. In that case, area-sector-time fixed effects in equation 11 will absorb this area-sector-time specific variation. In this case, the plague may well have worsened serfdom and its effects on labour mobility. As long as these changes are symmetric within an area, the ϕ ratio will be absorbed by fixed effects.

A special case is presented by Denmark (including Norway and large parts of modern-day Schleswig Holstein), which is the only country in this area that re-introduced serfdom in 1733 (Gary et al., 2022). The ϕ ratio simplifies to $(1 + \phi_{it})^{-\gamma\theta}$ when plugging in that region i in Denmark did not use to have serfdom ($\phi_{it'} = 0$) and that reference region i' had serfdom at no point in time ($\phi_{i't} = \phi_{i't'} = 0$). Therefore, for a value of ϕ_{it} in Denmark and parameter values γ, θ, the fixed effect δ_{ikt} can be cleaned for the change in serfdom. For both manufacturing productivities in areas that reintroduced serfdom, this adjustment is necessary when including Denmark and Norway and making the first assumption on serfdom, not the second. Figure 8 shows the value of ϕ_{it} for Copenhagen and her hinterland, based on wage data by Gary et al., 2022. The wage wedge takes a few years to materialise after 1733. The mean of ϕ_{it} after 1740 is 0.8, which means that urban wages were 80% higher than rural wages in the region of Copenhagen.

Regarding choosing a reference region i', I show that the choice of the reference region is irrelevant with the appropriate specification. The reference region matters for regressions on productivity growth without any fixed effects. Appendix Table 25 regresses a plague dummy on log productivity growth in capital-intensive agriculture for different choices of reference regions: London, Amsterdam, Rouen, Edinburgh, and Oslo, none of which were plagued. I show that the choice of reference region cancels out when introducing region and time fixed effects. Regarding the reference time t', I transform the recovered growth ratios such that they are at 1 in the first year of my data, 1668.

Table 25: Impact of plague on capital-intensive agriculture productivity growth, by reference region and specification

	No fixed effects					Fixed effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Plague Dummy	2.337***	3.284***	2.274***	2.124***	0.198	0.805***	0.805***	0.805***	0.805***	0.805***
	(0.203)	(0.244)	(0.246)	(0.218)	(0.324)	(0.265)	(0.265)	(0.265)	(0.265)	(0.265)
Reference Region	London	Amsterdam	Rouen	Edinburgh	Oslo	London	Amsterdam	Rouen	Edinburgh	Oslo
Fixed Effects:										
– Region						✓	✓	✓	✓	✓
– Area x Year						✓	✓	✓	✓	✓
Observations	36,326	36,326	36,326	36,326	36,326	36,162	36,162	36,162	36,162	36,162

Notes: Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is capital-intensive agricultural productivity growth by reference region and specification. The independent variable is a plague dummy that equals 1 for plagued regions after the plague hit. Columns 6-10 include fixed effects which ensure that the choice of reference region does not affect results.

Section 2 outlined how the end of the Little Ice Age saw temperatures rise across Northern Europe. Non-plagued regions will therefore have seen agricultural productivity growth as outlined by Waldinger, 2022. To account for exogenous and spatially varying temperature change at the end of the Little Ice Age, I permit agricultural productivity growth also in non-plagued regions as a function of temperature change. In plagued regions, I additionally allow for plague-induced productivity changes. I assume that for a non-plagued region i':

$$\frac{A_{i',At}}{A_{i',At'}} = \left(\frac{temp_{i',t}}{temp_{i',t'}}\right)^{\epsilon_A}. \tag{34}$$

I assume a value of $\epsilon_A = 1$ and correct the recovered agricultural productivity ratios for both labour- and capital-intensive agriculture for this term. This value is reasonable given that most regions are in Northern Europe (see Liu, Mishra, and Ray, 2020) and represents an average over estimates for different crops.

Finally, instead of estimating with OLS as in Costinot, Donaldson, and Komunjer, 2011 I use PPML on a balanced panel, which is required for the equivalence between their equations (17) and (18). There are a number of reasons for preferring PPML. First of all, the model generates a gravity equation for trade, so all arguments for PPML in Santos-Silva and Tenreyro, 2006 apply. The issue of zeros is much more prevalent in my data than in the data by Costinot, Donaldson, and Komunjer, 2011, whose trade data cover 21 countries and 13 industries. Mine cover 676 regions and 99% of observations in the balanced panel are zeros, highlighting the need for an appropriate estimation strategy. A share of zeros above 90% is common in granular historical trade studies (Jacks, O'Rourke, and Taylor, 2020).

D.2 Simulations

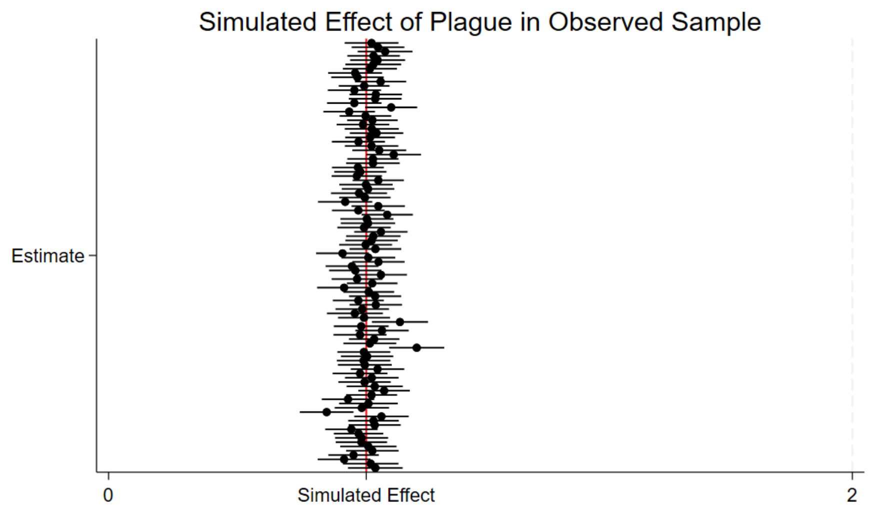
Figure 28 shows simulation results comparing simulated productivity growth between the hypothetical full sample and the observed sample. While in the observed sample only trade passing the Sound is registered, such that trade on only one side of the Sound is not observed, in the theoretical, full sample I simulate trade volumes also on these routes, for example from Amsterdam to London or Stockholm to Riga.

To simplify matters, I simulate only two sectors: a labour-intensive and a capital-intensive one. I choose reference levels for wages, market access, χ_k, α_k, and Y_j and compute trade costs as $d_{ij}^{-\theta}$, where d_{ij} is distance over sea. I simulate two time periods, where in the first all regions have the same capital-intensive sector productivity levels. Plagued regions then experience productivity growth in the capital-intensive sector and have higher levels in the second period, whereas non-plagued regions keep their period 1 capital-intensive sector productivity level. As all other variables and parameters are the same across regions, the simulated values imply that plagued regions' capital-intensive sector productivity growth was twice as high as that of non-plagued regions. Thus, the simulated effect is $ln2 = 0.693$. Below, I show results for a log-normal specification of noise, where I take the log of simulated trade values, add standard normally distributed noise, and then take the exponential of these noise-amended trade flows. Results with multiplicative and uniformly distributed noise display the same pattern. I then recover sectoral productivities as described in Section D.1, choosing unclassified goods as the reference sector, London as the reference region, and the first year as the reference year. I then regress a plague dummy on the recovered capital-intensive sector productivity growth and include region and time fixed effects.

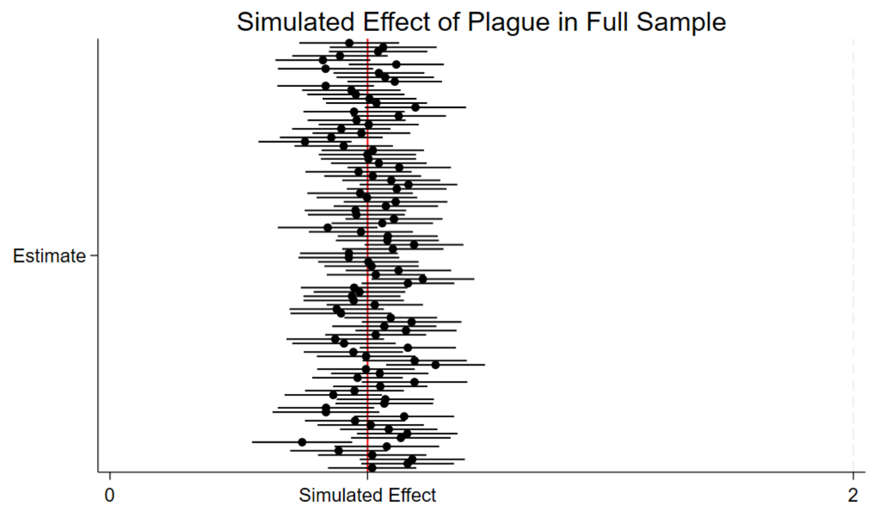
These results are displayed in Figure 28. The simulated effect lies at 0.693, which is within 96 out of 100 confidence intervals for the regressions on the full sample. For the observed sample, 97 out of 100 confidence intervals contain the simulated effect. Point estimates in all cases are centred around the simulated effect, but the variance in the full sample is larger.

I also simulate trade following equation 10 and find similar results when regressing simulated trade volumes in both samples on a plague dummy, including origin-destination and destination-time fixed effects. These results, presented in the bottom panels of Figure 28, show that a significant export increase is picked up in both samples. I run 100 simulations and show that the point estimates are very similar when comparing the full to the observed sample. In both samples, the estimates are centred around the simulated effect, suggesting no bias is introduced by restricting to the observed sample. I conclude that the sample restriction of only observing ships passing through the toll station is not introducing a bias in my productivity growth and trade estimates.

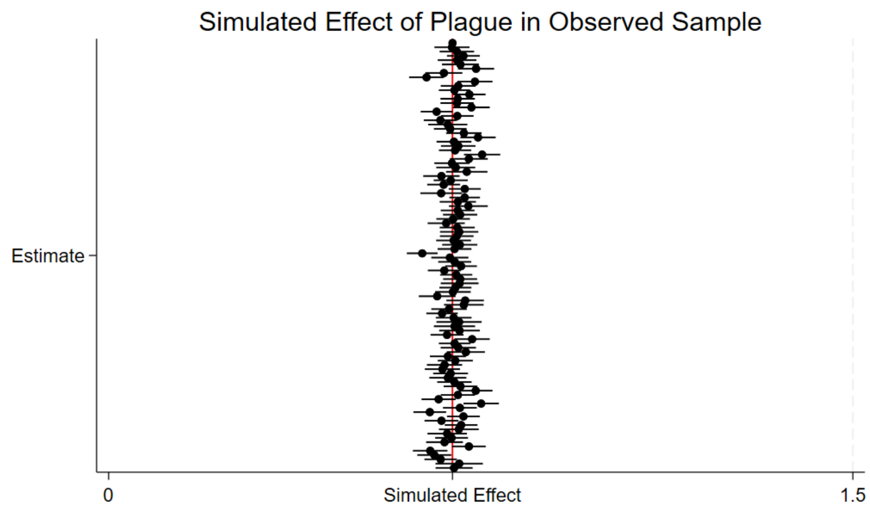
Figure 28: Simulated productivity growth and trade increase in observed vs. full sample



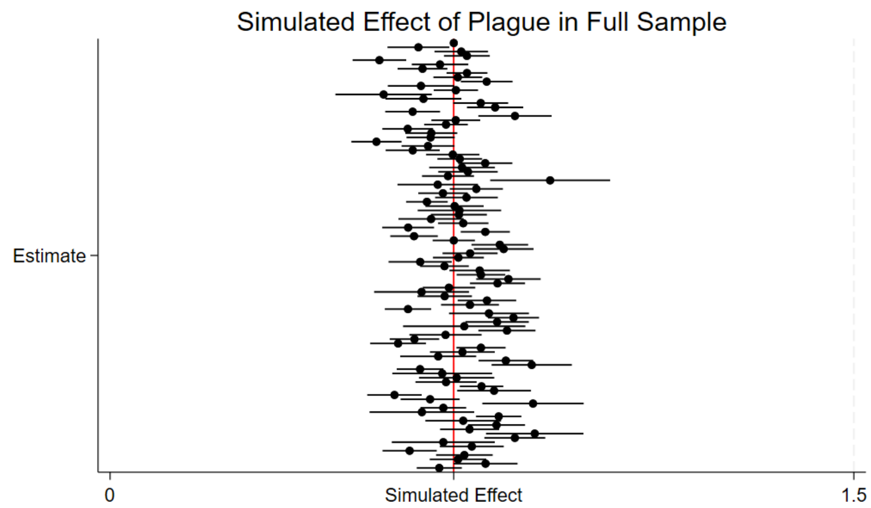
(a) Estimated productivity growth in observed sample



(b) Estimated productivity growth in full sample



(c) Estimated trade growth in observed sample



(d) Estimated trade growth in full sample

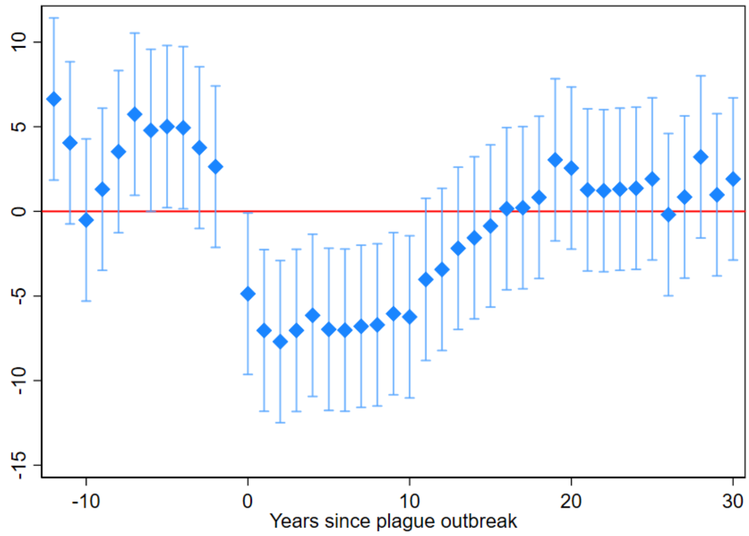
E Mechanisms Appendix

This Appendix shows results supporting the mechanism proposed in this paper. The structure follows the mechanism in the main part of the paper.

Step #1: The Plague Induces Labour Scarcity

Figure 29 shows an event study for the number of captains living in a region before and after the plague.

Figure 29: Dynamics of population recovery after the plague: number of captains as proxy for population



Notes: Event study with area-year and region fixed effects on the number of unique captains' last names living in a region. Captains with the same first and last name from the same region in the same year are assumed to be duplicates and thus dropped.

E.1 Step #2: Production Becomes More Capital-Intensive

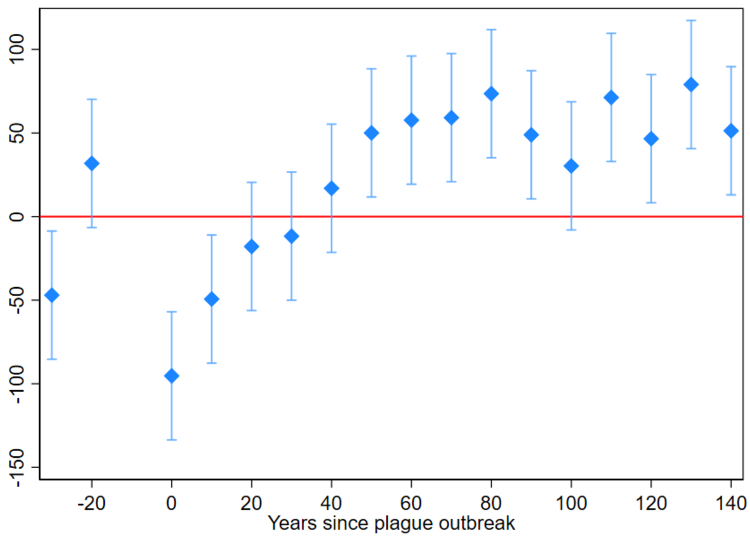
Table 26 shows that following a plague outbreak, ports significantly increased the number of ships they owned, which I interpret as a proxy for the capital stock. Figure 30 instead presents an event study on this proxy. Figure 31 shows Scania's overall shift out of arable and into pastoral farming after the plague. Table 27 shows for individual farms that this shift was stronger the closer a farm was to plagued cities. Figure 32 shows an event study for novel exports after the plague.

Table 26: Impact of plague on proxied capital stock

	# Ships							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Plague Dummy	166.218***	104.535***	164.057***	94.835***				
	(45.161)	(23.508)	(45.329)	(23.547)				
Mortality Rate					385.187***	248.952***	380.036***	226.573***
					(119.599)	(64.118)	(119.693)	(63.366)
Fixed Effects:								
– Region		✓		✓		✓		✓
– Decade			✓	✓			✓	✓
Observations	41,400	41,400	41,400	41,400	41,253	41,253	41,253	41,253

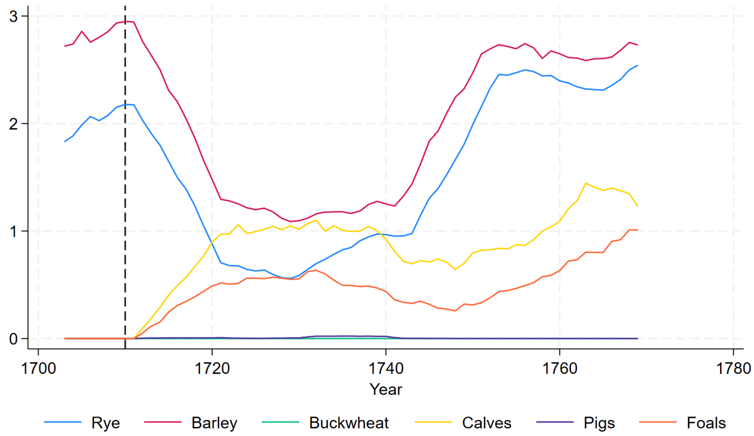
Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is the number of ships registered in a city. It is assumed that ships do not sit idle and therefore that every owned ship appears once a decade. Further I assume that ships from the same city with the same captain in the same year are duplicates and drop these. The independent variable is first a plague dummy that equals 1 for plagued cities after the plague hit. The second independent variable is the mortality rate, which for half of regions is imputed as the predicted value from regression results presented in Appendix Table 11.

Figure 30: Dynamics of capital accumulation after the plague: number of ships as proxy for the capital stock



Notes: Event study with area-time, region, and decade fixed effects on the number of ships registered in a harbour in levels. Decade -1 is omitted as the reference decade.

Figure 31: Agricultural production in Scania becomes more capital-intensive



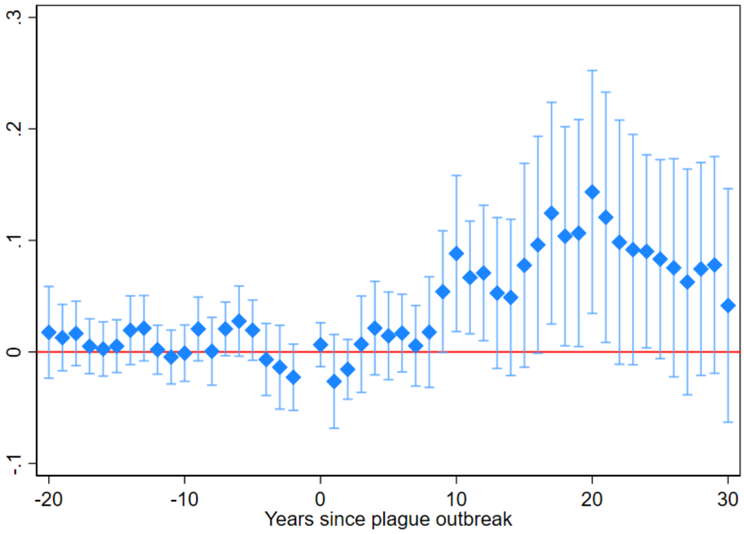
Notes: Figure 31 covers 119 Scanian farms and the composition of their production.

Table 27: Farm production and distance to plagued cities

	Calves	Pigs	Foals	Rye	Barley	Buckwheat
	(1)	(2)	(3)	(4)	(5)	(6)
Plague Distance x Post Plague	-0.00656**	-0.000395**	-0.00521***	0.0182***	0.0355***	0.000228**
	(0.00281)	(0.000156)	(0.00171)	(0.00138)	(0.00310)	(0.0000965)
Fixed Effects:						
– Year	✓	✓	✓	✓	✓	✓
– Farm	✓	✓	✓	✓	✓	✓
Observations	5,683	5,683	5,683	5,304	5,304	5,683

Notes: Standard errors clustered at the farm level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variables are farm's production of calves, pigs, foals rye, barley, and buckwheat. The independent variable is the sum of distances multiplied by a plague dummy over the four closest cities in Scania province. Both Ystad and Malmö suffered a plague outbreak in 1712 with a mortality rate of 38% and 35%, respectively, whereas Landskrona and Helsingborg did not suffer plague outbreaks.

Figure 32: New exports at the extensive margin



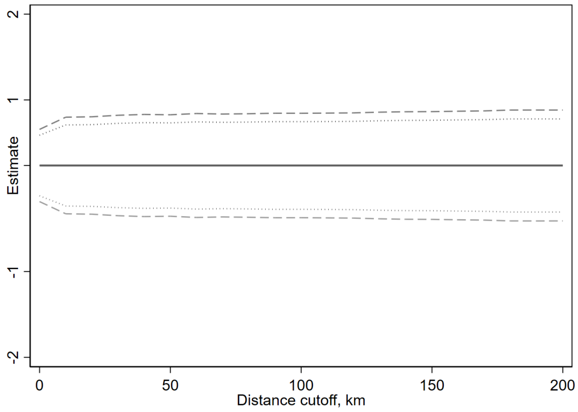
Notes: Estimation of equation 2 on the number of exported goods. A new export is defined as a good first exported by a city between 1689, 20 years before the onset of the plague in my study area, and 1732, 20 years after the last plague year in this region. Standard errors clustered at the origin level.

E.2 Step #3: Productivity Grows More in High β_k Sectors

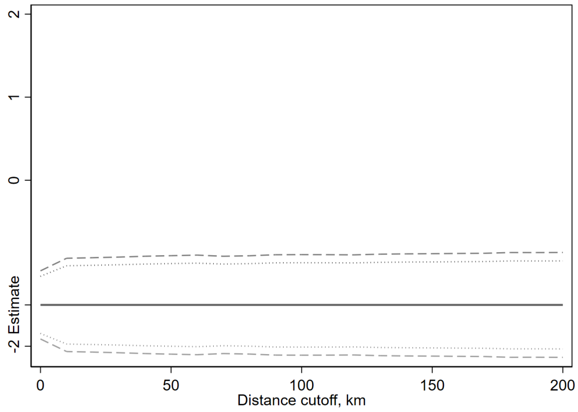
Figure 33 repeats Table 3 using Conley standard errors (Conley, 1999) and a range of different distance cut-offs. Table 28 adjusts manufacturing productivities in Denmark and Norway for the introduction of serfdom based on wage wedges identified in data by Gary et al., 2022. For full details, see Appendix D.1. I adjust manufacturing productivities in serfdom-switching areas after 1740, as the 1733 reintroduction did not immediately show an increased wage wedge between city and hinterland (see Figure 8). Table 29 shows the long run response of sectoral productivities.

Figure 34 shows output per farm in Scania, adjusting for farm size, and documents only a small and brief dip in output after the plague. Figure 35 decomposes the wharves producing ships for the Swedish East India Company. Ships that were built in wharves founded after the plague in plagued regions account for the majority on all accounts.

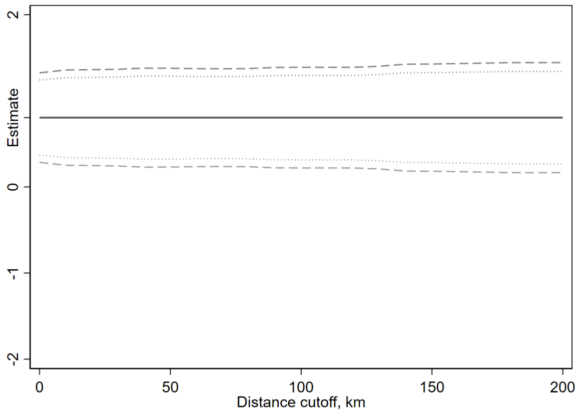
Figure 33: The Plague's Productivity Effect by Sector, using Conley Standard Errors



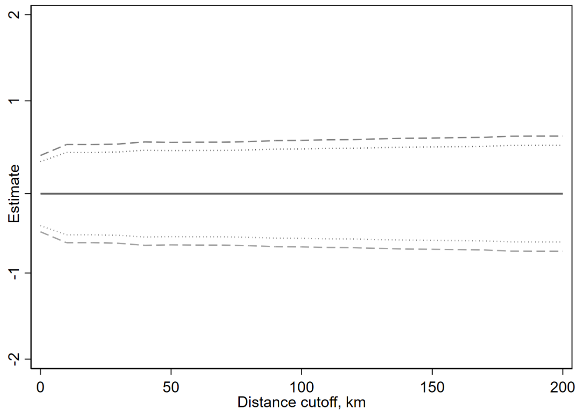
(a) Capital-intensive manufacturing



(b) Labour-intensive manufacturing



(c) Capital-intensive agriculture



(d) Labour-intensive agriculture

Notes: These Figures repeat columns 1, 3, 5, and 7 of Table 3 with Conley standard errors and distance cut-offs between 0 and 200 km in steps of 10 km. Distance cut-offs are denoted on the x axis and point estimates (solid line), 95% confidence intervals (dashed lines), and 90% confidence intervals (dotted lines) on the y axis. Implemented using Stata packages by Baum-Snow and Han, 2024, Thiemo Fetzer, and Hsiang, 2010.

Table 28: Impact of plague on sectoral productivity growth, by sector and factor intensity. Manufacturing productivity adjustment for Denmark reintroducing serfdom

	Agriculture				Manufacturing			
	Labour-intensive		Capital-intensive		Labour-intensive		Capital-intensive	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Plague Dummy	0.024		0.572***		-1.255***		0.039	
	(0.177)		(0.208)		(0.164)		(0.169)	
Mortality Rate		0.299		1.747***		-2.997***		0.632
		(0.463)		(0.543)		(0.427)		(0.440)
Fixed Effects:								
– Region	✓	✓	✓	✓	✓	✓	✓	✓
– Area x Year	✓	✓	✓	✓	✓	✓	✓	✓
Observations	50,010	50,010	50,020	50,020	50,020	50,020	50,020	50,020

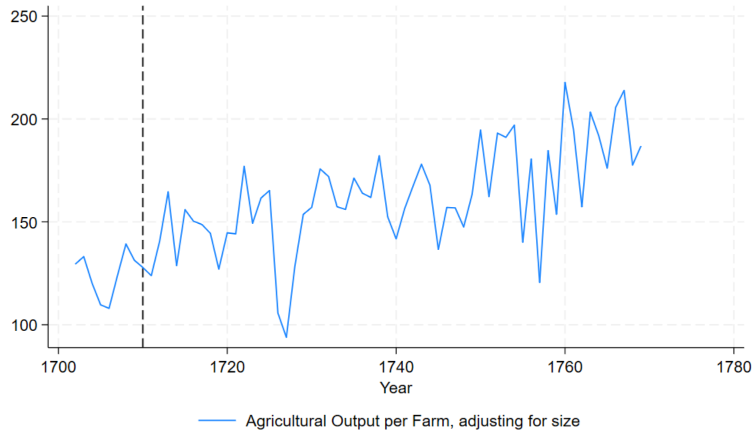
Notes: Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is log sectoral productivity growth. This has been adjusted for the introduction of serfdom in Denmark and Norway. The independent variable is first a plague dummy that equals 1 for plagued regions after the plague hit. The second independent variable is the mortality rate, which for half of regions is imputed as the predicted value from regression results presented in Appendix Table 11.

Table 29: Impact of plague on sectoral productivity growth in the long run

	Labour-intensive ag.	Capital-intensive ag.	Labour-intensive man.	Capital-intensive man.
	(1)	(2)	(3)	(4)
0-9 Years Post Plague	-0.553**	0.457	-0.732***	-0.226
	(0.246)	(0.292)	(0.229)	(0.252)
10-19 Years Post Plague	0.165	0.360	-1.576***	0.178
	(0.246)	(0.292)	(0.229)	(0.252)
20-29 Years Post Plague	-0.141	1.026***	-1.395***	0.298
	(0.246)	(0.292)	(0.229)	(0.252)
30-39 Years Post Plague	-0.289	0.826***	-1.697***	1.131***
	(0.246)	(0.292)	(0.229)	(0.252)
40-49 Years Post Plague	0.248	0.550*	-1.328***	1.616***
	(0.246)	(0.292)	(0.229)	(0.252)
50-59 Years Post Plague	0.647***	1.639***	-1.694***	1.773***
	(0.246)	(0.292)	(0.229)	(0.252)
60-69 Years Post Plague	1.182***	1.558***	-1.125***	1.986***
	(0.246)	(0.292)	(0.229)	(0.252)
70-79 Years Post Plague	1.287***	1.717***	-1.587***	0.629**
	(0.246)	(0.292)	(0.229)	(0.252)
80-89 Years Post Plague	1.706***	1.816***	-1.641***	0.308
	(0.246)	(0.292)	(0.229)	(0.252)
90-99 Years Post Plague	1.074***	0.912***	0.110	1.295***
	(0.246)	(0.292)	(0.229)	(0.252)
Fixed Effects:				
– Region	✓	✓	✓	✓
– Area x Year	✓	✓	✓	✓
Observations	170,403	170,430	170,430	170,430

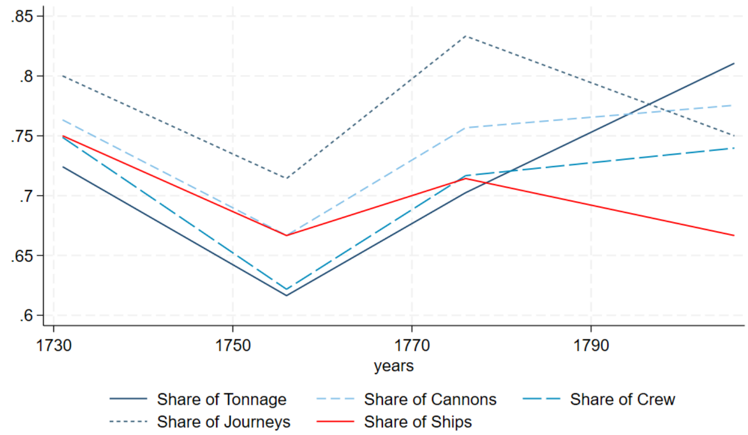
Notes: Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is log sectoral productivity growth. The independent variable is a plague dummy that equals 1 for plagued regions after the plague hit interacted with decade dummies after the plague. Denmark and Norway have been dropped from the sample as they reintroduced serfdom in 1733.

Figure 34: Total value of agricultural production per farm, controlling for farm size



Notes: Figure 34 includes all farms in Scania covered by the data and their total output.

Figure 35: Share of Swedish Wharf Output by Plague Status



Notes: Based on data on the production location of all ships (n=30) operated by the Swedish East India Company. Wharves founded in plagued regions after 1714 are classified as located in plagued regions. The y axis denotes the share of tonnage, journeys, cannons, crew and ships for four points in time produced in wharves founded after the plague in plagued regions.

E.3 Factor Adjustments & Serfdom

Table 30 shows how the plague interacted with serfdom in export data. Tables 31 and 32 differentiate post-plague productivity growth by serfdom.

Table 30: Impact of plague on shift into capital-intensive exports by sector & second serfdom

	Manufacturing		Agriculture	
	(1)	(2)	(3)	(4)
Plague	1.232*	0.627	1.205*	0.850
	(0.707)	(0.398)	(0.681)	(0.529)
Plague x Serfdom	-2.498***	-0.930**	-2.187***	-1.325**
	(0.419)	(0.409)	(0.591)	(0.526)
Plague x Capital-Int.	-1.855***	-0.809	0.653	0.868
	(0.546)	(0.528)	(0.915)	(0.922)
Plague x Capital-Int. x Second Serfdom	2.544***	0.930*	-0.478	-0.715
	(0.539)	(0.525)	(0.849)	(0.911)
Fixed Effects:				
– Origin x Sector	✓	✓	✓	✓
– Sector x Year	✓	✓	✓	✓
Estimator	PPML	OLS	PPML	OLS
Observations	29,798	5,040	53,088	9,576

Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable are sectoral exports in levels (columns 1 and 3) and logs (columns 2 and 4). In columns 2 and 4, values are weighted by exports in levels. The independent variables are a plague dummy, a second serfdom dummy, a capital-intensive sector dummy, and their interactions. I additionally control for growing season temperatures.

Table 31: Impact of plague on sectoral productivity growth, by second serfdom

	Agriculture		Manufacturing	
	Labour-intensive	Capital-intensive	Labour-intensive	Capital-intensive
	(1)	(2)	(3)	(4)
Plague	-0.435	0.936***	-1.244***	0.196
	(0.296)	(0.347)	(0.274)	(0.281)
Plague & Serfdom	0.790*	-0.291	-0.571	0.090
	(0.423)	(0.496)	(0.391)	(0.401)
Fixed Effects:				
– Region	✓	✓	✓	✓
– Area x Year	✓	✓	✓	✓
Observations	36,152	36,162	36,162	36,162

Notes: Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is log sectoral productivity growth. The independent variable is a plague dummy that equals 1 for plagued regions after the plague hit interacted with a dummy for second serfdom. Denmark and Norway have been dropped from the sample as they reintroduced serfdom in 1733.

Table 32: Impact of plague on sectoral productivity growth, by second serfdom. Manufacturing productivity adjustment for Denmark reintroducing serfdom

	Agriculture		Manufacturing	
	Labour-intensive	Capital-intensive	Labour-intensive	Capital-intensive
	(1)	(2)	(3)	(4)
Plague	-0.435	0.915***	-1.210***	0.173
	(0.265)	(0.311)	(0.244)	(0.252)
Plague & Serfdom	0.792**	-0.592	-0.079	-0.232
	(0.339)	(0.398)	(0.313)	(0.323)
Fixed Effects:				
– Region	✓	✓	✓	✓
– Area x Year	✓	✓	✓	✓
Observations	50,010	50,020	50,020	50,020

Notes: Standard errors in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variable is log sectoral productivity growth. This has been adjusted for the introduction of serfdom in Denmark and Norway. The independent variable is a plague dummy that equals 1 for plagued regions after the plague hit interacted with a dummy for second serfdom. Denmark and Norway have been dropped from the sample as they reintroduced serfdom in 1733.

E.4 Non-Homotheticity

Table 33 compares prices after the plague based on data from Allen and Unger, 2018. Tables 34 and 35 analyse the effect of the plague on import and export prices recorded at the Sound. Figure 36 tests for changes in demand ratios.

Table 33: Product-level prices by sector and year in Danzig and Amsterdam

	Labour-int. Agriculture				Capital-int. Agriculture				Labour-int. Manufacturing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post Plague	10.53***	32.82	114.2*	702.0***	-41.24***	-59.72	-16.44**	4.615***	0.665***
	(3.15e-14)	(21.90)	(16.61)	(8.00e-12)	(6.44e-14)	(10.04)	(0.663)	(1.99e-14)	(3.70e-15)
Fixed Effects:									
– City	✓	✓	✓	✓	✓	✓	✓	✓	✓
– Year		✓	✓			✓	✓		
– Product			✓				✓		
– Product x Year				✓				✓	
Observations	4140	4140	4140	452	5116	5116	5116	248	191

Notes: Standard errors clustered at the city level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variables are prices of products by sector in Amsterdam and Danzig. The independent variable is 1 after the plague in Danzig in 1709. The second, third, and fourth specifications cannot be estimated for labour-intensive manufacturing due to lack of observations. No data on capital-intensive manufacturing products are contained in the data set.

Table 34: Good-level logarithmic import prices

	(1)	(2)	(3)	(4)
Post Plague	0.281***			
	(0.0597)			
Post Plague x Capital-Int.	-0.0997		0.0875	
	(0.116)		(0.136)	
0-10 Years Post Plague		0.143		
		(0.124)		
11-20 Years Post Plague		0.386***		
		(0.0832)		
21-30 Years Post Plague		0.493***		
		(0.0982)		
>30 Years Post Plague		0.248***		
		(0.0703)		
0-10 Years Post Plague x Cap-Int.		0.0200		0.303
		(0.224)		(0.195)
11-20 Years Post Plague x Cap-Int.		-0.0243		0.0534
		(0.129)		(0.176)
21-30 Years Post Plague x Cap-Int.		-0.122		0.0776
		(0.123)		(0.138)
>30 Years Post Plague x Cap-Int.		-0.107		0.0603
		(0.117)		(0.152)
Fixed Effects:				
– Area x Sector x Year	✓	✓	✓	✓
– Origin x Destination x Year			✓	✓
– Origin x Destination x Sector	✓	✓	✓	✓
– Origin x Sector x Year	✓	✓	✓	✓
Observations	132411	132411	89334	89334

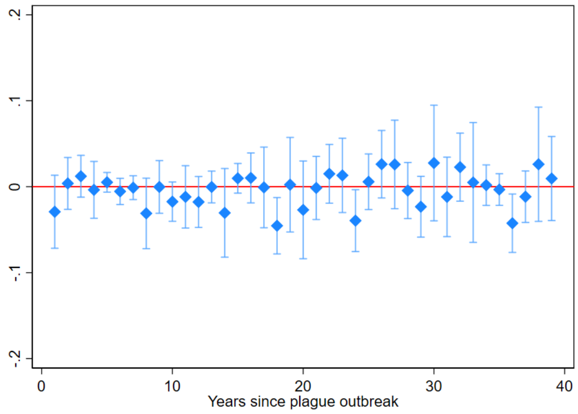
Notes: Standard errors clustered at the destination level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variables are prices of goods by sector, origin, destination, and year as recovered from the Soundtoll data. Specifically, the recorded duty amount per good is divided by the weight whenever it is recorded (46% of observations), thus creating comparable prices per kilogram. The independent variables are a post plague dummy that is 1 after the plague and the interaction of this post plague dummy with a dummy for a capital-intensive sector. Columns 2 and 4 split up this dummy and the interaction by time horizon after the plague.

Table 35: Good-level logarithmic export prices

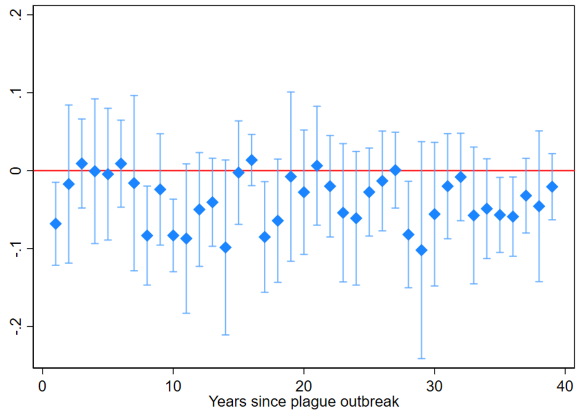
	(1)	(2)	(3)	(4)
Post Plague	0.526***			
	(0.185)			
Post Plague x Capital-Int.	-0.511**		-0.664**	
	(0.224)		(0.298)	
0-10 Years Post Plague		0.253**		
		(0.103)		
11-20 Years Post Plague		0.501***		
		(0.169)		
21-30 Years Post Plague		0.546***		
		(0.183)		
>30 Years Post Plague		0.548***		
		(0.205)		
0-10 Years Post Plague x Cap-Int.		-0.246		-0.375*
		(0.153)		(0.224)
11-20 Years Post Plague x Cap-Int.		-0.558***		-0.814***
		(0.203)		(0.296)
21-30 Years Post Plague x Cap-Int.		-0.639**		-0.801**
		(0.248)		(0.341)
>30 Years Post Plague x Cap-Int.		-0.505**		-0.657*
		(0.252)		(0.340)
Fixed Effects:				
– Area x Sector x Year	✓	✓	✓	✓
– Origin x Destination x Year			✓	✓
– Origin x Destination x Sector	✓	✓	✓	✓
– Destination x Sector x Year	✓	✓	✓	✓
Observations	118108	118108	73091	73091

Notes: Standard errors clustered at the origin level in parentheses. * p <0.10, ** p <0.05, *** p <0.01. The dependent variables are prices of goods by sector, origin, destination, and year as recovered from the Soundtoll data. Specifically, the recorded duty amount per good is divided by the weight whenever it is recorded (46% of observations), thus creating comparable prices per kilogram. The independent variables are a post plague dummy that is 1 after the plague and the interaction of this post plague dummy with a dummy for a capital-intensive sector. Columns 2 and 4 split up this dummy and the interaction by time horizon after the plague.

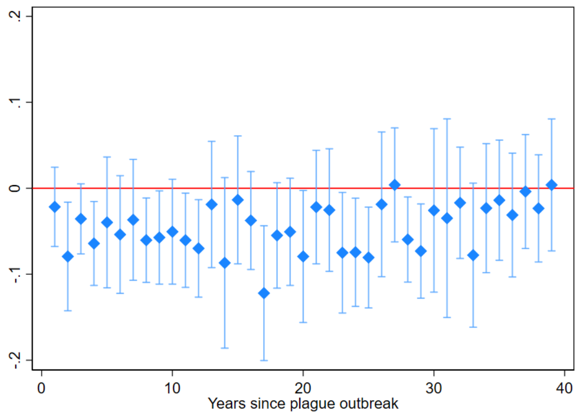
Figure 36: Event studies testing for non-homotheticity



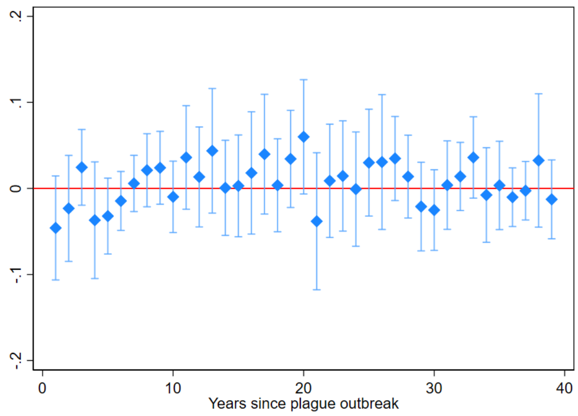
(a) Capital-int. & Labour-int. Manufacturing



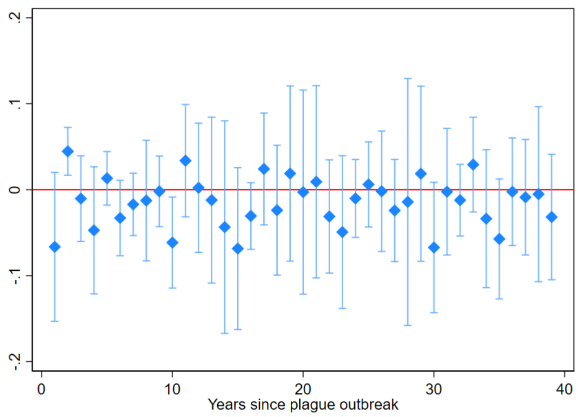
(b) Capital-int. Manufacturing & Labour-int. Agriculture



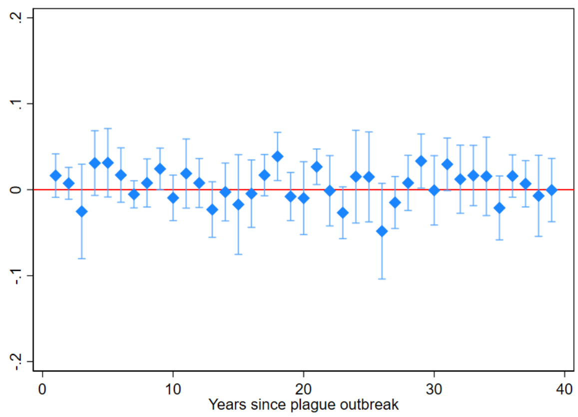
(c) Capital-int. Manufacturing & Agriculture



(d) Capital-int. Agriculture & Labour-int. Manufacturing



(e) Capital-int. Agriculture & Labour-int. Agriculture



(f) Labour-int. Manufacturing & Agriculture

Notes: Event study on the log of the left-hand side of equation 21. The independent variable is a plague dummy on the importer side. Origin-time and destination fixed effects are included and standard errors are clustered at the destination level.

F Counterfactuals

This appendix provides details on the counterfactuals provided in Section 6. Constructing export shares, the outcome of equation 2, according to gravity equation 10, I find that shares can be expressed as:

$$s_{ijk} = \frac{X_{ijk}}{\Sigma_i X_{ijk}} = \frac{A_{ik}(w_{ik})^{-\gamma_k \theta} d_{ijk}^{-\theta}}{\Sigma_i A_{ik}(w_{ik})^{-\gamma_k \theta} d_{ijk}^{-\theta}}. \tag{35}$$

When plugging in equation 9 for wages and equations 7 for firm and consumer market access, I arrive at an equation defining market shares as a function of productivities, sectoral employment, trade costs, wages, and total income:

$$s_{ijk} = \frac{A_{ik}^{\frac{1}{1+\gamma_k\theta}} L_{ik}^{\frac{\gamma_k\theta}{1+\gamma_k\theta}} \left(\Sigma_j d_{ijk}^{-\theta} Y_j \left(\Sigma_i A_{ik}(w_{ik})^{-\gamma_k\theta} d_{ijk}^{-\theta} \right)^{-1} \right)^{\frac{-\gamma_k\theta}{1+\gamma_k\theta}} d_{ijk}^{-\theta}}{\Sigma_i A_{ik}^{\frac{1}{1+\gamma_k\theta}} L_{ik}^{\frac{\gamma_k\theta}{1+\gamma_k\theta}} \left(\Sigma_j d_{ijk}^{-\theta} Y_j \left(\Sigma_i A_{ik}(w_{ik})^{-\gamma_k\theta} d_{ijk}^{-\theta} \right)^{-1} \right)^{\frac{-\gamma_k\theta}{1+\gamma_k\theta}} d_{ijk}^{-\theta}}.$$

To shut down the productivity channel, I assume A_{ik} to be fixed. I also assume fixed trade costs d_{ijk} and destination income Y_j. Only trade between the Baltic and North Seas is observed, and the plague struck almost exclusively on the Baltic Sea, rendering this a reasonable assumption. I also make an assumption on the sum $\Sigma_i A_{ik}(w_{ik})^{-\gamma_k\theta} d_{ijk}^{-\theta}$ to keep changes tractable. Essentially, I assume that wage changes in plagued regions leave the entire sum almost unchanged.

Let PRE denote pre-plague, POST immediately after the plague, and t the number of years since the plague. Assume $\Sigma_i A_{ikPOST} w_{ikPOST}^{-\gamma_k\theta} d_{ijkPOST}^{-\theta} \approx \Sigma_i A_{ikPOST} w_{ikPOST}^{-\gamma_k\theta} d_{ijkPOST}^{-\theta}$. While individual regions' wages changed and I assume productivities and trade costs to be fixed, I essentially assume that wage increases in a few plagued regions do not move the entire sum over all regions by much.

In the estimation equation, destination-sector-time fixed effects absorb changes in these sums regardless. When counterfactually shutting down the productivity channel, one can then write $s_{ijkt}^c = \left(\frac{L_{ikt}}{L_{ikPRE}}\right)^{\frac{\gamma_k\theta}{1+\gamma_k\theta}} s_{ijkPRE}$.

I model the population recovery from L_{iPOST} to L_{it} to happen exponentially over 40 years. This is the upper bound, as by 1750 plagued cities had recovered their populations. I assume that after 40 years, regional and not just urban populations had recovered. This yields:

$$s_{ijkt}^c = (1 - m_i)^{\frac{\gamma_k\theta}{1+\gamma_k\theta}} \left(\frac{1}{1 - m_i}\right)^{\frac{\gamma_k\theta t(1+\gamma_k\theta)^{-1}}{40}} s_{ijkPRE}.$$