# 10 years of BLIK. Changes in payments and the economy of Poland

Technical Appendix

March 2025

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# Contents

# 1. Introduction

BLIK is the most popular mobile payment system in Poland. The document "10 years of BLIK. Changes in payments and the economy of Poland. Technical Appendix" explains the methodology applied in the report "10 years of BLIK. Changes in payments and the economy of Poland" (hereinafter referred to as the "Report").

The Report provides an overview of BLIK's role in the retail payment market in Poland, analyzes how its development creates the electronic transaction market, and estimates the aggregated impact of BLIK payments on the Polish economy. It also examines the e-commerce sector's significance for BLIK and its economic influence.

The study and this document were prepared by the EY Economic Analysis Team, consisting of Marek Rozkrut, Michał Kowalczuk, Piotr Dybka, Maciej Łopusiński, Stanisław Bartha, and Anna Komisarska. The report was commissioned by the Polish Payment Standard, the owner of BLIK. The publication aligns with the team's extensive body of work covering various aspects of electronic payments, carried out in many countries around the world.

# 2. Impact of BLIK payments use on the Polish economy

We explain our calculation of the impact of BLIK payments on the Polish economy. First, we discuss our econometric analysis which determines the relation between electronic payments use and GDP. Second, we describe the transformation of the obtained econometric results into effects of BLIK for GDP, employment, individual income and tax revenues.

## 2.1 Econometric estimation of the impact of electronic payments use on GDP

Our econometric analysis is based on a panel data set for 36 countries (OECD countries and EU member states), observed at an annual frequency over the 2000-2019[1] period. Since the economic effects might vary by the level of economic development, there is an argument that the results based on international data may sometimes not be adequate for a specific country. We reduce such risks for Poland by performing an international analysis for a limited set of countries that are at a relatively similar level of economic development as the aforementioned countries.

In order to obtain the necessary econometric estimates, we use the System General Method of Moments (GMM) estimator that allows us to handle the likely problem of endogeneity of electronic payments with respect to GDP (the 'chicken-and-egg problem"). In addition, we consider alternative estimators, such as pooled ordinary least squares (OLS), two-stage least squares (2SLS), fixed effects (FE) and the random effects (RE) panel estimators to check for robustness of the GMM-based findings and verify the statistical properties of particular models. Based on that, we select the baseline model to be used in further calculations.

We focus on panel models explaining log GDP per capita in country *i* in year *t*. The models under consideration are based on the following equation:

$$log(GDP)_{it} = \mu_i + \gamma log(GDP)_{it-1} + \beta_1(electronic\ payments\ value)_{it} + \sum_{k=2}^{K} \beta_k(control\ variable\ k)_{it} + \varepsilon_{it}, \quad (1)$$

where $log(GDP)_{it}$[2] stands for natural logarithm of gross domestic product per capita, expressed in purchasing power standards (PPS, to assure comparability of the GDP figures for different countries in terms of the underlying price levels), in constant 2011 prices (to assure comparability over time). Most models considered are dynamic and include a lag of the explained variable on the right-hand-side of the corresponding econometric equation. In one case the specification is static, i.e., $\gamma=0$.

Note that equation (1) describes a model that is not in first differences. A similar approach is taken in the work of Hasan (2013),[3] where the impact of electronic payments on, i.a., log real GDP per capita is estimated. However, the sample in that study includes only EU Member States for the 1995-2009 period, while in our estimations we include a larger number of more developed countries and cover more recent years when electronic payments were used more frequently. The undifferenced model is also considered in Zandi et al (2016),[4] yet with log real consumption per capita as the explained variable. The key problem with the latter study is that it does not use econometric estimation techniques that would address the chicken-and-egg problem described above.

[1] The analysis has not been extended beyond these years for two reasons. First, the years 2020-2021 were highly atypical due to the COVID-19 pandemic, which disrupted the relationships between various economic factors and resulted in less reliable statistical data. Second, including a few years of additional data should not significantly impact the estimation results.

[2] We take the logarithm of this variable in order to reduce the problem of heteroskedasticity.

[3] Hasan I., De Renzis T., Schmiedel H. (2013), Retail Payments and the Real Economy, ECB Working Paper Series, Working Paper No. 1572.

[4] Zandi, M., Koropeckyj S., Singh, V., & Matsiras, P. (2016), The impact of electronic payments on economic growth, Moody's Analytics.

Log of real GDP per capita is also used as the explained variable in a related strand of literature, focusing on a more general concept of financial development, e.g. in a study of Van et al. (2019).[5] However, the GDP-related variable can also be transformed in the studies of determinants of GDP. For example, in Levine et al. (2000)[6] models in first differences, undifferenced models and a combination of both (in a system approach) are considered, while in Rousseau and Wachtel (2011),[7] the percentage change in GDP per capita is explained.

As regards other right-hand-side terms in the equation (1), intercept $\mu_i$ is the country-level individual effect (indicating any characteristics of a given country that do not change over time), whose inclusion is crucial for assuring the comparability of different countries and for drawing general conclusions. In the case of the FE approach, it is treated as a country-specific constant, and in the System GMM and RE approaches, it is treated as part of the error term. In this Appendix, a single intercept is reported in the econometric tables for each model reflecting the weighted average intercept for all the units in the panel.

*(electronic payments value)*$_{it}$ is the value of electronic payments made with domestic cards at POS terminals and via e-commerce both domestically and abroad (the issuing side data).[8] It is the key explanatory variable in the econometric model. In most of our models, it is expressed as a % of household final consumption expenditure. In one of the considered models, log of electronic payments per capita in PPS is used instead for the purpose of a robustness check.

The $\sum_{k=2}^{K} \beta_k$*(control variable k)*$_{it}$ term is the joint term describing any other explanatory variables included in the econometric models, which are referred to as control variables (K is the total number of explanatory variables, excluding lagged GDP variable and the country-level individual effects). Those variables describe the macroeconomic factors explaining GDP growth, as well as the institutional factors that change over time. Among the variables that we considered here were those analyzed in the research on the impact of financial inclusion on the economic growth (see Table 1.1). Other variables either used in the literature or similar to those used in the literature were considered in our model as well. Those variables described the human capital, trade openness, price level (in the form of GDP deflator), interest rates or the education level. However, those variables were either statistically insignificant or produced counterintuitive results.

Finally, $\varepsilon_{it}$ is the idionsyncratic shock affecting GDP in a particular country $i$ in period $t$.

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[5] Van L. T.-H., Vo A. T., Nguyen N. T., Vo D. H. (2019), Financial Inclusion and Economic Growth: An International Evidence, Emerging Markets Finance and Trade.

[6] Levine R., Loayza N., Beck T. (2000), Financial intermediation and growth: Causality and causes, Journal of Monetary Economics 46 (2000) 31-77.

[7] Rousseau P.L. and Wachtel P. (2011), What is happening to the impact of financial deepening on economic growth?, Economic Inquiry, 49(1), 276-288.

[8] A broader measure than card payments could not be utilized due to limitations in data availability and consistency. Specifically, comprehensive data on all forms of electronic payments were not uniformly accessible across the various countries analyzed. This lack of standardized data made it challenging to ensure comparability and reliability in the econometric model. Consequently, focusing on card payments, which are well-documented and widely used, provided a more robust and consistent basis for analysis.

In the case of dynamic panel models with the fixed effects considered here, a number of issues arise. The first one is the fundamental problem of endogeneity of the lagged dependent variable (the so called *dynamic panel bias*). In the case of pooled OLS and FE estimators, inclusion of the lagged (log) GDP as an explanatory variable generates the endogeneity problem "by nature". Another problem is endogeneity of the explanatory variables (which arises in the case of the electronic payments variables used in this study). The final issue that renders many estimators unreliable (especially in the GMM family) is insufficient number of countries included in the analysis (36 in our case). The available papers suggest that the Blundell and Bond system general method of moments (referred to as System GMM in this Appendix) used here not only helps solve the abovementioned endogeneity problems but also performs relatively well in small sample environments.[9]

[9] Behr A. (2003), A comparison of dynamic panel data estimators: Monte Carlo evidence and an application to the investment function, Discussion paper 05/03 Economic Research Centre of the Deutsche Bundesbank; Hayakawa K. (2007), Small sample bias properties of the system GMM estimator in dynamic panel data models, Economics Letters, 95, 32-38; Soto M. (2009), System GMM estimation with a small sample, Barcelona Economics Working Paper Series, Working Paper No. 395.

**Table 1.1 The description of explanatory variables in the models explaining GDP**

| Variable | Units of measurement and role | Source |
|---|---|---|
| *log(GDP)$_{it-1}$* | It is the first lag of the dependent variable and is considered in the case of dynamic panel models explaining the logarithm of real GDP per capita in purchasing power standards (PPS, at 2011 prices).<br><br>This variable allows us to account for the persistence inherent in GDP. For instance, a high GDP level in one year will remain relatively high in the following, which has little to do with the development of the electronic payments market or other driving variables included in econometric equations.<br><br>Inclusion of the first lag of the dependent variable in the model explaining the logarithm of the level of GDP makes it possible to see the "additional value" generated due to electronic payments. Such a dynamic form of a model of log GDP per capita was estimated, i.a., by Hasan et al. (2013).[10] A more general analysis of multiple System GMM models explaining the levels of (log) GDP was carried out by Próchniak and Witkowski (2013) and lagged log of GDP was the critical variable in multiple specifications.[11] | World Bank |
| *(electronic payments penetration ratio)$_{it}$* | The value of card payments expressed as a % of HFCE (household final consumption expenditures) is an important indicator of electronic payments market development. The various socio-economic impacts of electronic payments are discussed in the Report, focusing on BLIK payments.. Inclusion of that variable in an econometric model allows us to calculate the joint impact of electronic payments use on economic activity. Such a definition of electronic payments penetration ratio was used, i.a., in the work of Zandi et al (2016).[12] A similar variable for electronic payments was used by Hasan (2013), but with GDP in the denominator.[13] Many other studies describing the relationship between finance and growth are presented in a review of Levine (2005).[14]<br><br>Importantly, electronic payments market development is also affected by economic growth – the "chicken-and-egg problem" arises. We address this through the use of the System GMM model with an appropriate instrument set. | Bank for International Settlements, European Central Bank, US Federal Reserve System, World Bank, US Bureau of Economic Analysis |
| *log(electronic payments per capita in PPS)$_{it}$* | The log of card payments per capita in PPS (at 2011 prices) is an alternative indicator of electronic payments market development, with a similar economic interpretation as in the case of the electronic payments penetration ratio (described above).<br><br>Also in the case of log of electronic payments per capita in PPS the "chicken-and-egg problem" arises, which we address through the use of the System GMM model with an appropriate instrument set. | Bank on International Settlements, European Central Bank, US Federal Reserve System |
| *(government effectiveness) it* | The government effectiveness indicator is an important determinant of economic growth because it describes the quality of institutions that are responsible for facilitating the economic activity. | World Bank Worldwide Governance Indicators |

[10] Hasan I., De Renzis T., Schmiedel H. (2013), op.cit.

[11] Próchniak M., Witkowski B. (2013), Time stability of the beta convergence among EU countries: Bayesian model averaging perspective, Economic Modelling 30, 322-333.

[12] Zandi, M., Koropeckyj S., Singh, V., & Matsiras, P. (2016), op. cit.

[13] Hasan I., De Renzis T., Schmiedel H. (2013), op.cit.

[14] Levine R. (2005), Finance and Growth: Theory and Evidence, Handbook of Economic Growth, Volume 1A. Edited by Aghion P. and Durlauf S. N., Elsevier B.V.

| Variable | Units of measurement and role | Source |
|---|---|---|
| *log(capital stock) it* | This variable describes the log of capital stock per capita in PPS (at 2011 prices) that reflects important factors of physical production used in the process of generating GDP. A variable reflecting the capital formation was considered in the study of Van et al. (2019) on the effects of financial inclusion for economic growth.[15] Here we consider the capital stock, which is the result of accumulation of capital over an extended period of time. | Penn World Table 9.1 |
| *(output gap)$_{it}$* | Output gap is the difference between the actual and potential GDP and is expressed in % of potential GDP (that describes the theoretical value of GDP if the economy was in equilibrium in macroeconomic terms). This variable describes the factors that are related to the business cycle, reflecting, in particular, the periods of crises (e.g., the 2008 financial crisis) and economic slowdowns that occurred in the analyzed sample period. Inclusion of this variable in the econometric model in addition to the electronic payments variable means that the estimate for the latter should be more related to the productive potential of the economy created due to electronic payments development rather than to short-term macroeconomic developments. In addition, inclusion of the output gap variable reduces the problem of serial correlation in the dynamic panel models. | AMECO, OECD |
| *(financial development index)$_{it}$* | The IMF Financial Development Index has been considered as a control variable in the main regression equations, but – when put together with other variables included in the models – it produced counter-intuitive results (with a negative impact on economic growth). However, this variable is used in the System GMM models and 2SLS models as an additional instrumental variable, aimed at reducing the endogeneity issues related to the *(electronic payments penetration ratio)$_{it}$* and *log(electronic payments per capita in PPS)$_{it}$* variables.<br><br>The variables describing the level of financial development of particular countries were considered, e.g., in the study of Rousseau and Wachtel (2011)[16] and Van et al. (2019)[17]. The explanatory variables in the former paper include private credit to GDP ratio and monetary aggregates (M3 as % of GDP and the difference between M3 and M1 as % of GDP). In the latter study, Financial Inclusion Index was calculated based on the number of commercial bank branches per 100,000 adults, the number of ATMs per 100,000 adults and the private credit to GDP ratio (those variables were also included separately in the econometric specifications considered in that paper).<br><br>In our model, the IMF Financial Development Index is treated as the most accurate variable that includes various dimensions of financial development and assures a broad coverage in our sample. | IMF |

Note: all the variables remain untransformed in the undifferenced models and are included in first differences in the first-difference models considered here (except for *log(GDP)$_{it-1}$* , which is included only in the undifferenced models).
Source: EY.

The idea of System GMM is to estimate the parameters of two econometric equations at the same time: untransformed (see equation 1) and transformed one.[18] The main issue is the proper selection of the instruments for both equations that are used in the estimation. Most of instruments are generated according to some automated rules that solve the endogeneity problem – here we use the *xtdpdgmm* Stata package.[19] Apart from those instruments, the IMF Financial Development Index is

[15] Van L. T.-H., Vo A. T., Nguyen N. T., Vo D. H. (2019), op. cit.

[16] Rousseau P. L., Wachtel P. (2011), op.cit.

[17] Van L. T.-H., Vo A. T., Nguyen N. T., Vo D. H. (2019), op. cit.

[18] We use a special orthogonal deviations transformation instead of first differences in order to save the degrees of freedom, as suggested by Roodman D. (2009), How to do xtabond2: An introduction to difference and system GMM in Stata, The Stata Journal 9(1), 86-136 for a popular exposition and the literature related to that method.

[19] See Kripfganz, S. (2019), Generalized method of moments estimation of linear dynamic panel data models, Proceedings of the 2019 London Stata Conference.

included as an instrument as well, which is aimed at reducing the endogeneity problem in the case of electronic payments variables.

Such an approach allows the pool of instruments to be potentially huge. On the one hand, the higher the number of instruments we use, the more precise our estimates become. On the other hand, if we use too many instruments, we fail to remove the bias resulting from endogeneity as we over-fit the *first stage* regression.[20] This is especially important with a low number of countries in the sample. To set the number of instruments that is not too high relative to the number of units in the panel, but at the same time to include all the necessary information in the System GMM models estimated here, the instruments enter the estimation in a so-called collapsed variant (see Roodman, 2009, and Kripfganz, 2019, for more details[21]). In the baseline model, the number of instruments equals 39 while the number of countries equals 36.

**Table 1.2 The choice of the instruments for the system GMM estimation**

<table>
<tr><th>Basis for the instruments</th><th>Endogeneity of the basis variable</th><th>Lags of the levels, the transformed equation.</th><th>Lags of the first differences, the levels equation.</th></tr>
<tr><td>$log(GDP)_{it-1}$</td><td>First lag of GDP is the source of the dynamic panel bias.</td><td>According to the Arellano-Bond test, there is serial correlation of order 1 (for untransformed error term). A standard approach in such a situation is to use lag order of instruments starting from 3. However, this test is not very credible for a low number of countries. When the recommended number of lags was used, the estimate of coefficient for first lag of the explained variable fell beyond the credible range between the estimates of $\gamma$ from Pooled OLS and FE regressions (this is discussed in the main text of the Appendix below). For that reason, we use the lags of order starting from 5 which is the lowest starting lag order that produces credible results.</td><td>Due to serial correlation of order 1, we should use the lag of order 2, but for the reasons provided in the previous column, we use lag of order 4. The higher lag orders are made redundant by instruments used in the transformed equation.</td></tr>
<tr><td>*(electronic payments penetration ratio)*$_{it}$ and *log(electronic payments per capita in PPS)*$_{it}$</td><td>Electronic payments variables can to some extent be determined by GDP (higher level of economic development is related to a more developed electronic payments market) – we need to account for that potential source of endogeneity.</td><td colspan="2">The approach to lags is consistent with that adopted in the case of GDP-related instruments because this is an endogenous variable.</td></tr>
<tr><td>Other explanatory variables and the Financial Development Index variable</td><td>We consider the control variables as strictly exogenous.</td><td>We use all the available lags.</td><td>We use only the contemporaneous value (zero lag). All the remaining lag orders are made redundant by instruments used in the transformed equation.</td></tr>
</table>

Source: EY.

Description of the instrument sets both for the transformed and the levels equations is provided in Table 1.2. The number of lags of instruments used in the levels equations is very limited as compared to what is used for the transformed equations. This is because once we include the instruments for the transformed equation, most of the instruments for the levels equation become

[20] We define the *first stage* regression as a regression of each of the endogenous variables on the full set of instruments and exogenous variables. The purpose of this regression is to remove the 'endogenous term', leaving only the linear combinations of exogenous variables for the *second stage*, main regression. Therefore, the over-fitting means that these linear combinations are not much different from the initial endogenous variables – leaving us with the biased estimates of the main regression coefficients.

[21] Roodman D. (2009), op. cit., Kripfganz S. (2019), op. cit.

mathematically redundant. In addition, the lag length of some instruments is quite large, meaning that each GMM model should be estimated using as long data sample as possible so that enough information is included in the instrument set in each case.

The results of econometric estimations of undifferenced models are demonstrated in Table 1.3. The baseline System GMM model is included in column 1 and compared to the fixed effects (FE) and pooled Ordinary Least Squares (OLS) models (columns 2 and 3, respectively), a random effects panel model (RE, column 4), a System GMM model with additional lag for log GDP (column 5), a System GMM model with *log(electronic payments per capita in PPS)$_{it}$* variable (column 6) and a model without lag for log GDP, estimated using 2SLS (column 7). In this last model, the instruments include first lag of electronic payments, the Financial Development Index and the remaining explanatory variables (the electronic payments variable with no lags is not included among instruments because it is endogenous). In all the cases, p-values were calculated using robust standard errors.[22]

**Table 1.3 The results of econometric estimations of undifferenced models (explained variable: *Log of GDP per capita in PPS*)**

| | (1) Baseline System GMM model | (2) Pooled OLS model | (3) FE model | (4) RE model | (5) System GMM model with additional lags | (6) System GMM model with log of electronic payments | (7) 2SLS model with no lags |
|---|---|---|---|---|---|---|---|
| *log(GDP)$_{it-1}$* | 0.761*** | 0.974*** | 0.749*** | 0.934*** | 0.332*** | 0.651*** | |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | |
| *log(GDP)$_{it-2}$* | | | | | 0.395*** | | |
| | | | | | (0.000) | | |
| *(electronic payments penetration ratio)$_{it}$* | 0.121*** | 0.010** | 0.086** | 0.030*** | 0.116** | | 0.252*** |
| | (0.005) | (0.035) | (0.017) | (0.009) | (0.036) | | (0.000) |
| *log(electronic payments per capita in PPS)$_{it}$* | | | | | | 0.045*** | |
| | | | | | | (0.004) | |
| *(government effectiveness)$_{it}$* | 0.038*** | 0.0001 | 0.009 | 0.005 | 0.048*** | 0.049** | 0.073*** |
| | (0.004) | (0.974) | (0.198) | (0.284) | (0.002) | (0.020) | (0.000) |
| *log(capital stock)$_{it}$* | 0.102** | -0.003 | 0.158*** | 0.018* | 0.112** | 0.121** | 0.787*** |
| | (0.023) | (0.399) | (0.006) | (0.079) | (0.047) | (0.030) | (0.000) |
| *(output gap)$_{it}$* | 0.007*** | 0.006*** | 0.007*** | 0.006*** | 0.010*** | 0.007*** | 0.013*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| *Intercept* | 1.207*** | 0.323*** | 0.724* | 0.478*** | 1.449*** | 1.783*** | 1.309*** |
| | (0.000) | (0.000) | (0.082) | (0.000) | (0.000) | (0.001) | (0.005) |
| No. of observations | 587 | 587 | 587 | 587 | 562 | 588 | 538 |

Note: p-values in parentheses (* p<0.10, ** p<0.05, *** p<0.01)
Source: EY.

There are a number of ways to validate particular specification choices among the considered models. First of all, the OLS, FE and RE models are known *ex ante* to be biased due to the dynamic panel bias and can only be treated as auxiliary models, e.g., allowing one to verify other models. In particular, in the case of the System GMM models, the estimated coefficient for the first lag of the dependent variable should fall between the estimates given by the Pooled OLS (as upper limit) and

[22] We use the two-step GMM estimator to cope with the possible heteroskedasticity, but the estimates of standard errors in this method tend to be downward-biased. In order to account for this issue, we use the Windmeijer correction of the standard errors.

FE (as lower limit) methods, as the former method produces upward bias, whereas the latter – downward bias for $\gamma$. In our case, the coefficient produced with the FE method equals 0.749 (column 2), with the Pooled OLS method: 0.974 (column 3), whereas with the baseline System GMM specification (column 1) we obtain 0.761, which is within the plausible interval. Based on the same criterion, the system GMM with log of electronic payments per capita (column 6) should be rejected (the respective FE and OLS models with log of electronic payments per capita are not reported in Table 1.3).

Other models are rejected based on their economic interpretation. First, the results for the model with second lag of log GDP (column 5) should be rejected because the coefficient next to the second lag is larger than the coefficient for the first lag which is a counter-intuitive result (GDP in a given country should be most strongly related with GDP in consecutive periods). Secondly, as demonstrated by specifications in columns 1-6, the dynamic effects (confirmed with $\gamma$ being positive and statistically different from zero) are relevant in understanding what drives log GDP in different countries. For that reason, the 2SLS model without such a variable (column 7) should not be treated as baseline.

Finally, we carry out two additional quality checks of the baseline System GMM model. First, we consider the Sargan-Hansen test of overidentifying restrictions in which we do not reject the null hypothesis of the exogeneity of the instrument set at any usual significance level (p-value equals 0.330). Secondly, we carry out the Arellano-Bond test for serial correlation, which points at serial correlation of order 2 in the first differences equation used for the test, which means serial correlation of order 1 of $\varepsilon_{it}$ (p-value equals 0.0013 for order 2). We do not consider it as a fundamental problem, though, as we adjust the lags in the instrument set accordingly. Therefore, the baseline System GMM specification fares well in all the important diagnostic tests.

While the non-baseline models are rejected for various reasons, they allow for important robustness checks. In particular, all the models demonstrate a positive impact of electronic payments penetration ratio on GDP, which is statistically different from zero and the results are quite robust across specifications. In the baseline System GMM specification, the coefficient equals 0.121, while the largest effect is produced by the model with no lags with a coefficient equal to 0.252. However, the former coefficient should be interpreted as the short-term effect, while the latter – as the long-term effect. The comparable, long-term effect of electronic payments in the baseline System GMM specification equals 0.121/(1-0.761)=0.506, which is higher than the corresponding coefficient in the model with no lags.

To further test the robustness of the estimates of the effects of electronic payments on GDP, models in first differences are calculated, in which first differences are calculated for all the variables entering the econometric specification:

$$\Delta log(GDP)_{it} = \beta_1 \Delta \text{ (electronic payments value)}_{it} + \sum_{k=2}^{K} \beta_k \Delta \text{ (control variable } k)_{it} + \varepsilon_{it} \qquad (2)$$

Such a simple solution allows us to capture the impact of electronic payments on GDP without the need to resort to a dynamic specification. This is because GDP growth in one period is not as strongly related to GDP growth in the previous period as it is the case for log of GDP. In those specifications, only the electronic payments penetration variable is included to assure comparability with the baseline System GMM model. The respective results are provided in Table 1.4.

The Pooled OLS model is included in column 1, the FE and RE models are included in columns 2 and 3, respectively, while the 2SLS model is included in column 4. In this last model, the instruments are analogous as in the case of the 2SLS model included in Table 1.3, but they are differenced. The System GMM model is not calculated for the differenced models – using the system approach (so, including an equation in levels) improves efficiency of estimates.[23] Once again, in all the specifications, the robust standard errors are used. Apparently, in none of the cases, electronic penetration ratio (in first differences) has an impact on GDP growth that is statistically significant

[23] See Roodman (2009), op. cit., for more details.

(under any standard significance levels), yet the coefficient estimate itself is positive and quite similar across specifications. Insignificant results are related to high estimation errors of the parameters. While not always the models in differences provide insignificant results, the differenced data typically have much more noise, making the estimation more challenging. In addition, in the Report we refer to the impact of BLIK payments (use) on the level of economic activity, which naturally requires using an undifferenced model.

**Table 1.4 The results of econometric estimations of models in first differences (explained variable: difference of *log of GDP per capita in PPS)***

| | (1)<br>Differenced OLS model | (2)<br>Differenced FE model | (3)<br>Differenced RE model | (4)<br>Differenced 2SLS model |
|---|---|---|---|---|
| *Δ(electronic payments penetration ratio)$_{it}$* | 0.093 | 0.086 | 0.087 | 0.077 |
| | (0.113) | (0.233) | (0.215) | (0.873) |
| *Δ(government effectiveness)$_{it}$* | 0.013** | 0.005 | 0.006 | 0.003 |
| | (0.031) | (0.243) | (0.130) | (0.645) |
| *Δlog(capital stock)$_{it}$* | 0.800*** | 0.782*** | 0.789*** | 0.783*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| *Δ(output gap)$_{it}$* | 0.011*** | 0.011*** | 0.011*** | 0.011*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| *Intercept* | 0.003** | 0.004 | 0.003 | -0.004 |
| | (0.012) | (0.131) | (0.136) | (0.637) |
| No. of observations | 573 | 573 | 573 | 502 |

Note: p-values in parentheses (* p<0.10, ** p<0.05, *** p<0.01)
Source: EY.

To sum up, the estimation results show that electronic payments have a positive impact on GDP but it is not statistically significant for some sensitivity-check model variations. The estimation results for control variables, not least their statistical significance, confirm the need of their inclusion in our models – both in the undifferenced and differenced specifications. Based on various criteria, a baseline System GMM specification was chosen as a basis to calculate the impact of BLIK payments on economic activity in the Report.

## 2.2 Translating econometric results into the impact on the Polish economy

The key econometric result is the coefficient that describes the impact of the electronic payments penetration ratio on GDP per capita, which has the following interpretation: an increase in the electronic payments penetration ratio by 1pp increases GDP per capita by 0.12%, with all other factors unchanged.

This effect represents the aggregate, multichannel impact of card/electronic payments. Due to the high correlations among popularity of various forms of electronic payments, e-commerce, and related activities, it is difficult to distinguish their individual contributions. Since every econometric analysis based on observational data is subject to uncertainty, especially in terms of causality, these estimates should be interpreted with caution, as indicative of the scale of impact.

Our calculations of the impact of BLIK payments use on the economic activity are done in a number of steps, described below. Some of available data were expressed in EUR, and we converted the final results into PLN using the exchange rate provided by Oxford Economics.

**Step 1. Calculating the impact of the BLIK penetration ratio on GDP levels**

In mathematical terms, the result of econometric modelling is the impact of the electronic payments penetration ratio on log GDP per capita (in Purchasing Power Standards, 2011 prices). This means that the impact in percentage terms does not depend on the current population level or price level. For example, if in a given year GDP per capita in 2011 prices was X% higher due to electronic payments (vs. the counterfactual scenario without such payments), also GDP in current prices at the aggregate level (not divided by the population size) would be X% higher due to electronic payments transactions.

To calculate the contribution of BLIK payments to GDP level, we consider the electronic payments penetration ratio for BLIK payments, which is the value of BLIK payments related to consumption[24] divided by the value of household final consumption. In practice, we calculate the change in BLIK payments penetration ratio (*Δ(BLIK payments penetration ratio)* - "delta") vs. 2024[25]. In particular we analyze a counterfactual scenario in which BLIK payments disappear, leading to a reduction in GDP and economic activity in general. In other words, we calculate a negative delta. By comparing reduced economic activity in the counterfactual scenario with the actual economic activity, we calculate the positive contribution of BLIK payments. Taking into account the approach outlined above and the fact that our explained variable is in the logarithmic form, the resulting % change in GDP is calculated using the following formula:

$$(\%\ \text{change in GDP}) = -\exp(\beta_1 \Delta\ (\text{BLIK payments penetration ratio}))+1 \qquad (3)$$

where $\beta_1$ is the econometric coefficient for the BLIK penetration ratio variable estimated in the baseline econometric model. We apply the resulting % change in GDP to GDP level in 2024 to obtain the contributions of the expansion of BLIK payments in different horizons to the GDP level in 2024 (expressed in 2024 prices).

**Step 2. Translating the changes in GDP into changes in employment**

In order to calculate the impact of BLIK payments development on employment, we use the absolute changes in GDP driven by BLIK payments expansion (as calculated above) and divide them by labour productivity ratios (GDP divided by employment in 2024[26]). It is based on a simplified, yet commonly used assumption in economic modeling that additional GDP translates into employment in proportion to the average number of people required in the economy to generate this level of value added. Next, we divide obtained results by total employment level in 2024 to obtain the impact in relative terms.

**Step 3. Translating the changes in GDP into changes in individual income**

To obtain the impact of BLIK payments expansion on the average individual income, we multiply the percentage contribution of BLIK payments to the GDP in 2024 (as calculated in Step 1) by the average individual income in 2024 (based on data provided by Eurostat and Oxford Economics[27]). By doing so, we assume that the individual income and GDP changes due to BLIK payments were proportionate.

**Step 4. Translating the changes in GDP into changes in tax revenues**

To calculate the effects for tax revenues, we use publicly available data on taxes and social security contributions revenues for the government. The taxation data was sourced from Eurostat. We

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[24] We do not include BLIK ATM cash withdrawals or BLIK P2P transactions, since most of them are not a direct electronic form of consumption spending.

[25] The data were obtained from the client.

[26] Calculations were based on GDP data from the Eurostat and Oxford Economics databases, as we took the 2023 value from Eurostat and adjusted it by the 2024/2023 dynamics from Oxford Economics data due to the lack of GDP data for 2024 in Eurostat. Additionally, employment data was sourced from the Eurostat database.

[27] Due to the lack of data for Poland for the year 2024 in Eurostat database, we calculated missing value based on 2024/2023 dynamics from Oxford Economics data.

calculate the effective tax revenue rates by dividing tax revenues by GDP (due to the lack of data in 2024, we have assumed the same share for them as in 2023). We obtain the impact on tax revenues by multiplying the absolute impact of BLIK payments use on GDP at the national level (as calculated above) by the effective tax revenues rate.

To sum up, effects on GDP were translated into effects for employment, individual income and tax revenues using the average ratios between GDP and these variables in the analyzed country. In such approach, the shares of the estimated effects in totals for the whole economy (estimated GDP effect/total GDP, estimated employment effect/total employment, estimated tax revenues effect/total tax revenues) are the same.

# 3. The creation of electronic payments driven by BLIK

In this section we outline the methodology used to estimate the value of electronic payments in Poland attributed to BLIK. We start by employing counterfactual analysis based on the Synthetic Control method, and we support our findings with robustness checks conducted after the estimation process. Next, we incorporate additional adjustments to account for Poland-specific factors. Finally, we present the impact of BLIK on cashless payments.

## 3.1 Counterfactual analysis

In 2023, the value of consumption-related BLIK payments reached PLN 145bn, representing 7.4% of household consumption expenditure in Poland. However, this figure cannot be considered the total value of newly created electronic payments, as some transactions may have occurred in a cashless form regardless of BLIK's existence, potentially shifting from competitors. On the other hand, BLIK may have contributed to the creation of new payments by attracting new users to e-payments or by encouraging existing users to utilize cashless transactions more frequently and in varied contexts.

Our objective is to estimate the net effect of BLIK, i.e. the additional electronic payments generated in Poland as a result of its existence. This can be achieved through counterfactual analysis, which involves comparing the actual state of electronic payments in Poland with an alternative scenario in which BLIK was never established. We use Synthetic Control method to estimate the alternative path of electronic payments. This approach involves creating a synthetic control unit that closely resembles Poland in the pre-treated period (before BLIK's establishment in 2015) by using a weighted average of all other unaffected countries.

We use the setting proposed by Abadie (2021)[28] to apply synthetic control method to our dataset. We consider *J+1* units where the first unit *j=1* is the treated unit. The remaining *J* units comprise the donor pool, that is, the set of potential controls, out of which a linear combination is chosen to best replicate the treated unit. We define $Y_{1t}^{1}$ as the actual value of electronic payments (so called potential response under the intervention) and $Y_{1t}^{N}$ as the value of electronic payments that would have occurred had BLIK not been established (potential response without intervention). The effect of the treatment for the affected unit in period $t$ becomes

$$\tau_{1t} = Y_{1t}^{1} - Y_{1t}^{N}$$

A synthetic control is defined as a weighted average of the units in the donor pool. Given a set of weights, W, the synthetic control estimators are

$$\hat{Y}_{1t}^{N} = \sum_{j=2}^{J+1} w_j Y_{jt}$$

and

$$\hat{\tau}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j Y_{jt}$$

Additionally, each weight is non-negative ($w_j \geq 0$) and they sum to one ($\sum_{j=2}^{J+1} w_j = 1$) to avoid extrapolation. The weight matrix, $W^* = \left(w_2^*, \dots, w_{J+1}^*\right)'$ is chosen to minimize

$$\|X_1 - X_0 W\| = \left(\sum_{h=1}^{k} v_h \left(X_{h1} - w_2 X_{h2} \dots - w_{J+1} X_{hJ+1}\right)^2\right)^{1/2}$$

[28] Abadie, A. (2021). Using Synthetic Controls: Feasibility, Data Requirements, and Methodological Aspects. *Journal of Economic Literature*, *59*(2), 391–425. https://doi.org/10.1257/jel.20191450

where $X_1$ is a $(k \times 1)$ vector of pre-intervention characteristics and outcomes of the exposed unit and $X_0$ is a $(k \times J)$ matrix that contains the same variables for the unaffected units. A $(k \times k)$ vector $V = (v_1, \dots, v_k)$ reflects relative importance of the synthetic control reproducing the values of each of the $k$ predictors for the treated unit, $X_{11}, \dots, X_{k1}$. The optimal choice of $V$ is such that the synthetic control $W(V)$ minimizes the mean squared prediction error (MSPE) of this synthetic control with respect to $Y_{1t}^N$

$$\sum_{t \in T_0} \left(Y_{1t} - w_2(V)Y_{2t} - \dots - w_{J+1}(V)Y_{J+1t}\right)^2$$

for some set $T_0 \subseteq 1,2, \dots, T_0$ of pre-intervention periods.

We build a dataset covering the period from 2000 to 2023, consisting of European countries. The donor pool is further limited to countries where a mobile payments system similar to BLIK is either unavailable or has marginal usage[29]. Additionally, we exclude outliers, resulting in a final pool of 16 countries. In our model, the potential response is defined as the value of electronic payments relative to household final consumption expenditure. Given data availability, we proxy this by using the value of card payments in each country, sourced from the European Central Bank for EU countries and from local central banks for the remaining states. For Poland, we additionally include BLIK transactions conducted at POS and online. The set of predictors in our model includes socio-economic variables related to the size and structure of the economy, payment infrastructure, digital society, demographics, and the quality of public institutions, comprising over 20 variables primarily sourced from the World Bank and the International Monetary Fund. To fill the gaps in the dataset, we also conducted data imputations. To identify the best model, we have tested over 1000 specifications. Based on the fit measure, root mean squared prediction error (RMSPE), the V matrix, and economic reasoning, our final model includes the following predictors: GDP per capita (PPP), Financial Development Index[30], percentage of the population using the internet, percentage of the population enrolled in tertiary education, and the index of rule of law (see Table 3.1 for average values of predictors for Poland and its synthetic version). Ultimately, the synthetic Poland is constructed from five countries: Hungary (38.8% weight), Latvia (35.9%), Bulgaria (12.4%), Albania (7.1%), and Greece (5.8%), as detailed in Table 3.2.

**Table 3.1 Electronic payments predictor means before BLIK establishment**

| | Poland | Synthetic Poland |
|---|---|---|
| GDP per capita (PPP, thousand international dollars) | 24.409 | 24.404 |
| Financial Development Index | 0.404 | 0.366 |
| Internet access (% of population) | 43.724 | 43.724 |
| Tertiary Education (% of population) | 66.559 | 61.547 |
| Rule of Law Index | 0.625 | 0.625 |

Source: EY.

**Table 3.2 Country weights in the synthetic Poland**

| Country | Weight | Country | Weight |
|---|---|---|---|
| Albania | 0.071 | Hungary | 0.388 |
| Bulgaria | 0.124 | Italy | 0 |
| Bosnia and Herzegovina | 0 | Luxembourg | 0 |

[29] Marginal usage related to payments for goods and services. In this analysis we do not consider P2P transactions or ATM withdrawals.

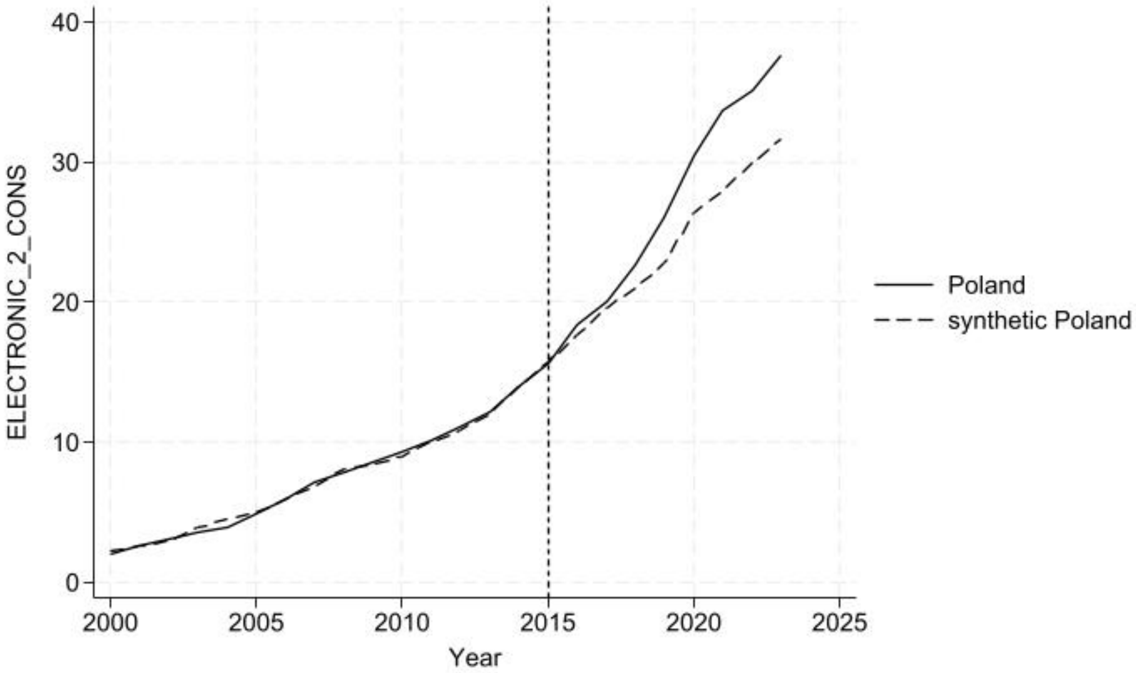
[30] Financial Development Index is a ranking of countries in the areas of depth, access, and efficiency of financial institutions and markets produced by the IMF. It includes data on the size of financial assets in the country (e.g. bank credit to private sector, stock market capitalization), financial infrastructure (number of bank branches and ATMs) as well as efficiency measures (banking sector net interest margin, stock market turnover ratio).

| | | | |
|---|---|---|---|
| Cyprus | 0 | Latvia | 0.359 |
| Czechia | 0 | Malta | 0 |
| Estonia | 0 | Romania | 0 |
| Greece | 0.058 | Slovakia | 0 |
| Croatia | 0 | Slovenia | 0 |

Source: EY.

Chart 3.1 demonstrates a strong alignment between Poland and synthetic Poland prior to 2015, followed by a noticeable divergence thereafter. The gap between the lines represents our initial estimate of the BLIK's impact on electronic payments in Poland. In the early years, the effect is minimal, however, as BLIK continues to expand, its influence also increases and becomes statistically significant. In 2023 the effect reaches 6%.

**Chart 3.1 Electronic payments in Poland and synthetic Poland**




Note: The vertical axis shows the value of electronic payments relative to household final consumption expenditure, in percentage.
Source: EY.

We also conduct a series of robustness tests, including the removal of countries that contribute to the construction of synthetic Poland and checking alternative years of intervention. While the results do exhibit some variation, they remain generally stable, consistently indicating a positive effect in the most recent years. The findings are more sensitive to the exclusion of countries with significant weights, such as Hungary and Latvia, but are largely unaffected when smaller contributors are excluded. Additionally, altering the date of intervention, whether by backdating or moving it forward, does not significantly impact the results.

## 3.2 Adjustment for other factors affecting electronic payments

Our initial results capture all the differences between Poland and the countries in the donor pool related to cashless payments. However, these differences should not be solely attributed to BLIK, as other factors could also contribute to the landscape and ignoring them would result in an overestimation of BLIK's impact. Notably, we have identified that during the analyzed period, electronic payments in Poland were also influenced by the Cashless Poland Program (CPP), which has been improving cashless payment infrastructure by offering merchants affordable POS terminals.

We obtain the impact of Cashless Poland Program on electronic payments in 3 steps:

**Step 1. Estimation of additional POS terminals available thanks to CPP**

In the first step, we divide the time series into two periods:
1. the period before the Cashless Poland Program was launched (from 2004Q1 to 2017Q4) and
2. the period during which the Cashless Poland Program has been active (from 2018Q1 to 2023Q4)

Next, we estimate an econometric model on the basis of period 1 data only, that aims to forecast value of the POS terminals number if there were no Cashless Poland Program. We use the ARIMAX(p, d, q) class model that can be written as:

$$y_t = a_0 + a_1\, y_{t-1} + \ \dots + a_p\, y_{t-p} + \epsilon_t + b_1\, \epsilon_{t-1} \ + \cdots + b_q\, \epsilon_{t-q} \ + cx_t$$

Where $y_t$ is our analyzed variable (number of POS terminals) and the $\epsilon_t$ is the residual from the period $t$ (i.e. the difference between the actual value of $y_t$ and the forecasted by the model value of $y$ in the period $t$). Such model contains three major components:
- The autoregressive component (AR), where the $p$ denotes the number of included AR lags
- The moving average component (MA), where the $q$ denotes the number of included MA lags
- The component containing additional explanatory variables ($x_t$)

The d-parameter in the ARIMA framework informs on the transformations of the $y\_t$:

$$\Delta^d y_t = \Delta^{d-1} y_t - \Delta^{d-1} y_{t-1}$$

Where d=0 means that we are using levels (no changes to $y_t$), $d = 1$ denotes first differences ($\Delta y_t = y_t \ - y_{t-1}$) and so on.

In our approach, we use $p = 2$, $d = 1$ and $q = 0$ parameters. As the supplementary control variables we use unemployment rate, GDP per capita and share of the population using internet (at least once in the last 3 months)[31].

Finally, the difference between the actual and forecast number of POS terminals is the number of additional POS terminals that would not be installed if were not for the Program. We estimate it to stand at around 375 thousand new devices in 2023.

**Step 2. Estimation of the impact of increase in the number of POS terminals on the value of electronic payments**

Using data for 42 countries covering the period from 2001 to 2021 and sourced from European Central Bank, Eurostat and World Bank, we estimate the impact of the number of POS terminals per capita on cashless payments relative to household final consumption expenditure. The model results are:

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[31] Our goal was to take into account major factors that affect the development of the card payments acceptance network that include: economic development and rising income (GDP per capita), business cycle factors (unemployment) and general digitalisation of the economy (measured by the share of the population regularly using the internet). We have tested several variables, and the model based on selected variables provided the best fit to the data.

*TRANSACTION_CONS = 621.4863 * TERMINALS_PER_CAPITA - 9.25904 * TERMINALS_PER_CAPITA x GDP_PER_CAPITA + 4.553237 * CARDS_ACTIVE_PER_CAPITA + 0.3758576 * GDP_PER_CAPITA + 1.057639 * GOV_EFFECTIVENESS + 1.158728 * URBAN_POPULATION*

Taking the coefficient for the number of POS terminals and its interaction with GDP, the effective coefficient of *TERMINALS_PER_CAPITA* in 2023 is equal to *621.486 - 9.259*38.012=269.535*.

**Step 3. Translating step 1 and 2 into CPP's effect on electronic payments**

Finally, we take the estimated number of POS terminals attributed to the Cashless Poland Program in 2023, divide it by the total population and multiply by the coefficient from step 2. The result of these calculations is 2.7% of household final consumption, which we interpret as the additional electronic payments generated by the CPP in 2023.

To obtain the net effect of BLIK, we subtract the CPP's effect from the initial estimates presented in the section 3.1. Thus, our estimate of BLIK's impact on electronic payments creation in Poland is equal to 6%-2.7%=3.3% of household final consumption expenditure.

# 4. The effects of e-commerce on the economy and the role of BLIK

In this section, we outline the methodology used to estimate the impact of BLIK on the economy through its role in enhancing the significance of the e-commerce sector. The first part details our approach to estimating the cost reductions in the retail sector facilitated by BLIK. Subsequently, we describe the structure of the EY-Upgrade General Equilibrium Model, which was employed to assess the broader economic impact.

## 4.1 Cost structure in e-commerce vs. traditional retail

The foundation for calculating cost changes in the retail sector (presented in Section 4.3 of the Report) is based on the cost structure derived from the AMADEUS dataset, as presented in the study "Cost behavior in e–commerce firms"[32]. By summing all the cost categories, we obtain an estimate of the average cost levels for online and traditional retailers. Our comparison indicates that the cost for e-commerce firms is, on average, 11.7% lower than that of traditional retailers.

To refine this estimate, we account for the difference in the average firm size between the two types of retailers. Based on AMADEUS revenue data, we observe that e-commerce firms are, on average, approximately 6% larger in terms of revenue. Adjusting our initial estimate accordingly, we obtain a revised difference in the average cost of revenue generation of 17.1%. In our analysis, we interpret this difference as the result of productivity gains driven by the transition to a more cost-efficient business model. The introduction of operational cost reductions into the model is implemented through an appropriate adjustment of retail sector productivity. Below, we present the productivity adjustment framework in the CGE model.

The productivity of sector A is inversely proportional to unit costs C:

$$A = \frac{1}{C}$$

Based on the above calculations, we can determine the new cost level of the sector as:

$$C' = C * (1 - 17.1\%)$$

The corresponding productivity level can be expressed as:

$$A' = \frac{1}{C'} = \frac{1}{C*(1-17.1\%)}$$

The productivity increase corresponding to this cost reduction is:

$$\Delta A = \left(\frac{A'}{A} - 1\right) * 100\% = \left(\frac{\frac{1}{C*(1-17.1\%)}}{\frac{1}{C}} - 1\right) * 100\% \approx 20.5\%$$

With the estimated cost difference, we proceed to quantify the contribution of BLIK to this process. We scale the calculated cost reduction using the following information:

- The share of e-commerce in total retail sales, which, according to data from Statistics Poland (GUS), stands at 8.9%.

[32] Argilés–Bosch, J. M., Garcia–Blandón, J., & Ravenda, D. (2022). Cost Behavior in E–commerce Firms. Electronic Commerce Research, 23(4), 2101–2134. https://doi.org/10.1007/s10660-021-09528-2

- The share of transactions conducted via BLIK within the Polish e-commerce market, estimated at approximately 50% (see Figure 11 in the Report).

Based on these figures, we estimate that BLIK contributes to approximately 4.5% of the cost reduction described above. Consequently, we estimate that BLIK may have reduced operational costs in the Polish retail sector by approximately 0.74%.

## 4.2 EY-UPGRADE model

**General overview of the model**[33]

Computable general equilibrium (CGE) models are a quantitative representation of the economy as a system of interconnected markets (e.g. commodity, labour, capital) where agents, including households, investors, firms and the government, interact with each other in accordance with the principles of optimal economic behaviour. To facilitate such representation, CGE models encompass two types of relationships:

1. **Behavioural relationships**: these describe agents' optimal choices given a number of constraints (e.g. income) and relevant decision variables (e.g. prices). Examples include firms' choices of primary factors (e.g. capital, labour, land) in production, households' and the government's decisions on purchases of goods and services or firms' choice on whether to purchase domestic or foreign production inputs.

2. **Accounting relationships**: equations depicting the circular flow of income in the economy. These show how value added generated by firms and the tax revenue collected by the government constitute the national income, which is distributed across households (for consumption and savings purposes) and the government, and then spent on domestic and foreign goods and services produced by firms. Part of this revenue received by firms is then devoted to the purchases of production inputs from other firms (intermediate consumption) and the rest constitutes the value added, which contributes to national income, thus completing the circular flow.

Since agents rely on relative prices and available income in their decision-making process, quantities such as household demand, government spending, employment, capital use in production etc. are usually determined by the model (i.e. are endogenous). By default, prices of commodities and production factors (e.g. wages, rents) are also computed by the model (endogenous) and adjust to ensure that supply is equal to demand in each market.

Certain variables, however, such as tax rates and production technology, which also affect prices and agents' economic decisions, are determined outside the model (i.e. set by the model user) and may be subject to shocks introduced as part of a policy experiment (e.g. a tax change or a productivity improvement). Moreover, in some applications, variables that are by default treated as endogenous (e.g. wages) can be set as exogenous in order to allow other variables (e.g. labour supply) to vary.

An important characteristic of the CGE model is that prices and quantities sold in one market affect other markets. This occurs because agents' choose among alternatives that originate from different sectors, e.g. consumers deciding on whether to buy a car or go on holiday, or firms choosing to employ labour vs. capital. This directly implies that a policy change (e.g. a tax rate increase) introduced in a given market will affect the rest of the economy as well. Accounting for individual markets and their combined aggregate outcome is an attractive feature of the CGE model, as it allows us to understand the economic impact of a policy change on different levels of aggregation,

[33] Corong, E. L., Hertel, T. W., McDougall, R., Tsigas, M. E., & van der Mensbrugghe, D. (2017). The Standard GTAP Model, Version 7. Journal of Global Economic Analysis, 2(1), 1-119. https://jgea.org/ojs/index.php/jgea/article/view/47

that is, to analyse effects on sectoral output and prices, as well as conventional macroeconomic variables such as real GDP, consumer price index, trade flows, aggregate employment etc.

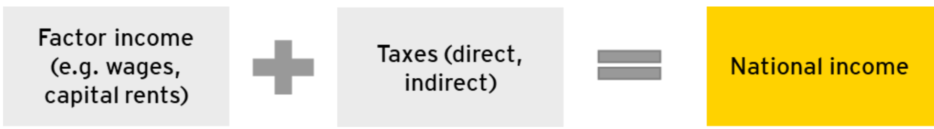
**Structure of the GTAP model**

1. **Final demand: step 1 – allocation of national income**

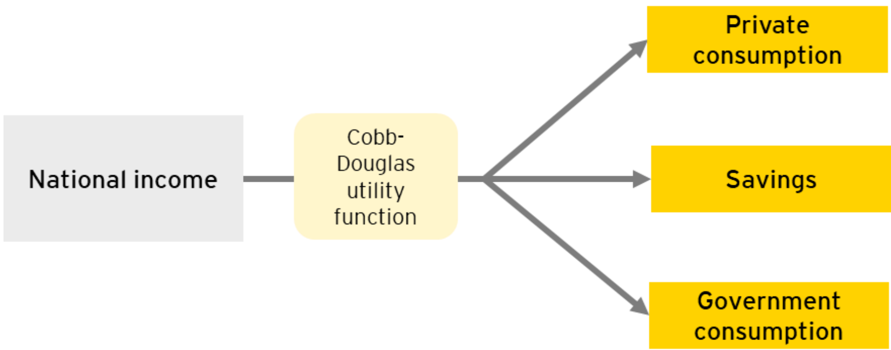
National income, which consists of factor income (i.e. income generated through factors of production) and the aggregate tax revenue, is allocated across private consumption, savings government consumption to maximise national utility represented by a Cobb-Douglas utility function. Importantly, private consumption in the GTAP model often involves necessity goods (e.g. food), which are income-inelastic at high levels of national income.[34] This implies that a large national income shock in developed countries will result in national income allocation towards savings (and indirectly, investment) rather than consumption.

Chart 4.1 Composition of national income and its allocation across economic agents

Aggregate income




Aggregate spending




Source: EY, based on GTAP model specification.

2. **Final demand: step 2 – agents' spending on goods and services**

Private households and the government maximise their utility by purchasing commodities subject to incomes allocated in Step 1 and taking into account the relative prices of different products. Commodities purchased by private households and the government are a mix of domestic and imported varieties – more details on how the domestic vs. imported quantities are determined in the GTAP model is provided in the import demand modelling details below.

Country savings are aggregated with other countries' savings in a so-called „global bank". Depending on the closure selected by the modeller, the savings are then allocated across different

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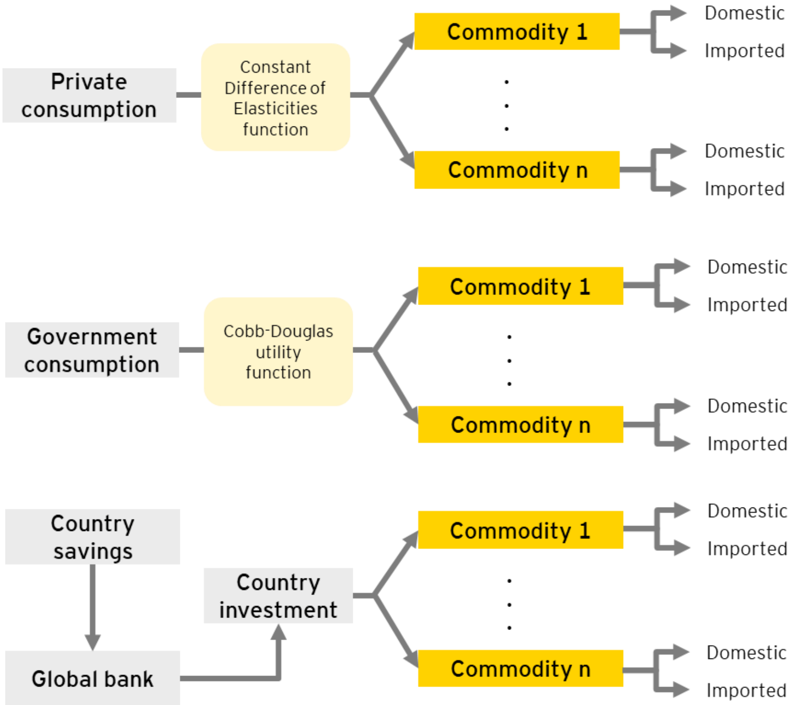
[34] In more technical terms, private households' preferences are non-homothetic. They are represented by a constant difference of elasticities (CDE) function.

countries.[35] This means that a given country receives a share of global savings, which is used to fund investment spending on domestic and imported goods and services.

Chart 4.2 Allocation of private household consumption, government spending and savings/investment on various goods and services




Source: EY, based on GTAP model specification.

### 3. Import demand

In the GTAP framework, import demand is modelled as a two-stage process described in the diagram below. Importantly, the GTAP model assumes that in general, imported and domestic varieties of the same commodity are different products, and thus, imperfect substitutes in consumption or production uses. This assumption is expressed in the values of Armington elasticities, which express agents' preferences over domestic vs. imported commodities.[36]

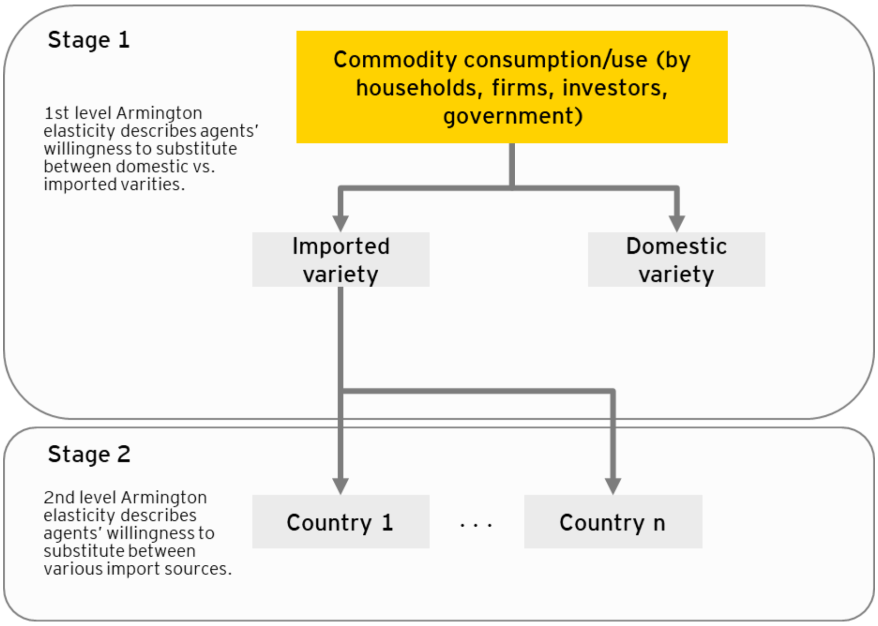
Given that agents have decided how much of a given commodity they wish to consume/use (as described in point 2 above), the next step involves a decision between imported vs. domestic varieties of the commodity in question. This choice is made based on the relative prices of (aggregate) imported vs. domestic varieties and the agents aim to choose imported vs. domestic quantities to minimise expenditure on the commodity.

[35] Savings can be allocated across countries in order to equalise rates of return on capital across the world (closure 1) or based on the assumptions that all countries have fixed shares in global net investment (closure 2). (Note: net investment = gross investment less of depreciation).

[36] For both stage 1 and 2 Armington elasticities, a high value implies that consumers are willing to substitute towards a relatively cheaper commodity as its price falls. Imperfect substitution is associated with low elasticities.

Once the agents have decided on the amount of imported variety, their next step is a choice between various import sources. This decision relies on the relative prices of products imported from various countries.[37]

Chart 4.3 Import demand in the GTAP model




Source: EY, based on GTAP model specification.

### 4. Production

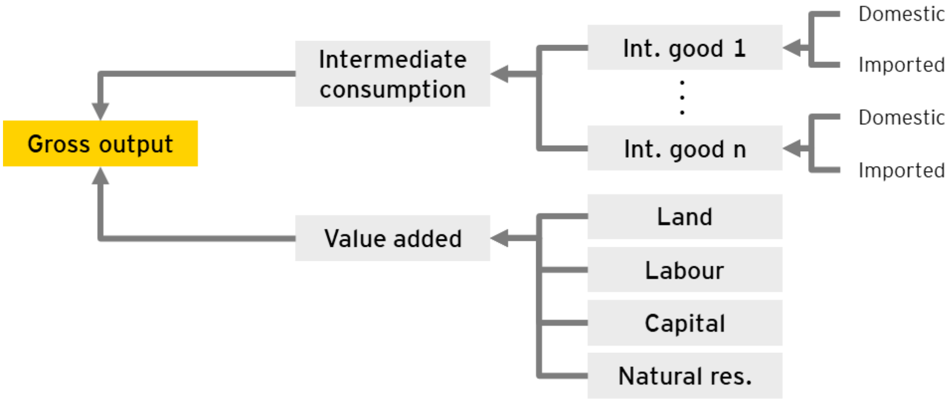
Firms' production behaviour in the GTAP model is based on the following assumptions:

a) Perfect competition: assumes a market where buyers and sellers are so numerous and well informed and have no control on setting of prices (i.e. the model does not take into account the existence of monopolies). Moreover, each market involves a very large number of small identical firms that make zero economic profits.
b) Constant returns to scale: assumes that an increase in inputs (e.g. capital and labour) causes the same proportional increase in output.
c) Producer optimisation: assumes that producer behaviour is governed my selecting inputs that minimize the cost of production, given the shape of the production function, the output quantity and input prices.

Gross output is produced using intermediate goods and primary factors of production (value added). Substitution is not allowed between different intermediate goods (i.e. a Leontief perfect complements structure is assumed), however, firms can decide on whether the intermediate goods are of domestic or imported origin. In most settings, firms can substitute between different primary factors used in production (e.g. capital and labour), according to a specified elasticity of substitution. Some primary factors, however, can be sector-specific (e.g. land can only be used for agricultural purposes), which rules out one sector's ability to attract them from another sector, which limits the substitution possibilities.

[37] In the standard GTAP model, the geographical import mix is the same for all agents. Thus, the decision on import sources is made on the economy-wide level and all agents' behaviour complies with this decision.

Chart 4.4 Production in the GTAP model




Source: EY, based on GTAP model specification.

**CGE model database**

Our CGE model is based on the latest version of the GTAP database (v10), with 2014 as the base year. It should be noted that the mismatch between the current period and the latest available year in the GTAP database is largely driven by the fact that country input-output tables are published with a few years delay. Nevertheless, this is not an important limitation of this approach, as the CGE model primarily relies on the shares (e.g. sector share in total value added), rather than nominal values of economic indicators, where the share are known to evolve more slowly throughout years compared to nominal variables.

The CGE model database consists of a social accounting matrix (SAM) and a parameters file. The SAM specifies the values of transactions occurring between different agents in the economy, such as sectors, households, investors, the government, as well as exporters and importers located in various countries. It is constructed by GTAP (and updated once every few years) based on input-output tables collected from various countries across the world. The parameters file includes different behavioural parameters, such as elasticities of substitution or transformation, which originate from past econometric studies.

**Model calibration**

Model calibration refers to the process in which we adjust the model parameters such that the CGE model represents the economy of our study. This process takes place after the database aggregation has been chosen and involves the following aspects:

1. Calibration of ratio parameters: some parameters in the GTAP model involve shares of one variable in another (usually an aggregate), e.g. the share of food in household consumption. These parameters are calculated automatically from the dataset that feeds the CGE model.

2. Calibration of behavioural parameters: behavioural parameters refer to those that guide agents' economic behaviour, e.g. households' willingness to substitute among different goods in consumption or firms' decisions to purchase domestic or imported production inputs. These parameters are separate from the social accounting matrix and have been estimated by the GTAP model developers and other researchers in a series of econometric studies. In some cases, however, such parameters could be subject to manual changes where appropriate, as well as robustness analyses, i.e. investigating whether model results are sensitive to changes in such parameters.

3. Closure adjustment: in CGE modelling, closure refers to the modeler's decision on which variables are exogenous (see above for a discussion of exogenous vs. endogenous variables). For example, one can either the labour supply or the wage rate as give (exogenous) to solve the model for the other variable. Analogous closure decisions are taken with respect to the global savings and capital market.

**Assumptions and limitations of the GTAP model**

Although the GTAP model is grounded in economic theory and provides economically coherent results, it nevertheless relies upon a number of assumptions that might not be fully satisfied in real-world settings. Key assumptions for our modelling exercise include:

1. Perfect competition: the GTAP model assumes that all markets are perfectly competitive, that is, they consist of a very large number of small identical firms that make zero profits and are price-takers rather than price-setters.

2. Restrictions on external accounts: foreign exchange of an economy covers only the trade in commodities and net inflow of savings. This means that there is no foreign direct investment, international aid flows or remittances.

3. Sourcing of imports at the border: all agents in the economy, that is, firms, households, investors and the government have the same geographical mix of imports. Therefore, the imposition of an import tariff on households will affect their substitution towards domestic goods, but it will not cause their import mix to differ from other agents in the economy.

4. Restrictions on international labour flows: in the GTAP model, workers are not allowed to relocate to other countries as a response to economic shocks. For instance, if a shock causes a reduction in employment in a given country, the employees who lost their jobs would not be able to find employment opportunities in other countries. Therefore, the GTAP model is not able to account for any changes in migration following a policy change.

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