The Euro and Price Convergence in Central and Eastern Europe*

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We examine the effect of the adoption of the euro by Central and Eastern European countries, on the convergence of their prices vis-á-vis the euro zone. Allowing for staggered adoption, we estimate the euro treatment effect using a difference-in-differences approach. We find strong and robust, positive convergence effects, albeit with some heterogeneity.

JEL Codes: C23, E31, E42, F01.

1. Introduction

The euro was launched and adopted by 11 European Union (EU) member states in 1999 (and by Greece in 2001) in non-physical form, and, in 2002, by all 12 in physical coins and bank notes. In the years since, seven new member states joined the currency area (Figure 1).[1] Their adoption of the euro was preceded, in 2004, by their accession to the EU, and thus to the European Single Market (ESM). The introduction of the common currency was the third and final stage in their integration within the European Monetary Union (EMU) of EU.

The hopes for economic benefits flowing from the common currency, and EMU more generally, were outlined by the European Commission (EC) in the report "One Market, One Money" (EC 1990)—"the addition of a single currency to a single market will perfect the resource allocation function of the price mechanism at the level of the Community as a whole." A variety of benefits were anticipated:

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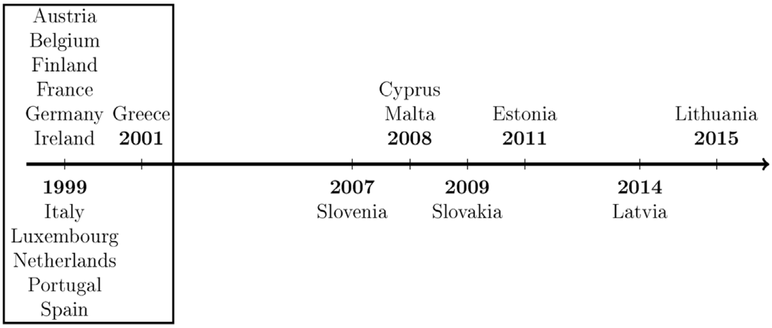
[1] In addition, Croatia joined the euro area on January 1, 2023.

Figure 1. Euro-Area Enlargement



- *Reduction in uncertainty* due to elimination of exchange rate risk; companies will be able to set prices with lower premiums, without having to insure against volatility.
- *Reduction in transaction costs;* costs of exchange to a foreign currency will be eliminated.
- *Price transparency;* direct comparability of prices between countries of the euro zone (EZ) will make it easier for investors/consumers to identify arbitrage opportunities and act on them.
- *Increased competition;* given lower risk/costs, due to companies expanding to foreign markets within the EZ.

It was expected that a common currency would lessen market frictions, boost arbitrage, and make markets more competitive, steering them closer to the law of one price (LOOP). Many barriers to LOOP would remain: transportation costs, differential tax rates, New Keynesian "menu costs," price stickiness, consumer habits, home bias, and legal and technical barriers, impeding the process of price convergence (EC 1990).

Evaluations focused on the ab initio adopters contended for the most part that the euro "failed" to induce price convergence. Many studies found no converging effect that could be attributed specifically to the common currency, but found a convergence pattern that began earlier and spanned the 1990s, in parallel with the establishment of the ESM and the advent of other integrating policies.

The adoption of the euro by the *new* EU entrants provides another natural experiment to revisit the euro-effect question. A careful study should serve to inform the ongoing debate on the reform of the euro zone and the rising euro skepticism amongst the Central and Eastern European (CEE) EU members. A more complete understanding of the costs and benefits in terms of price convergence or divergence following from euro adoption (which is required of all new EU member states) should provide useful guidance to prospective entrants.

We apply a difference-in-differences (DiD) identification strategy to a large and comprehensive data set of price level indices to estimate the euro effect, in terms of the LOOP, to five of the seven late entrants.[2] The existence of a control group of countries—CEE EU members that never adopted the euro but were similar in levels of development to the late (post-2004) euro adopters—allows us to estimate the euro effect on price convergence. We accommodate the time-staggered nature of euro adoption by these late entrants, augmenting the standard DiD method by exploiting recent developments in the econometrics of difference-in-differences analysis (Goodman-Bacon 2021).

We find a robust and significant convergence effect due to euro adoption for four out of five new adopters: Slovakia, Estonia, Latvia, and Lithuania. Since price levels were lower amongst CEE countries than in Germany or the EU, convergence took the form of rising prices. The heterogeneity in the euro effect attenuated over time. Slovenia is an exception, with a diverging euro effect.

2. Literature

The empirical literature has largely focused on the initial launch of the euro. The very first studies followed the introduction of the euro almost immediately, and many reported negative results.

In Lutz (2004), the analysis of four different data sets (Big Mac Index, *The Economist*, cars, and the UBS data set of goods and services) using the DiD approach yielded an overall divergence effect following euro adoption. Based on analyses of prices in European

[2] Our focus is on Central and Eastern Europe, and for that reason we exclude Cyprus and Malta from this study.

cities, Engel and Rogers (2004) and Rogers (2007) found no evident decrease in price dispersion post-1999.

Contrarily, Goldberg and Verboven (2004) found that car price differentials in the euro zone decreased by 1–2 percent during 1999–2002, while they increased in the non-euro control group. However, post-2002, after the euro–cash changeover, price differentials decreased faster in the non-euro area, raising the question of whether it was indeed the euro that generated the initial effect. Allington, Kattuman, and Waldmann (2005) report the most positive results: significant positive effect of the euro on price dispersion of tradable goods. Their data on comparative price level (CPL) indices for 200 product categories, sourced from Eurostat, is more comprehensive in coverage than any of the earlier studies.[3]

Almost all studies found a significant price convergence pattern during the 1990s (Engel and Rogers 2004; Rogers 2007; Baldwin et al. 2008; Parsley and Wei 2008; Glushenkova and Zachariadis 2016). This is also documented in the earlier, more general literature on trends in price dispersion (Rogers, Hufbauer, and Wada 2001; Rogers 2002). It has therefore been suggested that it was the ESM established in 1993, and other integrating policies of the early 1990s, that were crucial for the price convergence process, rather more than common currency (Engel and Rogers 2004; Rogers 2007).

A natural question relating to the early findings is whether sufficient time had elapsed since the launch of the euro for arbitrage mechanisms to take effect. Some of the aforementioned studies used data with only one or two years of post-cash-changeover observations (Engel and Rogers 2004; Allington, Kattuman, and Waldmann 2005), or no observations at all (Lutz 2004). This is an obvious drawback, as many channels through which arbitrage takes place rely on cash transactions. Furthermore, to the extent that the ESM and the euro are substitutes in inducing convergence, decreases in price differentials during the '90s might have exhausted the scope for further convergence. This study sheds light on the matter by considering the later adopters.

Later studies have also been unsupportive of a positive euro effect. Parsley and Wei (2008) find no euro effect on the speed of price

[3]This data series is equivalent to the price level indices series that we use in this paper.

convergence based on the analysis of Big Mac meals and their ingredients up to 2006. Fischer (2012) analyzed data covering 90 percent of washing-machine sales in the 1995–2005 period and found no euro effect after adjustment for machine quality. Guerreiro and Mignon (2013) found a non-linear price convergence pattern that occurred only above a certain threshold of the price differential. Their analysis was based on time-series data going back to 1970, with the larger portion reconstructed using relative consumer price indices (CPIs), raising questions about the validity of their results. Baldwin et al. (2008) note that in studies using consumer prices, issues of market power and demand and supply elasticities may confound the euro effect.

Ogrokhina (2015) analyzed prices of 120 traded goods from the Economist Intelligence Unit (EIU) for 1990–2011 and found support for the conjecture that the ESM, not the euro, caused prices to converge. She estimated a 5 percent ESM convergence effect, and (post-1999) a 2 percent euro divergence effect. New euro adopters were not considered. Glushenkova and Zachariadis (2016) found that empirical distributions of LOOP deviations over 1975–2010 grew more peaked after euro adoption, also for the new members who joined between 2005 and 2010. This suggests that many products moved towards the LOOP. However, the low frequency of data (five-yearly) does not permit attribution of the effect solely to euro adoption.

We provide a brief overview of econometric literature on DiD strategies with varying treatment timing in Section 4.2.

3. Data

We use data from the price level indices (PLI) series maintained by Eurostat. The data cover PLIs for 276 basic headings (product categories) across 37 countries[4] for the period 1995–2017. Other variables were sourced from the World Bank's World Development Indicators database.

[4]This includes EU28, three European Free Trade Association (EFTA) members (Iceland, Norway, Switzerland), EU candidate countries (Albania, Macedonia, Montenegro, Serbia, Turkey), and Bosnia.

The price level index (PLI) is calculated as the ratio of the purchasing power parity (PPP) to the nominal exchange rate (e):

$$PLI_{\frac{c}{EU15},pt} = \frac{PPP_{\frac{c}{EU15},pt}}{e_{\frac{c}{EU15},t}} \cdot 100,$$

where PLI and PPP for product p, in country c, at time t are calculated relative to the EU15 average. A PLI of 120 means the price level is 20 percent higher than the EU15 average. The series is invariant to the choice of base country/group.

The main advantage of Eurostat PLI data is the wide product coverage. The PPP measure for product category p and country c is calculated based on a group of specific products within the category, which is representative of the country. The PLIs are thus faithful to the product markets in each country. On the downside, product categories are not comparable between countries in an exact sense, as different specific products are sampled into categories depending on how representative they are for a given market.

The advantage and disadvantage reflect a fundamental trade-off in the empirical literature: between data comprising highly comparable products and data covering a wide range of broadly similar products. The LOOP is more likely to hold for the former, as the same product in two different locations are direct substitutes: car models, Big Macs, washing machines, or TV sets (Goldberg and Verboven 2004; Parsley and Wei 2008; Imbs et al. 2010; Fischer 2012). But obviously, factors specific to the particular market might drive results. Others have opted for large data sets (EIU, CPL/PLI series of Eurostat) of broadly similar products (Allington, Kattuman, and Waldmann 2005; Ogrokhina 2015). This supports broad generalizability, but at a cost of the mechanisms underlying the LOOP not directly applying. Our approach falls in the latter category.

A further issue relates to the method by which data is collected. Price surveys are the responsibility of national statistical institutes (NSIs), which have some degree of freedom in method of collection, within specified Eurostat guidelines. Additionally, for the majority of member states, prices relating to household consumption are collected only in the capital, and adjusted by NSIs. Both factors contribute to lower comparability and higher measurement error. However, Eurostat's rigorous validation procedures, and the large number of product categories, help to reduce the degree to which these issues bias results (Eurostat 2019).

3.1 Convergence Measures

The PLIs are "primarily suitable [for] comparisons referring to several geographical locations at a given point in time."[5] While they are not designed to capture price changes over time in any specific location, they can be used to characterize the time evolution of relative relations between price levels in different geographical locations.

As the largest and most stable EU15 economy, Germany is well suited to serve as a reference country for the analysis of price convergence. The EU15 group contains southern European countries that experienced long periods of instability, as well as small Scandinavian states characterized by high prices. Further, the CEE states have close trade links with Germany. Thus our primary measure of convergence is the standardized square differential relative to Germany, denoted Q^1:

$$Q^1_{c,pt} = \Big(\frac{PLI_{c,pt} - PLI_{DE,pt}}{100}\Big)^2.$$

To examine sensitivity we also use two additional measures of convergence, discussed in Section 5.3.[6] Given that the EU15 average PLI is equal to 100 for each time period, the measures are invariant to the euro entry of new members, as no members of the EU15 group are "treated" during the period under analysis.

3.2 Visual Inspection

Figure 2 presents the evolution of PLI differentials, Q^1, over time for the treated countries. We observe downward trends that turn almost flat around 2010 for all, and especially so for Slovenia, whose prices

[5] Eurostat (2019).

[6] Q^2: differential with respect to the EU15 average, and Q^3: the standard deviations (SD) of PLIs for EU15+1 and EU15.

$$Q^2_{c,pt} = \Big(\frac{PLI_{c,pt} - 100}{100}\Big)^2,\ Q^3_{c,pt} = \frac{SD_{EU15+1}(PLI_{c,pt})}{SD_{EU15}(PLI_{c,pt})}$$

Figure 2. Trends in PLIs Averaged over Products, Spline Function

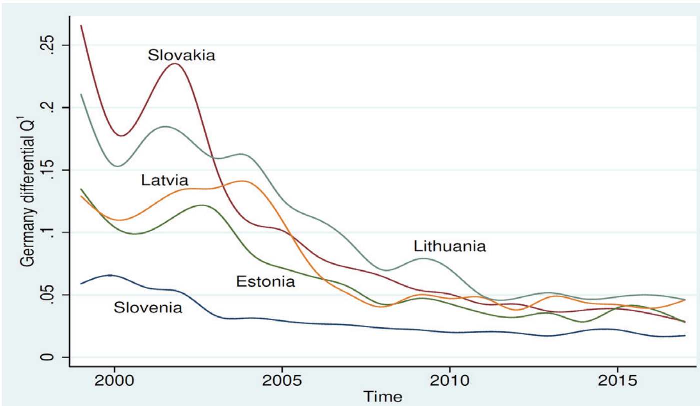
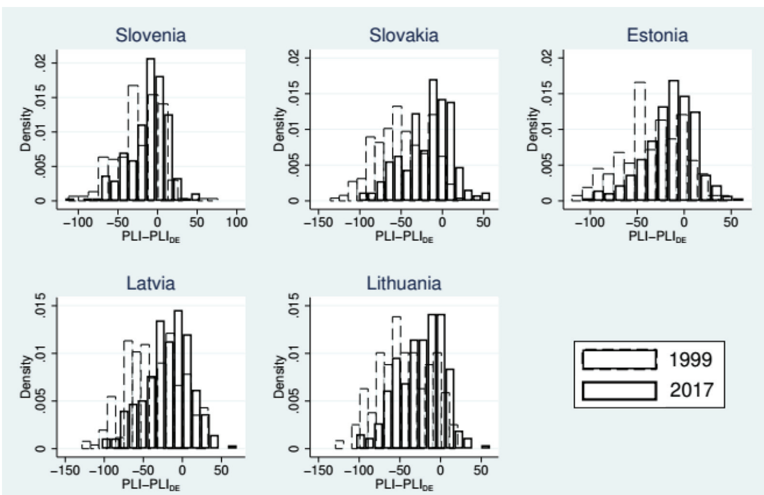


Figure 3. Shift in PLI Differential Distributions across Products between 1999 and 2017



have always been closest to those of the EU15. There is no evident trend break that might suggest impact of policy for any country.

Figure 3 presents the distributions of PLI differentials ($PLI - PLI_{DE}$) across product categories, for each "treated" country.

Between 1999 and 2017, all countries saw clear shifts in the distribution towards zero, and higher peaks around zero, implying moves towards the LOOP.

4. Method

Our identification strategy builds on the DiD approach that exploits the structure of quasi-experiments (Card 1992; Card and Krueger 1994). The set of countries that adopted the euro within a specified year fall in the "treatment" group, and the set of countries that did not, fall in the "control" group. Due to time-staggered adoption of the euro, the membership of the control group changes over time. The average treatment effect on the treated (ATT) is the (unobservable) difference in mean outcomes:

$$ATT = E[Q^1_{gt}] - E[Q^0_{gt}], \tag{1}$$

where Q_{gt} is the outcome variable, g denotes the group of countries, and the superscript is 1 if treated, 0 otherwise. The second term on the right-hand side being an unobservable counterfactual, the DiD estimator obtains the treatment effect as the difference in the differences of before-after treatment outcomes for treated and control groups. In a two time-period ($t = \{T_1, T_2\}$), two-group ($g = \{g_1, g_2\}$) setting, where countries $c \in g_1$ were treated between the periods, the DiD estimator β is

$$\begin{aligned}\beta &= E[Q^1_{g_1T_2} - Q^0_{g_1T_1}] - E[Q^0_{g_2T_2} - Q^0_{g_2T_1}] \\ &= ATT + E[\Delta Q^0_{g_1} - \Delta Q^0_{g_2}]. \end{aligned} \tag{2}$$

The identifying assumption required that in absence of treatment the two groups would have experienced identical trends in Q, resulting in the last term being zero, so that $\beta = ATT$. Of course, T_1, T_2 may include multiple periods before (T_1) and after (T_2) treatment. In this case the pre-/post-treatment outcome variable and ATT is averaged across periods.

4.1 Individual Countries Analyses

To start with, we consider each euro entry—by Slovenia (SI), Slovakia (SK), Estonia (EE), Latvia (LV), and Lithuania

(LT)—separately, against the *main control group* consisting of CEE EU members that never adopted the euro: Bulgaria (BG), Croatia (HR), Czech Republic (CZ), Hungary (HU), Poland (PL), and Romania (RO). The DiD approach is then equivalent to estimating the regression equation:

$$Q_{c,pt} = \alpha + \gamma Euro_c + \lambda PostT_t + \beta Euro_c \times PostT_t + \epsilon_{c,pt}, \quad \text{(M1)}$$

where $Euro_c$ is a dummy equal to one if country c is "treated" and $PostT_t$ is a dummy equal to one if the treatment had already occurred by time t. The coefficient β_c on the interaction term consistently estimates the treatment effect for country c under the parallel trends assumption.

Time-varying characteristics of the different countries may drive their individual trends. Including control variables can help satisfy the less stringent assumption of parallel trends, conditional on the vector of control variables $\boldsymbol{X}_{c,pt}$. So far, the time component consists of pre- and post-treatment periods, while the group-fixed component consists of the treated country and the *main control group*. We accommodate multiple periods and countries by including a full set of time and country dummies:

$$\begin{aligned} Q_{c,pt} = \alpha + \sum_c d_c + \sum_t d_t + \gamma Euro_c + \lambda PostT_t + \beta Euro_c \\ \times PostT_t + \delta X_{c,pt} + \epsilon_{c,pt}, \qquad \text{(M2)} \end{aligned}$$

where d_c and d_t denote country and time dummies, respectively. The vector of controls contains the following:

- *Tradability* (e.g., Engel and Rogers 2004): dummy variable equal to one for tradables; LOOP is more likely to hold for easily tradable products such as durable goods.[7]
- *Inflation differential* (e.g., Lutz 2004): difference between inflation levels in country c and Germany; persistent differences in growth rates of prices will lead to a divergence in price levels.
- *Income differential* (e.g., Ogrokhina 2015): difference between levels of real income per capita at constant prices, PPP

[7] Full classification provided on request.

adjusted, in country c and Germany; higher real income induces more demand for certain products, causing their prices to increase.

- *Tax* (e.g., Fischer 2012): general measure of tax level on goods and services; persistent cross-country differences in taxes will lead to divergent prices.

4.2 Time-Staggered Treatment

Unlike the empirical context that prevailed in 1999 when 11 countries adopted the euro contemporaneously, the 5 Central and Eastern European late entrants that we study adopted the euro at different points in time over an eight-year period from 2007 to 2015. This empirical setting introduces some potential sources of bias in the estimation of the aggregate average treatment effect—which necessarily combines the treatment effects of individual countries over different time periods. The prospects of time-varying treatment effects and country-specific departures from common trends are particularly important given the fairly long period over which conceivably heterogeneous countries were "treated" in a time-staggered way.

Goodman-Bacon (2021) presents details of how ignoring the time-staggered nature of adoption runs the risk of biased estimation of the ATT and of mistaken conclusions. In the analysis that follows, we apply a weighting and decomposition procedure to understand how the aggregate ATT is composed in terms of its constituents and use it to gauge the magnitude of potential bias.

4.2.1 Econometrics of Time-Staggered DiD

We present a very brief review of the most relevant DiD-pertinent variations of the "two-way fixed effects" model (Cameron and Trivedi 2005, p. 738; Pesaran 2015, p. 657):

$$y_{it} = \alpha_i + \gamma_t + \beta D_{it} + \epsilon_{it}. \tag{3}$$

Athey and Imbens (2018) and Goodman-Bacon (2021) have comprehensive reviews. In the context of DiD, (3) differs from the usual specification in that the treatment group × post-treatment interaction variable is replaced by the dummy D_{it}. Given treatment date T_i for i we have $D_{it} = 1 \ \forall t \geq T_i$ and zero otherwise.

The decomposition of the ATT parameter β, when there are multiple treatment groups and their treatments have been staggered over time, has been a focus of recent contributions to the econometrics of the DiD approach. Given common counterfactual trends, β has been shown to be a weighted average of treatment effects across all treatment groups and all periods (Borusyak and Jaravel 2017; Abraham and Sun 2018; de Chaisemartin and D'Haultfœuille 2018). Under the assumption that the assignment to treatment is random, the coefficient has been shown to be a weighted average of causal effects from changing the date of treatment (Athey and Imbens 2018). Goodman-Bacon (2021) derives the exact formula for β as a weighted average of all possible 2×2 DiD coefficients of the form of Equation (2). This decomposition, which does not rest on any specific assumptions, is very useful in understanding and interpreting ATT in the complex setting.

Consider the following version of (3):

$$Q_{c,pt} = \alpha + \sum_c d_c + \sum_t d_t + \beta D_{ct} + \epsilon_{c,pt} \tag{M3}$$

with notation as before. This specification has the unrealistic restriction of a single undifferentiated treatment effect β, regardless of country and time. We can decompose the β coefficient in (M3) in terms of its makeup (Goodman-Bacon 2021).

Consider the full "design" of the natural experiment, for the sample of 11 countries. We restrict the analysis to the period 2004–17, to avoid the confounding effects of ESM entry.

$$\begin{aligned} C &= \{\underbrace{SI, SK, EE, LV, LT}_{\text{Treated (K)}}\} \cup \{\underbrace{BG, HR, CZ, HU, PL, RO}_{\textit{Main control group}\text{ (U)}}\} \\ &= K \cup U \end{aligned}$$

The treatment timings are the one-to-one mapping,

$$K = \{SI, SK, EE, LV, LT\} \rightarrow \{2007, 2009, 2011, 2014, 2015\},$$

preserving the time order $t(k)$ for $k \in K$.

Our purpose is to decompose the aggregated β coefficient in (M3), in terms of its component treatment effects—the multiple DiD coefficients that are specific to each separate treatment/control pair for its own pre-/post-treatment period, as conceived in the standard specification (M1). From pairing each of the five treated countries ($k \in K$) with the *main control group* (U), we have five specific standard DiD coefficients. Denote these coefficients by $\beta_{kU}^{2\times 2}$.

Now consider pairs among the set of five treated countries ($k, l \in K$). We have 5×4 combinations. The corresponding DiD coefficients, denoted $\beta_{kl}^{2\times 2}$, can relate to either the sub-period where k is treated and l is not ($\beta_{kl}^{2\times 2,k}$), the latter acting as a control, or the sub-period when k had already been treated and so acts as control for l, which is now being treated ($\beta_{kl}^{2\times 2,l}$). Let $t(l) > t(k)$. Then $\beta_{kl}^{2\times 2,k}$ compares outcomes between periods $t < t(k)$ and $t(k) \leq t < t(l)$, while $\beta_{kl}^{2\times 2,l}$ compares periods $t(k) \leq t < t(l)$ and $t \geq t(l)$.

There is thus a total of $4 \times 5 + 5 = 25$ two-by-two DiD coefficients nested within the aggregated β coefficient in (M3).

The difference-in-differences decomposition theorem in Goodman-Bacon (2021) expresses the estimator for the aggregated β coefficient in (M3) as a weighted average:

$$\hat{\beta} = \sum_{k \in K} s_{kU} \hat{\beta}_{kU}^{2\times 2} + \sum_{k \in K} \sum_{\substack{l \in K \\ t(l) > t(k)}} s_{kl} \left[\mu_{kl} \hat{\beta}_{kl}^{2\times 2,k} + (1 - \mu_{kl}) \hat{\beta}_{kl}^{2\times 2,l} \right], \tag{4}$$

where the first term on the right-hand side is a weighted sum of the 2×2 DiD coefficients relating to the treated countries and the untreated group U, while the second term sums over weighted 2×2 coefficients relating to two distinct treated countries.

The weighting scheme squares with intuition.[8] Larger group size naturally implies a higher weight. Weights are also increasing in the

[8] Weights are given by

$$s_{kU} = \frac{n_k n_U \bar{D}_k (1 - \bar{D}_k)}{\hat{var}(\tilde{D}_{it})}$$

$$s_{kl} = \frac{n_k n_l (\bar{D}_k - \bar{D}_l)(1 - (\bar{D}_k - \bar{D}_l))}{\hat{var}(\tilde{D}_{it})}$$

variance of the treatment variable. If k is treated at the very beginning or at the end (i.e., low variance), it provides little information about treatment effects, as we either only observe its treated or its untreated status. Conversely, treatment in the middle of the sample is most informative and carries the highest weight.

The coefficients $\beta_{kU}^{2\times 2}$ and $\beta_{kl}^{2\times 2,k}$ are as DiD coefficients in Equation (2), given that l was treated later than k, i.e., $t(l) > t(k)$. The coefficients $\beta_{kl}^{2\times 2,l}$ take a different form, accounting for the fact that k had already received treatment. Denoting by $ATT_m(T)$, the ATT for group m across period T, and denoting by $\Delta Q_m^0(T_1, T_2)$ the change in counterfactual outcomes for group m between periods T_1 and T_2:

$$\begin{aligned}\beta_{kl}^{2\times 2,l} &= ATT_l(t \geq t_l) \\ &\quad + \Delta Q_l^0(t \geq t_l, t_k \leq t \leq t_l) - \Delta Q_k^0(t \geq t_l, t_k \leq t \leq t_l) \\ &\quad - \left[ATT_k(t \geq t_l) - ATT_k(t_k \leq t \leq t_l)\right],\end{aligned}$$

where the last term represents the potential change in treatment effect for the already treated group k, which now acts as a control for l.

$\hat{\beta}$ converges in probability to the population parameter β, which is a sum of three terms: "variance-weighted average treatment effect on the treated" (VWATT), "variance-weighted common trends" (VWCT), and the change in treatment effect (ΔATT), all terms that follow naturally from (4):

$$plim_{N\to\infty}\hat{\beta} = \beta = VWATT + VWCT + \Delta ATT.$$

- $VWATT$: weighted sum of ATTs, equivalent of ATT in the 2×2 case.
- $VWCT$: contains all the terms of the form ΔQ_k^0, and represents bias from departure from common trends.

$$\mu_{kl} = \frac{1 - \bar{D}_k}{1 - (\bar{D}_k - \bar{D}_l)}.$$

n_i are group sizes, so in our case $\forall_{k\in K} : n_k = 1$ and $n_U = 6$. The terms $\bar{D}_k(1 - \bar{D}_k)$ and $(\bar{D}_k - \bar{D}_l)(1 - (\bar{D}_k - \bar{D}_l))$ are variances of treatment and difference in treatment, respectively, with $\tilde{D}_{it} = (D_{it} - \bar{D}) - (\bar{D}_i - \bar{D}) - (\bar{D}_t - \bar{D})$ with $\bar{D} = \frac{1}{NT}\sum_i \sum_t D_{it}$.

- ΔATT: represents bias from time-varying treatment effects; comprising terms in the last part of Equation (5).

The above decomposition (Goodman-Bacon 2021) explains the basis of the β coefficient in (M3). The decomposition highlights the assumptions required for identification of VWATT: a weighted version of the common trends assumption, and no time variation in treatment effects. The weighting can be analyzed and adjusted, as we do in Section 5.2.

5. Results

All estimates reported below are based on data for 238 basic headings (out of the 276).[9] Product categories excluded those relating to government expenditures, and non-profit institutions serving households (NPISHs). The model specification included three leading and three lagging years—the parallel trends assumption is more likely to hold for short time periods. The standard errors reported are cluster robust, with clustering at the country level.

5.1 Individual Country Regressions

Table 1 presents the results from model M1. A negative coefficient signifies decreasing price differential and convergence to German prices. All euro adopters except for Slovenia present with statistically and economically significant convergence. The magnitude of the euro effect is greatest for Slovakia at around –0.026.[10] Slovenia's treatment coefficient alone is positive and significant, suggesting divergence from German price levels.

The results are fairly robust to the inclusion of controls and a full set of country/time dummies as in model M2 (Table 2). The magnitude of the converging (diverging) effect for Slovakia and Estonia (Slovenia) increases, while the effect for Latvia and Lithuania

[9] List provided on request.

[10] To illustrate the economic magnitude, with reference to Slovakia's average PLI of 78.8 just before euro adoption, the expected post-adoption average PLI would be 86.9, i.e., a converging effect of around 8 percentage points.

Table 1. Model 1

Variables	Slovenia (1)	Slovakia (2)	Estonia (3)	Latvia (4)	Lithuania (5)
EuroSIPost07	0.0157*				
	(0.00699)				
EuroSKPost09		–0.0257**			
		(0.00971)			
EuroEEPost11			–0.0154**		
			(0.00589)		
EuroLVPost14				–0.0171***	
				(0.00348)	
EuroLTPost15					–0.00871***
					(0.00207)
Constant	0.202***	0.171***	0.166***	0.162***	0.171***
	(0.0243)	(0.0196)	(0.0186)	(0.0170)	(0.0166)
Observations	9,996	9,996	9,996	9,996	9,996
R-squared	0.028	0.002	0.009	0.005	0.002

Note: Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 2. Model 2

Variables	Slovenia (1)	Slovakia (2)	Estonia (3)	Latvia (4)	Lithuania (5)
EuroSIPost07	0.0204**				
	(0.00688)				
EuroSKPost09		–0.0300***			
		(0.00538)			
EuroEEPost11			–0.0210**		
			(0.00730)		
EuroLVPost14				–0.0105*	
				(0.00530)	
EuroLTPost15					–0.00598***
					(0.00136)
Constant	0.360**	0.293***	0.279***	0.249**	0.271**
	(0.110)	(0.0331)	(0.0449)	(0.0908)	(0.0749)
Observations	9,828	9,828	9,828	9,360	7,722
R-squared	0.243	0.237	0.254	0.251	0.255

Note: Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

weakens. This is consistent with some of the omitted-variable biases being removed. Inflation, for example, positively affects the price differential, but high-inflation countries would not have met the

Maastricht criteria and so inflation is negatively correlated with euro adoption, i.e., the bias due to omission of inflation is negative.

The illustrative magnitudes of the treatment effects, in percentage points, relative to Germany's PLI, are –5.2 (divergence) for Slovenia and convergence for the other countries to the extent of 10.0 for Slovakia, 6.0 for Estonia, 2.8 for Latvia, and 1.3 for Lithuania.

Setting Slovenia aside, the later the euro adoption, the weaker the convergence effect. This is consistent with the euro and ESM being substitutes to a degree in inducing convergence—as time passes beyond the EU entry date (2004), the scope for further convergence decreases.

Average PLI levels before treatment tell a slightly different story. Latvia and Lithuania, countries for which the convergence effect is weakest, entered the euro zone when their PLI levels were at 76 and 71, respectively, compared with 79 and 77 for Slovakia and Estonia. So countries closest in price levels to Germany at the point of euro entry saw their prices converge by more due to the euro. It is plausible that high initial convergence permitted countries to reap the benefits of the common currency more fully.

Slovenia is atypical. It might be said that Slovenia's euro entry broadly coincided with the Great Recession, but so did Slovakia's entry. Slovenia has always been the closest to Germany in terms of price levels, with a mean PLI of 81 pre-entry. The trend in differential remained all but flat in the years that followed. It might be that the convergence potential was closer to being exhausted, leading the country to settle at a relative version of the LOOP, given transportation costs and usual frictions. But divergence is unexplained—Slovenia remains an interesting case for further analysis.

The signs of the coefficients on controls are as expected. Tradability has a strong and significant, negative (convergence) effect, and accounts for the considerable increases in R^2 between M1 and M2. Inflation differentials have a significant positive (divergence) coefficient.

5.2 Combined Regressions

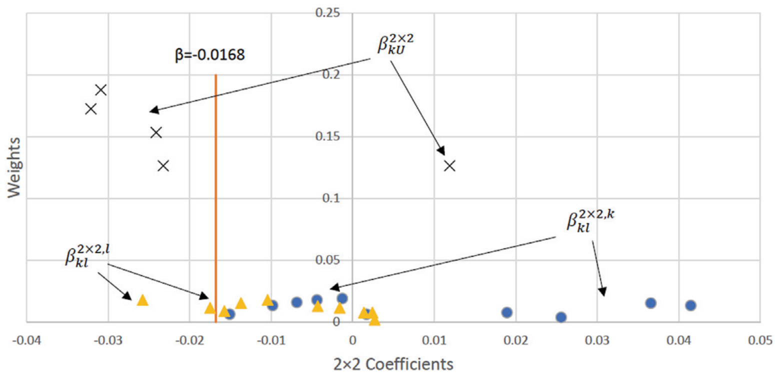
The aggregate euro-entry effect estimate from M3 is negative at –0.0168, and significant at 10 percent—Table 3, Equation (1). As per the decomposition theorem in (4), this aggregate effect can be

Table 3. Model 3

Variables	C (1)	C-SI (2)
Euro_t	–0.0168* (0.00878)	–0.0220*** (0.00533)
Constant	0.129*** (0.00908)	0.216*** (0.00421)
Observations	36,652	28,560
R-squared	0.045	0.029

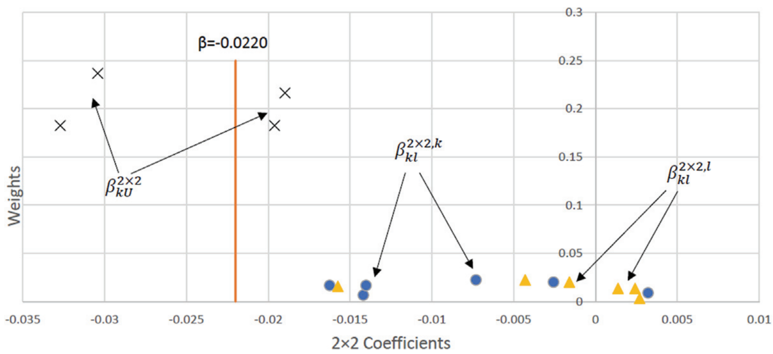
Note: Robust standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Figure 4. Decomposition of M3 Coefficient into 2 × 2 Coefficients with Weights



apportioned into 25 2 × 2 DiD coefficients. In Figure 4 we plot their weights against the values of these components, highlighting the sources of variation. The largest weights are on the five $\beta_{kU}^{2\times2}$ type coefficients (crosses: between pairs consisting of different euro entrants and the *main control group*), accounting for 77 percent of the variation. The remaining two groups ($\beta_{kl}^{2\times2,k}$, circles, and $\beta_{kl}^{2\times2,l}$, triangles) of "timing-only" coefficients (between pairs consisting of different euro entrants who entered at different dates) have similar

Figure 5. Decomposition of M3 Coefficient into 2 × 2 Coefficients with Weights, No Slovenia

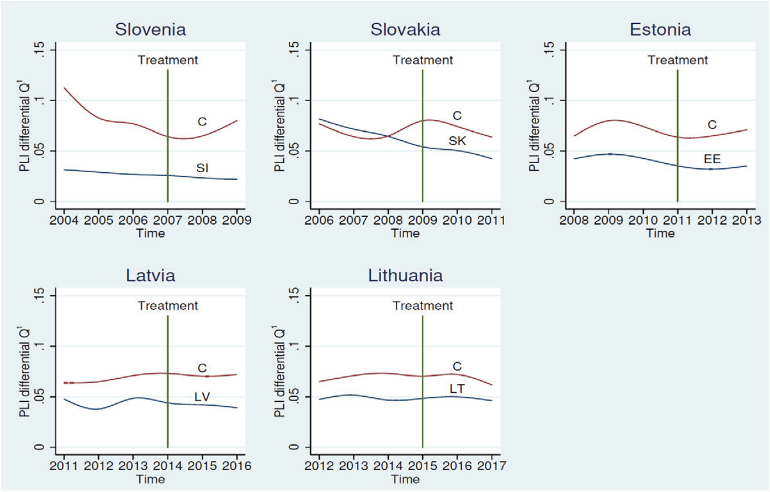


weights, 11–12 percent, so 23 percent of the variation is due to the timing of adoption.

The cases where the already treated countries act as controls ($\beta_{kl}^{2\times2,l}$) are worth examining. As seen in (5), the coefficients can potentially contain biases from time-varying treatment effect. The average value of these estimates is approximately –0.0083, significantly lower than the 0.0087 average for estimates for cases where the controls have not been treated yet. This suggests that there is a negative bias from time-varying treatment effects. This would mean that the term $ATT_k(t \geq t_l) - ATT_k(t_k \leq t \leq t_l)$ is positive, i.e., the average treatment effect increases over time. This is consistent with intuition in that it takes time for firms/agents to adapt to the new currency environment.

Slovenia accounts for nearly half of the number of coefficients that are likely to be biased due to time variation. Results from Section 5.1 show that it is also an outlier. We now exclude it and restrict the sample to 10 countries, starting three years (2006) before the treatment of the first, Slovakia. The results are in column 2 of Table 3. The treatment effect is more strongly significant at –0.0220. Figure 5 replots weights against values of 2 × 2 coefficients. The timing-only coefficients jointly explain 18 percent of the variation, with an average of -0.0025 for the $\beta_{kl}^{2\times2,l}$ (potentially time-biased) coefficients and -0.0085 for $\beta_{kl}^{2\times2,k}$ coefficients. Surprisingly, the time bias, if any, is now positive. This

Figure 6. Parallel Trends Averaged over Products, Spline Function



contradicts our previous interpretation. An alternative explanation might be that the euro's strong immediate impact was through firms adjusting their prices upwards, towards levels in western Europe.

The decomposition theorem has helped us determine that differences in treatment timing have a small impact on the β coefficient, and thus on the final result. Considering the new euro entrants together has led us to the conclusion that, on average, the common currency has caused prices to converge.

5.3 Diagnostic Tests and Sensitivity Analysis

We first inspect parallel trends, the key identifying assumption, visually. Figure 6 shows that pre-adoption trends are broadly similar between each treated country and the *main control group*.[11] Note

[11] The apparent divergence for Slovakia just before treatment results from the way the graphs were plotted. The year 2009 is in fact part of the post-treatment period and so it is appropriate to look at the trend for years 2006–08.

that model M2 relies on the conditional parallel trends, which is less stringent.

The tradables dummy is introduced to take note of the fact that the extent to which the LOOP holds might differ between tradables and non-tradables. Reestimation of model M2 on tradables only yields qualitatively very similar results; with fewer observations, significance is lost for Latvia and Lithuania, but the estimates are slightly higher in value.

The same analysis for non-tradables shows that the convergence effects are in fact stronger for that group of product categories. Divergence for Slovenia is not significant for non-tradables. Analysis of PLI trends for the two groups explains this counterintuitive result. There were huge differences between pre-treatment price levels for the two groups. For example, Slovakia's pre-treatment mean PLI for tradables was only 9 percent lower than Germany's, at 90, while the mean for non-tradables was, at 57, 42 percent lower than Germany's. Convergence is bound to be stronger the larger the PLI differential, and it would appear that size of PLI differentials for non-tradables outweighed the limitation on tradability.

We examine sensitivity with respect to the convergence measure, by using alternative measures Q^2 and Q^3, both of which use the EU15 PLIs as reference points for convergence (see Section 3.1). The first uses the mean and is a direct alternative to Q^1; the second uses the dispersion of prices—the ratio of the standard deviation (SD) of PLIs in the group of EU15 enlarged by the new euro entrant (EU15+1) to the SD of PLIs of the EU15 group only. For Slovenia, Slovakia, and Estonia qualitative results remain the same, and change little quantitatively. Significance disappears for Latvia and Lithuania. Note however that Germany's price levels are actually below the EU15 average of 100, mainly due to the influence of countries like Norway or Denmark. This underpins the motivation in choosing Germany as the reference country.

Removing any single country from the *main control group* does not affect our conclusions. Finally, we check if clustering of standard errors is not perhaps bigger within product categories rather than countries. This is not the case; using product instead of country clusters increases significance to 1 percent level in most models. Point estimates are, by definition, not affected.

Overall, our convergence results are substantially robust.

6. Conclusions

Our aim was to investigate whether the adoption of the euro by Central and Eastern Europe countries had any impact on the convergence of their price levels with that of euro zone. Notwithstanding theory that suggested that a common currency area would accelerate the process of convergence to the LOOP, empirical studies of initial adopters had broadly agreed that there was no positive converging effect. The literature has paid little or no attention to the subsequent CEE entrants to the euro zone. This paper was aimed at filling that void.

We find a significant and robust positive impact of the euro on price convergence between, the new entrants—Slovakia, Estonia, Latvia, and Lithuania—and Germany. A time-staggered model for euro adoption, estimated with data on all the above countries along with Slovenia, yields a significant converging effect for the euro. Two reasons might be offered for why studies on the initial euro adopters found no convergence: arguably, the 11 countries that adopted the euro in 1999 were characterized by a higher initial degree of integration amongst them; secondly, the early results were based on short post-treatment periods.

We also found notable heterogeneity. Converging effects of the euro vary from as much as 10 percentage points for Slovakia to 1.3 percentage points for Lithuania, in a pattern where the convergence effect declined with time elapsed since EU entry. It cannot be a coincidence that this pattern is also related to their initial (pre-treatment) price level differentials relative to Germany. The sources of this heterogeneity, in terms of structural differences and dimensions of integration, which might have prevented later adopters from reaping the full converging effects of the euro, are worth inspection. The robustly significant diverging effect seen for Slovenia is also worth further investigation—particularly, the role of the Great Recession. One limitation of this study is that price level indices at basic heading level are not comparable in an exact sense. Further studies using multiple comparable products would be useful.

Our empirical results imply that the initial expectations of policymakers were not misplaced. In the context of the current debate on reforming the currency area, it is important that the euro has worked, albeit in a somewhat heterogeneous way, to bring the market closer to the law of one price, which is widely acknowledged to underpin potential gains in efficiency and welfare.

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