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Trade Shock and Labor Earnings: Difference-in-Differences Evidence from Local Labor Markets

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Abstract

This paper investigates the impact of an export demand shock triggered by the 2014 Russian import ban on labor earnings in Poland. We implement an event-study using traditional and doubly-robust difference-in-differences estimators, supplemented by a variance decomposition. Our findings indicate that the shock has caused substantial consequences for regional inequality. Specifically, we document a persistent decline in average relative earnings between the exposed group of counties and the rest of the country. The analysis of between-group variance shows that the import ban has reduced the earnings premium, shifting the exposed counties from relatively higher-earnings positions toward the national average.

Keywords:
Poland, Russian import ban, economic sanctions, regional inequality, local labor markets, difference-in-differences.

JEL Classification:
F16, F51, J31, R23

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1 Introduction

Trade sanctions have recently seen a resurgence as one of the most widely used tools of foreign policy (Felbermayr, Kirilakha, Syropoulos, Yalcin, & Yotov, 2020). Despite their growing prevalence, the distributional consequences of such shocks for workers in exposed local labor markets remain poorly understood. If a given region's exports were to sharply decline due to an external import ban, what would happen to local labor earnings?

Our analysis examines the consequences of the 2014 Russian import ban (henceforth: import ban), which was one of the largest trade disruptions of the European Union (EU) agricultural exports in recent history, with Poland ranking among the most exposed EU economies (Boulanger, Dudu, Ferrari, & Philippidis, 2016; Cheptea & Gaigné, 2020; Crozet & Hinz, 2020). Yet the within-country distributional effects on workers and regions remain unexamined. To address this gap, we use a novel dataset on labor earnings at the *powiat* (county) level, which allows us to identify and quantify how the ban propagated across local labor markets within Poland.

The goal of this paper is to identify the causal effect of the import ban on county-level labor earnings. We focus on the exposed group of counties that specialize in the production of agricultural goods. To identify the exposed counties, we use census records on land use together with the geographical location of major dairy producers. We estimate the effect of the import ban using a difference-in-differences regression. We perform a number of sensitivity and robustness checks including various changes to the exposed and control groups of counties, adjustment for spatial and serial correlation, use of the Callaway and Sant'Anna (2021) estimator, implementation of continuous exposure measures, and placebo-in-time tests. Finally, we examine the consequences of the import ban for regional inequality by decomposing the total variance of earnings into between-group and within-group components.

The empirical results suggest that the decline in average gross earnings was up to 2.2% between the exposed group and the rest of the country. Notably, we find strong effects for the group of counties that focus on beef production, where the decline is estimated to be up to 3.2%. Sensitivity analysis indicates that the adjacent administrative neighbors have also experienced negative effects of the ban on earnings. Finally, the ban had substantial consequences for regional inequality. Analysis of the between-group variance of earnings shows that the ban reduced the earnings premium of the exposed counties, shifting them from relatively higher-earnings positions toward the national average in Poland.

Our findings carry implications for the economic policy at the regional level. Specifically, the results indicate the need for policies that facilitate access to alternative export markets and sectoral diversification as well as provide income assistance that could possibly span a couple of years. These recommendations follow directly from the nature of the shock: its effects are geographically concentrated, persistent, and sector-specific, suggesting that broad national policies are unlikely to be sufficient without targeted regional components.

This paper is related to the following strands of the literature. The first strand consists of studies that investigate the relationship between shocks and inequality: Adão, Carrillo, Costinot, Donaldson, and Pomeranz (2022); Amberg, Jansson, Klein, and Picco (2022); Andersen, Johannesen, Jørgensen, and Peydró (2023); Autor, Dorn, and Hanson (2013); Coibion, Gorodnichenko, Kueng, and Silvia (2017); Furceri, Loungani, and Zdzienicka (2018); Guvenen (2007); Guvenen, Ozkan, and Song (2014); Hoffmann and Malacrino (2019); Karahan and Ozkan (2013). The contribution to this strand is twofold. First, we provide estimates of an export demand shock on labor earnings in a small open economy. This contributes to a growing literature on the local labor market effects of trade shocks (Adão et al., 2022; Autor et al., 2013; Faccini, Mumtaz, & Surico, 2016). Second, we document that the shock reshaped regional inequality by eroding the earnings premium of exposed counties, shifting them from above-average earnings positions toward the national average, providing novel evidence on the distributional consequences of trade shocks at the local level.

The second strand comprises papers that study inequality in the context of Poland: Berkowitz and Jackson (2006); Brzeziński and Kostro (2010); Brzezinski, Myck, and Najsztub (2022); Bukowski and Novokmet (2021); Gorecki (1994); Jędrzejczak (2015); Keane and Prasad (2002, 2006). Specifically, our study is the closest to Keane and Prasad (2006), who apply a variance decomposition of labor earnings to the state-private sector divide during Poland's economic transition; we adopt a similar decomposition but apply it to the between-group dimension defined by exposure to the trade shock rather than sector ownership. In addition, Berkowitz and Jackson (2006); Jędrzejczak (2015), and Bukowski and Novokmet (2021) study regional inequality in Poland using voivodeship- and county-level data; our contribution to this strand is to provide the first quasi-experimental estimates of how an external trade shock shaped county-level labor earnings inequality, exploiting the import ban as a source of exogenous variation in export demand.

The third strand comprises articles that provide assessment of the import ban: Boulanger et al. (2016); Cheptea and Gaigné (2020); Crozet and Hinz (2020); Crozet, Hinz, Stammann, and Wanner (2021); Kutlina-Dimitrova (2017); Larch, Luckstead, and Yotov (2024); Oja (2015); Tyazhelnikov and Romalis (2024). While the existing studies rely on trade data to estimate losses, we provide the first region-level evidence on how the import ban affected labor earnings and inequality within one of the most exposed economies, exploiting county-level variation in agricultural specialization for causal identification.

This paper is structured as follows. Section 2 presents background information, stylized facts, and our identification strategy. Section 3 details data and methodology. Section 4 reports empirical findings. Section 5 examines the consequences of the import ban for regional inequality through a variance decomposition of labor earnings. Section 6 concludes.

2 Background and identification

2.1 Background

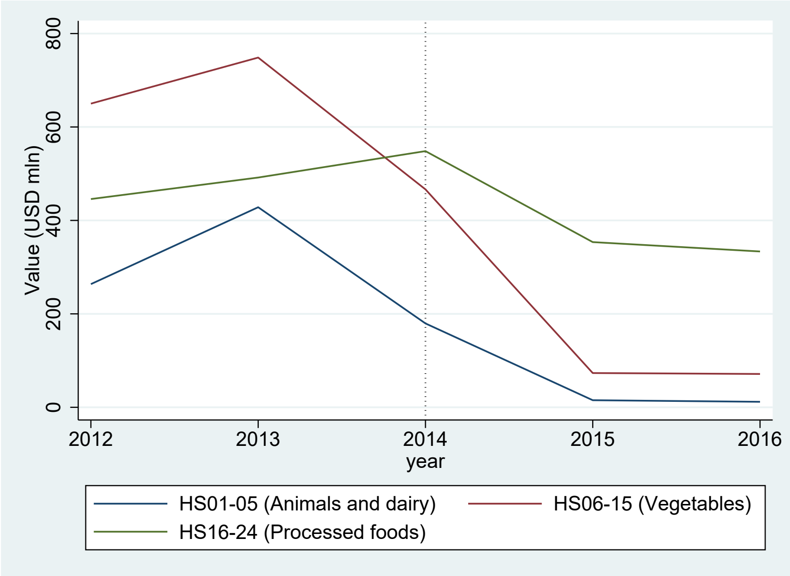
A number of papers have already investigated the import ban using European data and provided various accounts of the event, see Boulanger et al. (2016); Cheptea and Gaigné (2020); Crozet and Hinz (2020); Kutlina-Dimitrova (2017). Hence, we only summarize this event, the scope of the introduced ban as well as the existing headline estimates and stylized facts that are relevant for the context of the paper.

On 7 August 2014, Russia imposed a one-year import ban on a wide list of agricultural goods originating from the EU, the United States, Norway, Canada, and Australia. The introduction of the ban was sudden and took place immediately without giving the EU exporters no time to adjust. The list of banned goods includes almost all meat products (beef, pig-meat, poultry, etc.), milk and dairy products, fruits and vegetables, as well as fish. Since then, Russia has repeatedly prolonged this ban, and the list of countries was extended at least once (in 2016) to include Albania, Iceland, Liechtenstein, and Montenegro. According to Boulanger et al. (2016), out of all the targeted countries, the EU was potentially the most affected as it has accounted for the largest Russian import share in the aforementioned goods prior to the ban. Further, Russia constituted the second most important destination for EU agricultural exports, accounting for approximately a 10% trade share in terms of value.

Estimates of Crozet and Hinz (2020) and Cheptea and Gaigné (2020) indicate that the economic cost on private actors of the import ban was unevenly distributed among countries, with the EU bearing 92% of the sanctioning countries' impact (most impacted members: Finland, Poland, Germany). Headline results suggest there has been an average 80% drop in the value of EU export flows of banned products to Russia. The overall loss of EU exports to Russia is about €125 million per month with Germany and Poland compensating their large losses on the Russian market by an increase in exports to other trade partners. This reorientation came at the expense of other EU markets, notably France and Denmark.

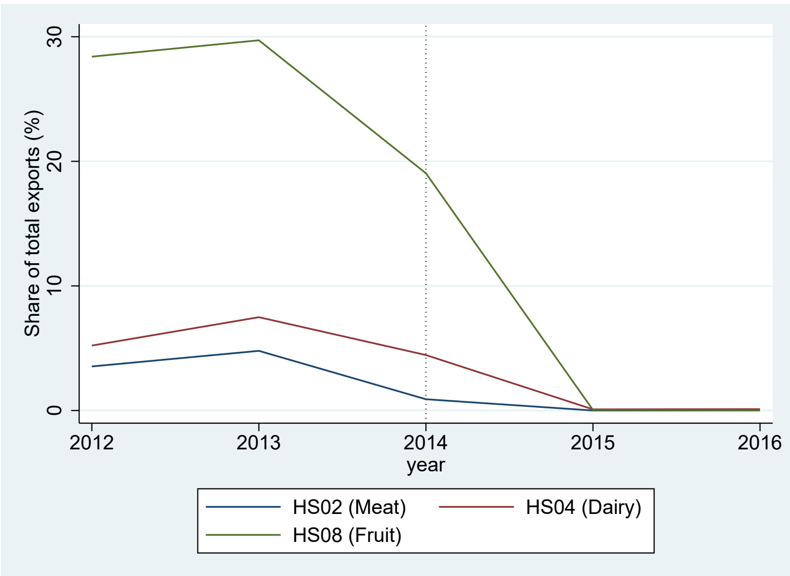
Poland's overall exposure to the import ban was especially severe, given its strong pre-ban trade ties with Russia. In 2013 alone, Russia was the fifth largest export market (US$10.8 billion) for Poland and accounted for 5.3% of total export value (World Bank, 2013). Figure 1 plots the export value of the impacted groups of goods (HS2 level) between Poland and Russia for 2012-2016. Trade in goods that fall between HS01-05 (animal origin) and HS06-15 (vegetables) chapters collapsed to near zero following the introduction of the ban in 2014, whereas trade in processed foods declined only moderately. Additionally, we document that in 2013, Russia accounted for approximately 29.7% of total fruit exports, 7.5% of total dairy exports, and 4.8% of total meat exports (see Figure 2).

Figure 1: Export value of the impacted product groups, 2012-2016.



Note: gray dashed line represents the introduction of the import ban, based on WITS.

Figure 2: Share of exports of the impacted product groups to Russia relative to total Polish exports, per HS2, 2012-2016.



Note: gray dashed line represents the introduction of the import ban, based on WITS.

2.2 Identification

To identify the potentially exposed counties we proceed as follows. For fruit and beef production, we use land-use census records on orchard and pasture areas collected by Statistics

Poland (GUS) in 2010[1] and select the top ten counties with the largest orchard area and pasture area respectively[2]. We use these two proxies because they allow us to identify counties specializing in staple agricultural goods exported by Poland, such as apples, pears, and plums, while pasture areas proxy for the primary input used in beef production. We acknowledge that pasture areas can also serve as a proxy for dairy production. We address this limitation in two ways. First, for dairy exposure we use the location of major producers: Mlekovita, Mlekpol, Piątnica, Polmek, and Łowicz, rather than pasture area, precisely because facility locations capture industrial-scale dairy exposure. Crucially, the counties hosting the major producers do not overlap with the pasture-based counties (except one county - Grajewski) selected for beef exposure, suggesting that the two proxies capture geographically distinct production margins despite both relating to cattle farming broadly. Second, we construct a pooled measure for the three groups, which is robust to any misclassifications between beef and dairy county groups.

In terms of coverage, the selected counties cover about 38.8% of total orchard area, 21.6% of total pasture area, and just over 40% of total dairy production. Table 1 lists the identified counties, while Figure 3 plots their geographic distribution. As the figure illustrates, the counties are predominantly concentrated in the northeastern and eastern parts of the country traditionally known for specialization in agriculture. They are also known to generally feature a high degree of inequality and relatively low representation in the top 1% of the income distribution (Bukowski & Novokmet, 2021; Jędrzejczak, 2015).

Table 1: List of counties identified as exposed.

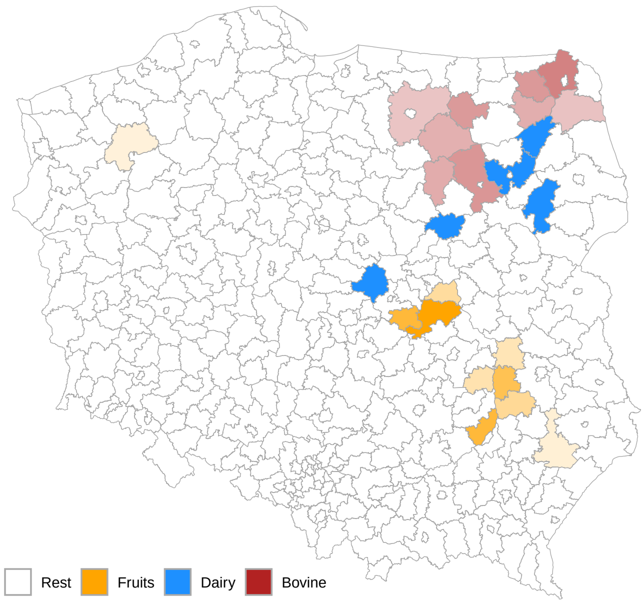
Fruits	Beef	Dairy
Grójecki (42.9%)	Suwalski (16.4%)	Wysokomazowiecki
Sandomerski (27.88%)	Ostrołęcki (12.6%)	Grajewski
Rawski (27.82%)	Olecki (11.9%)	Łomżyński
Opolski (22.0%)	Mrągowski (11.7%)	Pułtuski
Kraśnicki (10.1%)	Grajewski (9.9%)	Łowicki
Puławski (6.2%)	Przasnyski (8.8%)	
Piaseczyński (9.1%)	Ełcki (8.4%)	
Biłgorajski (3.1%)	Szczycieński (8.2%)	
Lipski (6.8%)	Augustowski (5.8%)	
Drawski (2.8%)	Olsztyński (5.5%)	

Note: shares of orchards and pastures to total county area are reported in parentheses, own summary based on GUS (2026).

[1]Latest pre-ban publicly available data. Given that orchard and pasture classifications are slow-moving by nature, we treat this as a close proxy for pre-ban agricultural specialization.

[2]This choice is later tested as a part of our sensitivity analysis in Section 4.2 and robustness tests in Section 4.3.3.

Figure 3: Location of exposed counties on the map of Poland.



Note: darker gradient colors indicate a higher proportion of orchards or pastures in total county area. Own calculations based on GUS (2026).

3 Data and methodology

3.1 Data

The annual data on labor earnings across Polish counties come from GUS. The data span all of the current counties (380 administrative units, LAU level 1, formerly NUTS level 4) between 2006 and 2021 (GUS, 2026). We restrict our sample to the period 2009–2019 to isolate the effect of the import ban and avoid contamination from major international shocks. Our variable of interest is the pre-tax annual average labor earnings expressed as a monthly equivalent (nominal, in PLN) at the county level. It is computed as the ratio of total gross earnings to the total number of employed workers in a given year. In terms of scope, it represents wages earned in economic entities employing 10 or more persons as well as all public sector entities.

As we are interested in studying whether there has been a significant change in the labor earnings across counties that are identified to be exposed relative to the control group following the import ban. We restrict the control group by excluding counties that are cities. The final control group consists of 290 counties. Figures A1 and A2 (Appendix) plot the log of labor earnings across exposed and control groups showing the descriptive evidence that supports the existence of a substantial shift in the earnings premium following the import ban that we discuss in Section 5. Finally, we use the employment rate (per 1000) as a control variable to account for changes in local labor market conditions that can affect observed changes in earnings. Summary statistics are presented in Table 2.

Table 2: Summary statistics, 2009-2019.

Variable	Mean	SD	Min	Max	N
Labor earnings (in PLN, per month)	3394.37	630.27	2020.27	8274.57	3443
Employment rate (per 1,000)	168.75	50.41	70.00	498.00	3443

Source: GUS (2026).

3.2 Methodology

We estimate the following equation:

$$y_{i,t} = \beta_1 \left(\text{County}_i^k \times \text{Sanct}_t\right) + \gamma E_{i,t} + \alpha_i + \lambda_t + \varepsilon_{i,t} \tag{1}$$

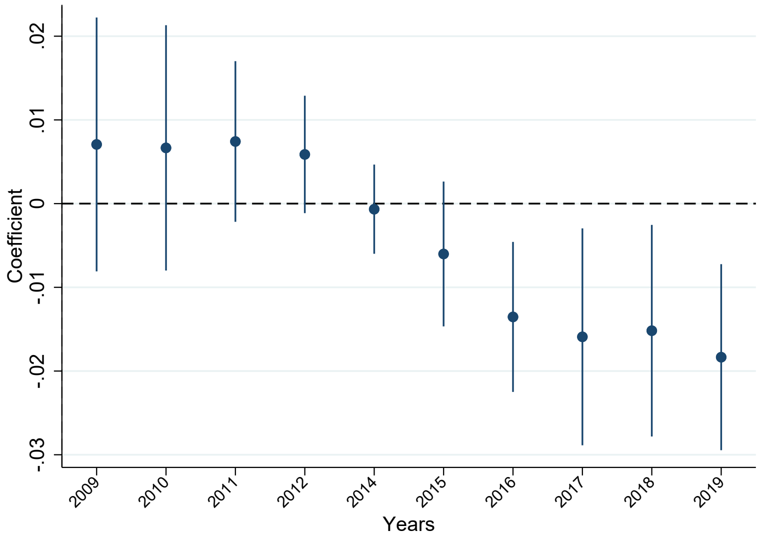
where y_{it} is the log of the average labor earnings in county i in year t; County_i^k is a time-invariant indicator variable equal to 1 if county i specializes in sector k, where $k \in \{\text{fruits, dairy, beef}\}$ or an aggregate of the three; Sanct_t is an indicator variable equal to 1 for the post-ban period (2014 onward). The coefficient of interest is β_1, which captures the average effect of the import ban on labor earnings in the exposed counties relative to the control group. $E_{i,t}$ is the log of employment per 1,000 inhabitants in county i in year t, α_i and λ_t denote county and year fixed effects.

4 Empirical findings

4.1 Main results

We present the results as follows. First, we test for the presence of parallel pre-trends by plotting the dynamic treatment effects of the import ban on the log of earnings (see Figure 4) using an aggregate of the three sectors. As can be seen, both the exposed and control groups of counties were on comparable trajectories prior to 2014. After the shock, we observe a stark divergence, the treatment effects become sharply negative and statistically significant from $t + 2$ onward. Further testing shows that the event-study design supports the presence of unconditional parallel trends when we exclude the control for the employment rate (see note under Figure 4).

Figure 4: Dynamic treatment effects of the import ban on wage, 2009-2019.



Note: dashed horizontal line represents the omitted base period, $t-1$ (2013). Vertical lines indicate 95% confidence bands based on heteroskedasticity-robust clustered errors. The estimation includes control for the employment rate (per 1000, log), county and year fixed effects. The p-value for the joint F-test of all pre-treatment coefficients is 0.532. We also test if the results hold without controlling for the employment rate, the p-value for the joint F-test of all pre-treatment coefficients in this case is 0.548.

Next, we report the main results from the estimation of equation (1) using OLS in Table 3. Columns (1)-(3) list sector-specific estimates. For comparability, we omit counties from the other exposed groups (i.e., for apples we omit beef and dairy) and only compare the specific exposed group of counties to the control group. In the exposed counties focused on fruit production, the average relative wage decline is estimated at 1.6% (significant at the 5% level). Next, we find no statistically significant effect for the dairy group of counties, while in counties producing beef, the relative decline is about 2.4% (significant at the 1% level). Column (4) shows the results obtained using an aggregate of the three county groups, the relative decline is estimated to be at 1.7% (significant at the 1% level). As a result of the export demand contraction, producers in the exposed counties have adjusted labor costs by either reducing wages directly or by limiting wage growth. The heterogeneity across sectors reveals an interesting disconnect between pre-ban export dependence on Russia and the magnitude of earnings effects. In 2013, Russia accounted for one third of total Polish fruit exports, by far the highest dependence among the affected product groups, observed the second largest relative earnings decline documented for fruit counties, with beef counties exhibiting the largest effect despite Russia absorbing only 4.8% of total Polish meat exports. The dairy sector was considerably less dependent and may have been partially insulated due to stronger firm-level capacities to absorb the ban (i.e., consolidated dairy cooperatives being relatively more resilient than individual farms).

In Appendix, we report the results from a full panel that spans 2006-2021 (see Table A1), we find the aggregate effect to be driven by the same two groups of counties. However, these results should be treated with caution as the data contain the pandemic shock.

Table 3: Effects of the import ban on the log of wage, 2009-2019.

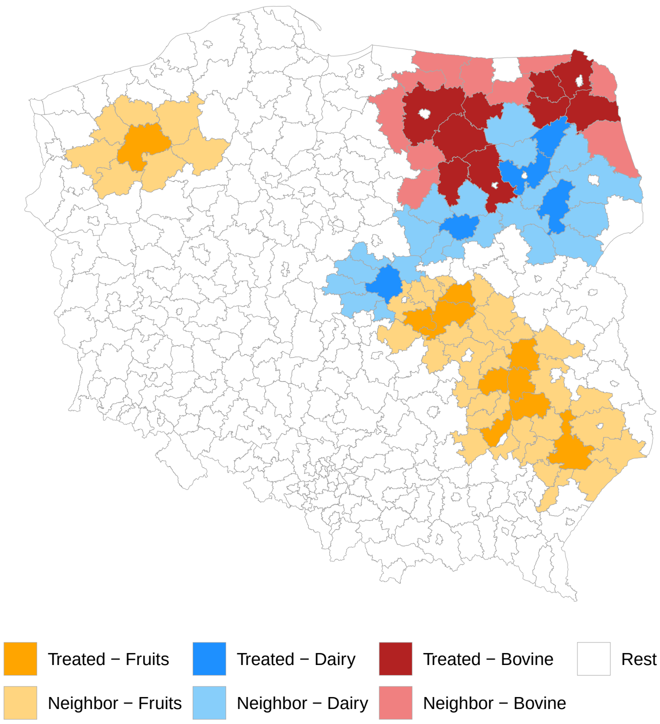
ln(Wage)	(1)	(2)	(3)	(4)
$\text{Fruits}_i \times \text{Sanct}_t$	-0.016**			
	(0.008)			
$\text{Dairy}_i \times \text{Sanct}_t$		-0.006		
		(0.017)		
$\text{Beef}_i \times \text{Sanct}_t$			-0.024***	
			(0.007)	
$\text{Agg}_i \times \text{Sanct}_t$				-0.017***
				(0.005)
$\text{E}_{i,t}$	0.082**	0.084**	0.082**	0.080**
	(0.035)	(0.035)	(0.035)	(0.035)
N	3300	3234	3289	3454
R^2	0.98	0.98	0.98	0.98

Note: all columns include county and year fixed effects. $E_{i,t}$ stands for the log of employment rate (per 1000). Heteroskedasticity-robust clustered errors. Significance levels: $^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Sensitivity

We assess the sensitivity of the main results by conducting a number of empirical exercises. First, we restrict the control group to counties that only share an administrative border (neighbors, excluding cities) with the exposed counties (see Table 4). Our approach is twofold: alongside all neighbors we include the mixed group - neighbors that border the exposed counties from different sectors, i.e., beef and dairy (columns 1-4). As can be seen from Figure 5, there is a substantial overlap between neighbors in the northeastern part of Poland. Further, we construct a more restrictive sample, where we exclude all of the mixed neighbors from the control group (columns 5-8) and only include unique neighbors. In both cases, the results provide support for the fact that the resulting negative shock also affected the neighbors as the differential effect is largely absent. This indicates that our main results report the lower bound of the ban effect. Second, we change the control group to include only counties that do not share an administrative border (non-neighbors) with the exposed group (Table 5). In this case, the obtained results are slightly larger relative to the main results, indicating that the average relative wage decline was between 1.9% and 2.5%. Finally, we study the concentration of the effect by only keeping the top 5 counties (by orchard and pasture area) for fruit and beef sectors. In this case we find the wage drop to be larger for both sectors relative to the baseline (Table 6).

Figure 5: Location of exposed counties and their neighbors.



Note: excluding cities, own summary based on GUS (2026).

Table 4: Effects of the import ban on the log of wage, neighbors as control group.

	All neighbors (including mixed)				Only unique neighbors			
ln(Wage)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Fruits}_i \times \text{Sanct}_t$	-0.003				-0.002			
	(0.009)				(0.009)			
$\text{Dairy}_i \times \text{Sanct}_t$		-0.002				-0.008		
		(0.015)				(0.016)		
$\text{Beef}_i \times \text{Sanct}_t$			-0.013				-0.020^{+}	
			(0.009)				(0.011)	
$\text{Agg}_i \times \text{Sanct}_t$				-0.008				-0.009
				(0.006)				(0.006)
$\text{E}_{i,t}$	-0.027	-0.026	-0.114^{+}	-0.21	-0.036	-0.059	-0.089	-0.018
	(0.047)	(0.052)	(0.044)	(0.036)	(0.047)	(0.071)	(0.056)	(0.040)
N	495	297	297	990	484	209	220	902
R^2	0.98	0.98	0.98	0.981	0.98	0.98	0.98	0.98

Note: all columns include county and year fixed effects. $E_{i,t}$ stands for the log of employment rate (per 1000). Heteroskedasticity-robust clustered errors. Significance levels: $^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effects of the import ban on the log of wage, non-neighbors as control group.

ln(Wage)	(1)	(2)	(3)	(4)
$\text{Fruits}_i \times \text{Sanct}_t$	-0.019**			
	(0.008)			
$\text{Dairy}_i \times \text{Sanct}_t$		-0.009		
		(0.014)		
$\text{Beef}_i \times \text{Sanct}_t$			-0.025***	
			(0.007)	
$\text{Agg}_i \times \text{Sanct}_t$				-0.020***
				(0.005)
$\text{E}_{i,t}$	0.111***	0.113***	0.111***	0.106***
	(0.037)	(0.037)	(0.037)	(0.037)
N	2574	2519	2574	2728
R^2	0.98	0.98	0.98	0.98

Note: all columns include county and year fixed effects. $E_{i,t}$ stands for the log of employment rate (per 1000). Heteroskedasticity-robust clustered errors. Significance levels: $^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects of the import ban on the log of wage, top 5 counties by orchard and pasture area only.

ln(Wage)	(1)	(2)
$\text{Fruits}_i \times \text{Sanct}_t$	-0.018**	
	(0.009)	
$\text{Beef}_i \times \text{Sanct}_t$		-0.026***
		(0.006)
$\text{E}_{i,t}$	0.083**	0.084**
	(0.036)	(0.036)
N	3245	3245
R^2	0.98	0.98

Note: all columns include county and year fixed effects. $E_{i,t}$ stands for the log of employment rate (per 1000). Heteroskedasticity-robust clustered errors. Significance levels: $^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 Robustness

4.3.1 Spatial and serial correlation

Because the exposed counties are spatially clustered[3], we check the robustness of our main results by estimating equation (1) using Conley spatial-HAC standard errors (Colella, Lalive, Sakalli, & Thoenig, 2019; Conley, 1999). This approach allows us to account for the existing spatial dependence of the exposed counties based on centroids (cutoff set to 100 km[4]) as well as serial correlation up to three annual lags. The results are robust to this correction (see Table 7), confirming that spatial and serial correlation do not materially affect our main findings.

Table 7: Effects of the import ban on the log of labor earnings, spatial-HAC standard errors.

	With neighbors				Without neighbors			
ln(Wage)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{Fruits}_i \times \text{Sanct}_t$	-0.016***				-0.019***			
	(0.005)				(0.005)			
$\text{Dairy}_i \times \text{Sanct}_t$		-0.006				-0.009		
		(0.017)				(0.008)		
$\text{Beef}_i \times \text{Sanct}_t$			-0.024***				-0.025***	
			(0.007)				(0.006)	
$\text{Agg}_i \times \text{Sanct}_t$				-0.017***				-0.020***
				(0.005)				(0.004)
$\text{E}_{i,t}$	0.082***	0.084***	0.082***	0.080***	0.111***	0.113***	0.111***	0.106***
	(0.024)	(0.024)	(0.024)	(0.023)	(0.025)	(0.025)	(0.025)	(0.025)
N	3300	3234	3289	3454	2574	2519	2574	2728
Centered R^2	0.034	0.032	0.036	0.039	0.060	0.057	0.063	0.061

Note: all columns include county and year fixed effects. $E_{i,t}$ stands for the log of employment rate (per 1000). Conley spatial-HAC standard errors in parentheses, adjusting for spatial correlation within a 100 km radius and serial correlation up to three-year lags. Significance levels: $^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3.2 Alternative estimator and placebo tests

We check the robustness of the main results by estimating equation (1) using the estimator proposed in Callaway and Sant'Anna (2021) (henceforth CS). This approach provides a flexible alternative to the standard two-way fixed effects OLS and allows us to assess whether the

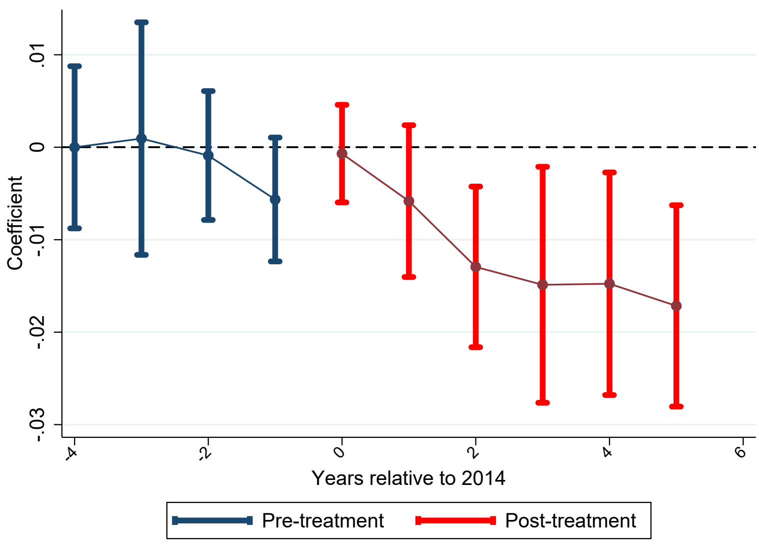
[3]For fruit, beef, and aggregate groups, Moran's I tests confirm significant spatial clustering (fruit: $I = 0.173$; beef: $I = 0.386$; aggregate: $I = 0.219$), all significant at the $p < 0.001$ level. Dairy counties show no significant clustering ($I = 0.041$, $p = 0.075$).

[4]We also test options with 50 and 150 km, the obtained significance levels are the same as reported in Table 7.

results are possibly driven by treatment effect heterogeneity. In particular, this estimator accommodates heterogeneous treatment effects across counties and provides valid inference under such heterogeneity via bootstrapped standard errors. The resulting dynamic treatment effects are presented in Figure 6. The effects closely follow the previously obtained dynamic estimates in Figure 4. The average decline in labor earnings across the three exposed group counties relative to the rest of the country is estimated at 1.1% and 1.3% (1% significance level, see Table 8), which is again close to what we obtain in column (4) of Table 3 and Table 5. For sector-specific estimates, the CS estimator yields notably more conservative effect of the ban for fruit-producing counties, while indicating a similarly strong effect of the ban for counties specializing in beef.

We also conduct two placebo treatment tests using the data for 2006-2013, where we assign a false timing of the import ban to 2010. The placebo ATTs for the three exposed groups are close to zero (see columns (5) and columns (6) in Table 8), which confirms that the previously reported estimates are not spuriously capturing pre-existing wage divergences between the exposed and control groups.

Figure 6: Dynamic treatment effects of the import ban on the log of labor earnings, Callaway and Sant'Anna (2021) estimator, 2009-2019.



Note: 95% bootstrapped confidence bands, unconditional parallel trends assumed, including time and county fixed effects. The estimated average treatment effect on the identified counties (ATT) is -0.013*** (0.004).

Table 8: Effects of the import ban on the log of labor earnings, robustness.

	With neighbors					
	Fruit	Dairy	Beef	Agg	Placebo CS	Placebo OLS
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.006	-0.012	-0.018***	-0.011***	-0.001	-0.009
	(0.005)	(0.009)	(0.005)	(0.004)	(0.005)	(0.006)
N	3300	3245	3300	3454	2512	2512
	Without neighbors					
	Fruit	Dairy	Beef	Agg	Placebo CS	Placebo OLS
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.008	-0.014	-0.019***	-0.013***	0.001	-0.007
	(0.005)	(0.009)	(0.005)	(0.004)	(0.005)	(0.007)
N	2574	2519	2574	2728	1984	1984

Note: bootstrapped heteroskedasticity-robust errors clustered at the county level in parentheses, except Placebo OLS which reports heteroskedasticity-robust errors. Placebo column uses pre-2014 data (2006–2013) with the import ban falsely assigned to 2010. All columns include county and year fixed effects, significance levels: $^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

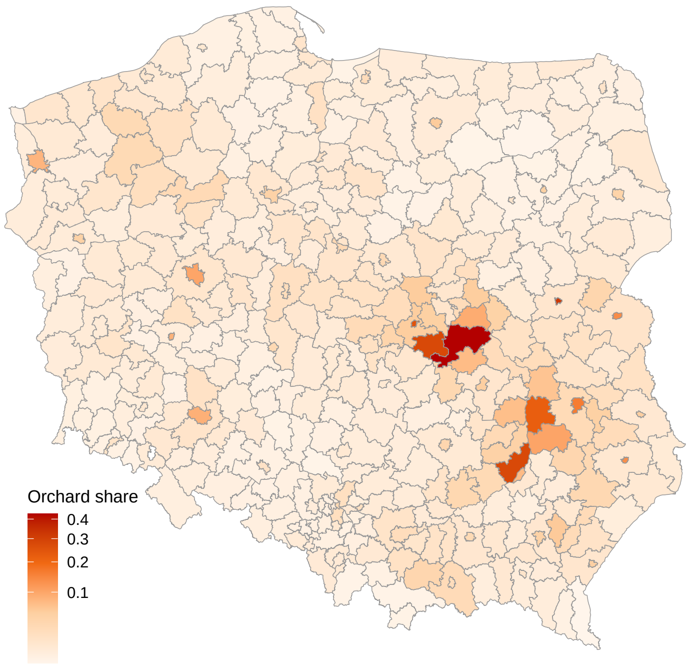
4.3.3 Continuous difference-in-differences

To address the arbitrary top-10 cutoff chosen for the binary specification, we compute the two shares (orchards or pastures) in total county area and replace the binary treatment indicator with a continuous measure. Figures 7 and 8 show the spatial distribution of orchard and pasture shares across counties. There are a couple of things worth noting. First, the computed relative shares are broadly consistent with the initial identification of the top 10 counties, providing reassurance that the binary cutoff was not arbitrarily distorting the treatment group. Second, in the case of pasture areas, a handful of cities located in the northeast of Poland observe relatively large shares because the total county areas are relatively small.

The continuous treatment approach offers two additional advantages over the binary specification. First, it allows us to include all treated counties together in the sample as exposure intensity is captured by the continuous land share rather than discrete group membership. Second, it shows how the effect of the import ban scales with the exposure intensity as counties with larger orchard or pasture shares are expected to experience larger earnings declines.

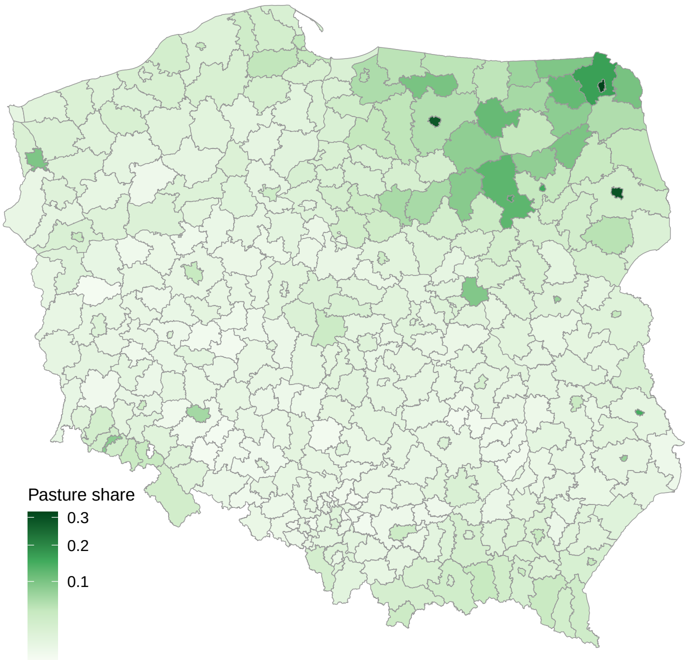
As shown in Table 9, this is indeed the case. We find that higher exposure to the import ban translated directly into larger relative earnings declines. The obtained estimates on the sample without cities are broadly consistent with the previous results. Taken together, the results across specifications show a consistent picture of the ban's effect on labor earnings in counties specializing in agriculture. Our preferred specification is the continuous DiD, which avoids the arbitrary county cutoff inherent in the binary classification and exploits variation in agricultural specialization intensity across all counties. The binary OLS specification serves as an illustrative baseline, while the CS estimator provides a heterogeneity-robust alternative and the Conley spatial-HAC correction addresses spatial dependence in standard errors. The consistency of sign and significance across all approaches strengthens confidence in the main findings.

Figure 7: County-level orchard shares in Poland, 2010 census.



Note: own summary based on GUS (2026)

Figure 8: County-level pasture shares in Poland, 2010 census.



Note: own summary based on GUS (2026)

Table 9: Effects of the import ban on the log of labor earnings, continuous difference-in-differences.

ln(Wage)	(1)	(2)	(3)
Orchards share$_i$ × Sanct$_t$	-0.106***		-0.120***
	(0.039)		(0.043)
Pastures share$_i$ × Sanct$_t$		-0.164**	-0.189***
		(0.064)	(0.065)
E$_{i,t}$	0.079**	0.077**	0.078**
	(0.035)	(0.034)	(0.034)
N	3454	3454	3454
R^2	0.98	0.98	0.98

Note: all columns include county and year fixed effects. $E_{i,t}$ stands for the log of employment rate (per 1000). Heteroskedasticity-robust clustered errors. Significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

5 Variance decomposition of labor earnings

To discuss the consequences of the import ban for regional inequality we decompose the total variance of labor earnings into between-group and within-group components. This is relevant because such decomposition allows us for granular quantification of the between-county contribution to total variance over time and complements the initial discovery of the fact that there was a convergence between exposed and control groups of counties in terms of labor earnings (as seen in Figures A1 and A2).

Let the economy be divided into two groups indexed by an indicator variable D_i, where $D_i = 1$ for exposed (treated) counties and $D_i = 0$ for control counties. In a neoclassical model with perfect labor mobility, arbitrage ensures that earnings (w) equalize, such that the between-group earnings variance is zero:

$$\mathrm{Var}(E[\ln w \mid D_i]) = 0 \tag{2}$$

However, structural differences and agglomeration economies often generate a premium. As can be seen from Figures A1 and A2, prior to the import ban, the treated counties enjoyed a positive earnings premium $\pi > 0$ relative to the control group:

$$\overline{\ln w}_{D=1,\mathrm{pre}} = \overline{\ln w}_{D=0,\mathrm{pre}} + \pi \tag{3}$$

When the import ban hit the treated group, local labor market frictions prevented workers from immediately reallocating to the control counties. Consequently, the import ban is capitalized into earnings as a penalty $\delta > 0$, depressing the average labor earnings in the treated group:

$$\overline{\ln w}_{D=1,\mathrm{post}} = \overline{\ln w}_{D=1,\mathrm{pre}} - \delta \tag{4}$$

By the Law of Total Variance, the total variance of earnings can be decomposed into between-group and within-group components:

$$\mathrm{Var}(\ln w) = \underbrace{\mathrm{Var}(E[\ln w \mid D_i])}_{\text{between-group variance}} + \underbrace{E[\mathrm{Var}(\ln w \mid D_i)]}_{\text{within-group variance}} \tag{5}$$

Defining the county employment shares as ω_1 for $D_i = 1$ and ω_0 for $D_i = 0$, the between-group variance is proportional to the squared earnings gap:

$$\mathrm{Var}(E[\ln w \mid D_i]) = \omega_1\omega_0 \left(\overline{\ln w}_{D=1} - \overline{\ln w}_{D=0}\right)^2 \tag{6}$$

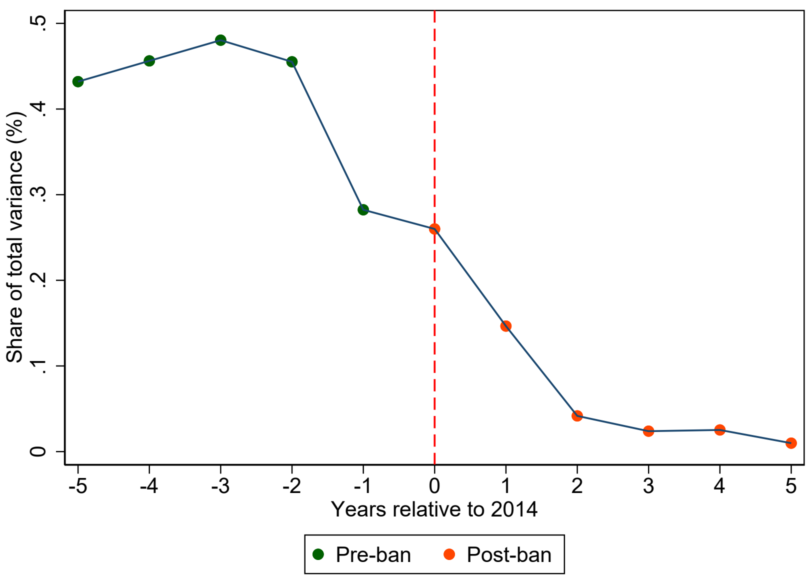
Substituting the pre-ban premium (π) and the post-ban penalty (δ) as well as assuming that the average earnings in the control group remain unaffected by the import ban, the post-ban between-group variance becomes:

$$\mathrm{Var}(E[\ln w \mid D_i])_{\mathrm{post}} = \omega_1\omega_0(\pi - \delta)^2 \tag{7}$$

Equation (7) predicts a decline in between-group variance when the trade penalty (δ) fully offsets the earnings premium (π), assuming that within-group variance remains relatively stable over the ban period[5]. Figure 9 confirms this prediction by plotting the share of between-group variance in total variance (in percent). Prior to 2014, the between-group component is elevated, reflecting the earnings premium in the treated counties relative to the control counties. Following the import ban, the share of between-group variance steadily declines toward zero, indicating convergence. The cumulative shock penalty offset the pre-existing premium, as labor earnings in treated counties converged to the rising earnings levels observed in the rest of the country, effectively eliminating the earnings gap between the two groups. Similar result is obtained if we exclude administrative neighbors, see Figure 10 for details.

This finding goes beyond the average treatment effect obtained using difference-in-differences regression and complements the initial discovery of the fact that there was a convergence between exposed and control groups of counties in terms of labor earnings. It captures the structural erasure of a historical geographic earnings premium and highlights how exogenous trade shocks can affect regional inequality.

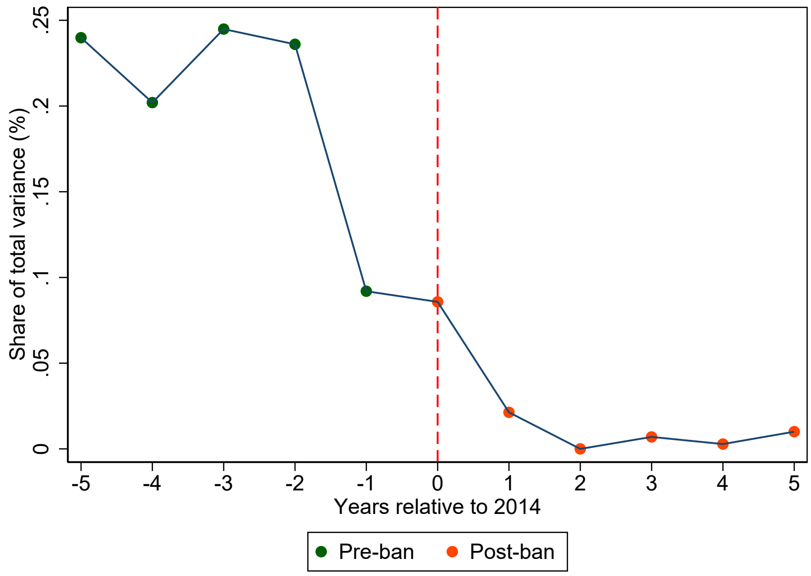
Figure 9: Between-county variance as a share of total variance in log wages, 2009-2019.



Note: excluding cities, based on GUS (2026).

[5]The within-group component accounts for approximately 99% of total variance throughout the sample period.

Figure 10: Between-county variance as a share of total variance in log wages, without neighbors, 2009-2019.



Note: excluding cities and neighbors, based on GUS (2026).

6 Concluding remarks

In this paper, we have used a difference-in-differences design to estimate the causal impact of the 2014 Russian import ban on labor earnings in Poland. Our headline results imply that the average relative wage decline between agricultural counties and the rest of the country was up to 2.2%. We find especially strong results for the group of counties that specialize in beef production, where the relative decline was up to 3.2%. Further, our sensitivity analysis indicates that adjacent administrative neighbors of the agricultural counties have also experienced the effect of the ban. Finally, the import ban had substantial consequences for regional inequality. Our analysis of between-group variance of wages suggests that the import ban reduced the wage premium of agricultural counties, shifting them from relatively higher-earnings positions toward the national average in Poland.

These findings carry several policy implications. Specifically, the studied trade shock has generated geographically concentrated and persistent distributional effects, highlighting the need for targeted regional sectoral policies aimed at facilitating economic adjustment. In particular, policies that support access to alternative export markets and sectoral diversification, as well as income assistance may help mitigate the observed effects in potentially exposed counties, including neighboring areas.

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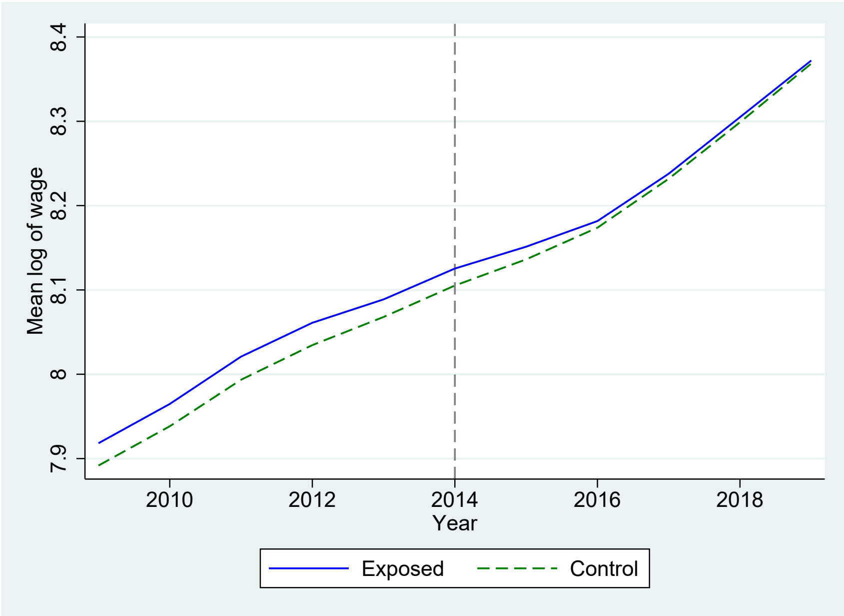
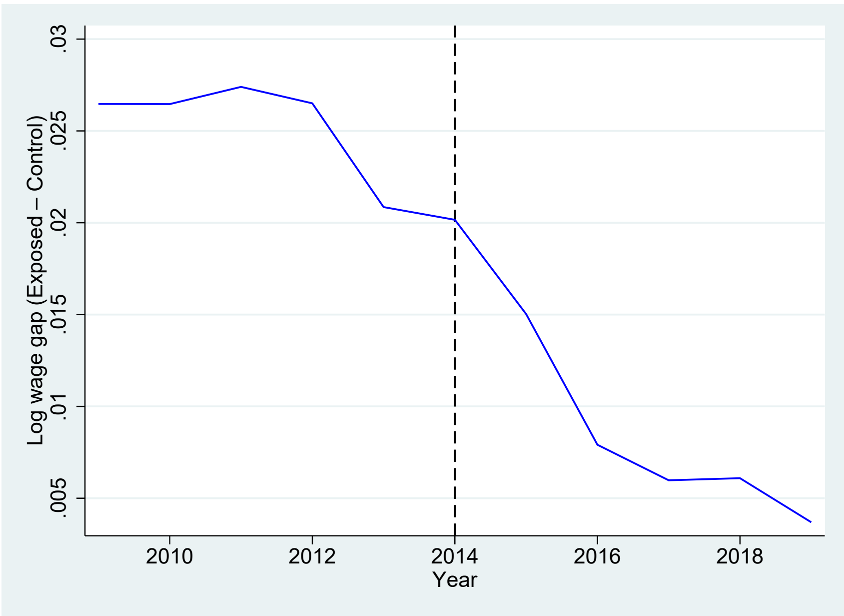
Appendix

Figure A1: Mean log labor earnings, exposed and control counties.



Note: excluding cities, gray dashed line represents the timing of the import ban, based on GUS (2026).

Figure A2: Log labor earnings difference, exposed and control counties.



Note: excluding cities, gray dashed line represents the timing of the import ban, GUS (2026).

Table A1: Effects of the import ban on the log of labor earnings, 2006-2021.

ln(Wage)	(1)	(2)	(3)	(4)
$\text{Fruits}_i \times \text{Sanct}_t$	-0.023**			
	(0.008)			
$\text{Dairy}_i \times \text{Sanct}_t$		0.003		
		(0.014)		
$\text{Beef}_i \times \text{Sanct}_t$			-0.032***	
			(0.011)	
$\text{Agg}_i \times \text{Sanct}_t$				-0.022***
				(0.007)
$\text{E}_{i,t}$	0.051^{+}	0.050^{+}	0.048	0.050^{+}
	(0.030)	(0.031)	(0.031)	(0.030)
N	4800	4704	4784	5024
R^2	0.98	0.98	0.98	0.98

Note: All columns include county and year fixed effects. $E_{i,t}$ stands for the log of employment rate (per 1000). Heteroskedasticity-robust clustered errors. Significance levels: $^{+}$ $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.