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Abstract

The liberalization of capital flows is generally associated with prospects of higher growth. However, in developing countries, opening the capital account may also facilitate the flow of capital out of the country through illicit financial flows (IFFs). Given that IFFs drain the scarce public resources available to finance the provision of public goods and services, the extent of illicit capital flows from developing countries is serious cause for concern. In this context, as a first step in analysing the social costs of IFFs in developing countries, this article studied the relationship between IFFs and infant immunisation coverage rates. Data for 56 low- and middle-income countries for the period 2002-2013 were used in the empirical analysis. The main result was that the relative level of IFFs to total trade negatively impacted vaccination coverage but only in the case of countries with very high levels of perceived corruption. In this case, the total effect of an annual 1 p.p. increase in the ratio of IFFs to total trade was to reduce the level of vaccination coverage rates over the coming years by 0.19 p.p. Given that there was an annual average of 18 million infants in this cluster of 25 countries, this result suggests that at least 34,000 children may not receive this basic health care intervention in the future as a consequence of this increase in IFFs in any particular year.

Introduction

In September 2015, the United Nations (UN) General Assembly established Sustainable Development Goals (SDGs) to guide global development efforts leading up to 2030. The year 2016 marked the beginning of the implementation of the new post-2015 development agenda, which replaced the Millennium Development Goals (MDGs) set out in the Millennium Declaration in 2000. During the period 2000-2015, the world has seen substantial progress in key non-income dimensions of welfare. Moreover, the UN has called the MDGs 'the most successful anti-poverty movement in history'. Alongside the progress made against absolute poverty globally, achievements in empowering women and girls and improvements in health and well-being have had a considerable impact on raising the quality of life (Ravallion 2016). However, the Global Sustainable Development agenda will require the massive mobilization of new investment resources for developing countries. According to estimates made by the UN Conference on Trade and Development (UNCTAD 2014), developing countries are facing a "daunting task" in their attempts to achieve relevant goals in SDG-related sectors. In terms of investment requirements, Greenhill and Ali (2013) estimated that US$ 50.2 billion would be needed annually to eliminate hunger by 2025, US$ 37 billion to achieve universal health care, and US$ 42 billion to implement universal primary and secondary education in developing countries. Given the realities of official development assistance (ODA) (e.g., many of the donor commitments have not been met, including the 0.7% target (Both 2015)), developing countries will need to mainly rely on domestic resource mobilization to finance this challenge.

In this context, national and international policy debates have tended to focus on the crucial issue of how to reduce resource leakages in order to accelerate progress in SDGs.

Since 1980, developing countries have lost US$16.3 trillion dollars through broad leakages in the balance of payments, trade misinvoicing, and unrecorded financial transfers (Centre for Applied Research *et al.* 2015). According to Global Financial Integrity (GFI) (Kar and Spanjers 2015), illicit flows from the developing world steadily increased to reach US$1.1 trillion in 2013 (the last year for which data are available). These illicit financial flows (IFFs) include kickbacks being transferred offshore by corrupt public officials, tax evasion by commercial entities, and the laundering of proceeds of transnational crime. However, although IFFs and corruption have a reciprocal causal relationship (Reed and Fontana 2011), differences in the relative size of these flows between countries are not directly linked to differences in the levels of perceived corruption as measured by aggregate indicators, such as the Corruption Perception Index[1] (CPI) provided by Transparency International. Thus, although it is widely accepted that corruption is a cross-cutting driver of such flows and undermines any efforts to curb them (OECD, 2014), the empirical analysis of the specific socio-economic effects of IFFs is justified on the grounds that indicators of perceived corruption (e.g., the CPI) and the IFFs estimates provided by GFI measure different facets of corruption and governance weaknesses. For this reason, and as an addition to the literature on the effects of corruption on health outputs and outcomes (Lio and Lee 2016; Li *et al.* 2017), it is relevant to study the specific effect of IFFs on the provision of basic health outputs such as immunisation programmes.

In recent years, IFFs have generated increased international attention from policy communities, including the OECD, G20, and the UN systems. The need to reduce IFFs is a key aspect of development policy. Efforts made by the international community to curb IFFs have strong links to the post-2015 agenda. In July 2015, the UN held the Third International Conference on Financing for Development in Ethiopia (Addis Ababa Action

Agenda). In this forum, international and non-governmental organizations negotiated the modalities for financing the Sustainable Development Goals (SDGs) and called upon the IMF, World Bank, and the UN to assist both source and destination countries to combat illicit flows and to publish estimates of their volume and composition. As a result, the aim of combatting IFFs has been incorporated into the SDGs of the UN in Target 16.4: "By 2030, significantly reduce illicit financial and arms flows, strengthen the recovery and return of stolen assets, and combat all forms of organized crime". Thus, SDGs and IFFs are inextricably linked: we cannot hope to achieve the former without addressing the latter (Cardamone 2016).

Meanwhile, immunisation is at the top of the list of basic health care interventions of proven effectiveness in improving health status (McGuire 2006). Coverage of interventions, such as vaccinations for measles, polio, and diphtheria, pertussis, and tetanus (DPT), are widely accepted indicators of progress toward improving health systems in developing countries and achieving SDGs (Corsi and Subramanian 2014). However, despite immense progress during the 1980s, an estimated 19.4 million infants worldwide are still not reached by routine immunization services. Close to 60% of these children live in 10 countries: Angola, the Democratic Republic of the Congo, Ethiopia, India, Indonesia, Iraq, Nigeria, Pakistan, the Philippines, and the Ukraine (Global Health Observatory WHO)[2]. Also, regarding the provision of basic vaccines for childhood diseases, every society recognises that immunisation is a government task: the demands of interest groups and households are not the most important determinants of infant vaccination programs (Gauri and Khaleghian 2002).

Given that IFFs drain the scarce public resources available to finance the provision of basic health interventions (e.g., immunisation programs) in the poorest countries, this article analysed the relationship between IFFs and the infant immunisation coverage rate as a first step in analysing the social costs of IFFs in developing countries. To the best of our knowledge, this article represents a novel contribution to the study of the global effects of IFFs on living conditions. A database was constructed that used data for 56 low- and middle-income countries for the period 2002-2013. The empirical analysis showed that, in the cluster of the most corrupt countries, the relative level of IFFs negatively impacted infant vaccination coverage rates.

The rest of the article is organised as follows. The 'Methods' section presents the background and the conceptual framework used to explain how IFFs may have an impact on immunisation coverage rates. This section also describes the data and explains the method used in the empirical analysis. The 'Results and Discussion' section reports and discusses the estimated results. The 'Conclusion' section offers conclusions and the implications of the research findings.

Methods

Background and conceptual framework

Illicit financial flows are cross-border transfers of funds that are illegally earned, transferred, or utilized. However, given its often furtive nature (cross-border capital flows are unrecorded hidden financial flows), the concept of IFFs is characterized by a lack of clear terminology. As noted by Murinde *et al.* (2015), differences in the definition of capital flight, estimation methods, and data availability would lead to differences in the estimates of the magnitude of capital flight (Hermes *et al.* 2003; Harrigan *et al.* 2007). These flows relate to a range of social, political and economic phenomena. They are often a symptom of deeper structural and governance problems and, as such, can arise from a wide range of activities. Such outflows are also driven by high levels of corruption in combination with weak institutions and sometimes illegitimate regimes (OECD 2013; Ritter 2015). However, IFFs are linked with a particular range of social, political, and economic phenomena, which are not fully reflected in the available national indicators used to measure what is considered to be corruption.

The conventional approach to breaking IFFs into the three main components of commercial activities, criminal activities, and corruption is widely accepted. According to Reuter (2017), the commercial sources of IFFs are larger than the non-commercial corrupt and criminal sources of these flows. In this regard, current estimates suggest that commercial activities account for 65 per cent of IFFs, criminal activities for 30 per cent, and corruption for around 5 per cent (IAEG-SDGs 2016; UN.ECA 2015). As shown in Figure 1, the commercial component is very often transmitted through the over-invoicing of imports and under-invoicing of exports. In this sense, Global Financial Integrity noted that, of the total estimated annual outflows, close to 80% of the funds are moved offshore using trade misinvoicing (i.e. invoice fraud) (Cardamone 2015).

Insert Figure 1

Nowadays, the "new significance" of IFFs is related to the publication of assessments of the size and severity of this problem, which is in excess of $1 trillion per year. This figure dwarfs the inflow of Official Development Assistance (ODA) (circa $100 billion per year).

Clearly, these figures have helped galvanize attention on illicit flows and ways to deal with them. In addition, the international movement of money illegally or illicitly generated in developing countries has become a major issue in the development agenda.

There is a broad consensus among researchers on the corrosive effects of IFFs on developing countries that are still struggling to meet their economic and social development needs. The last Human Development Report (UNDP, 2016, p. 141), warns of the immense challenge of IFFs for the developing world, pointing out that: "these flows weaken governance and reduce consumption, investment and social spending, hurting the long term construction of collective capabilities and the expansion of human development". Epstein (2005) also noted that capital flight can have significant social costs, which disproportionately affect the poorest countries and low-income, vulnerable, and marginalised populations within countries.

As shown in Figure 1, the immediate impact of IFFs is to reduce public and private domestic expenditure and investment (Dickinson 2014). Investments are vital for development but their benefits may remain insignificant if the profits they generate are transferred abroad. In addition, there is also a great need for public services and public investment in developing countries due to the pressures of poverty, disease, and low educational levels. IFFs contribute to reducing public activity in the countries where it is most needed. Although infrastructure shortages also create a demand for public investment, IFFs increase risk and uncertainty in the domestic economy, resulting in a movement of scarce resources away from domestic investment and productive activities (Lessard and Williamson 1987; Epstein 2005; Ndikumana and Boyce 2011; Nkurunziza 2012; Ajayi 2015). Thus, in general, the impact of IFFs are observed via direct channels, such as foregone investment in some crucial areas of the economy (e.g., programs to reduce poverty and improve health and education), or via indirect channels, such as low investment and its resulting effects on income (Ajayi 2015; Nkurunziza 2012). Moreover, Ajayi (2015) summarized the negative consequences of capital flight on developing countries into three critical issues: reduction of growth potential, erosion of the tax base, and adverse redistribution effects. In addition to this, in many developing countries, IFFs are accompanied by increased foreign borrowing. Sub-Saharan Africa (SSA) and Latin America are cases in point. As Rodriguez (1987) noted, the relationship between debt and illicit flows is a vicious cycle; as countries borrow more, capital flight accelerates as corrupt politicians and officials divert loans offshore. In this sense, capital flight has worsened the debt crises in many developing countries (Naylor 1987).

However, there is little research on the specific social costs of IFFs because it is as difficult to gauge the specific impact of illicit outflows that damage living standards of millions of people as it is to estimate their size. O'Hare *et al.* (2014) found that IFFs had a significant impact on achieving the fourth MDG target in sub-Saharan Africa countries (SSA). Similarly, O'Hare and Curtis (2014) studied the gaps in health care financing in Malawi and showed how foregone taxes could fill these gaps. Also, according to Cobham (2008), the application of the estimates to the period 2000-2007 shows that the revenues lost to transfer mispricing and false invoicing could have prevented an estimated 350,000 children under 5 years from dying each year, including up to 250,000 infants.

The UNODC/World Bank (2007) estimated the "collateral damage" of outflows produced by embezzlement, the diversion of public property, and the plundering of the public treasury, and pointed out that "every $100 million recovered could fund full immunizations for 4 million children or provide water connections for some 250,000 households… The total benefit would far exceed that associated with the asset restitution itself, assuming that the released funds are well spent". Also, the effect of the reduction of public resources on the provision of basic health outputs, such as routine immunisation programmes, could worsen when inefficiencies and leakages of funds (due to fraud and corruption) have an additional impact on health expenditures. In addition, Gupta *et al.* (2002) showed that corruption has an additional impact on the budget allocation process: corrupt countries tend to spend less on education and health and more on military spending.

Thus, illicit financial flows could drain the public resources available to finance the provision of basic health outputs such as infant immunisation programmes. This effect could be especially important in low-income countries given that, as Gauri and Khaleghian (2002) pointed out, the demands of households and interest groups, which are very relevant in other areas of health services provision, are not the most important determinants of immunisation programmes. For this reason, in these countries, immunisation is mainly a task for government and international organisations. It is therefore a social, economic, and political imperative to address this problem if developing countries wish to reach the path to sustainable development.

Data

This study used annual data for 56 low- and middle-income countries for the period 2002-2013. Tables 1 and 2 show the variables included in the database and the list of countries included in the sample, respectively. All data are open access. The variables and country selection were constrained by data availability.

Insert Tables 1 and 2 here

In this study, the two key variables were the infant immunisation coverage rate (*Cov*) and the ratio of IFFs to total trade (*IFFT*) in each country. On the one hand, the infant immunisation coverage rate was constructed as a composite metric comprising the percentage of children less than 1 year who received measles, polio, and DPT immunisations in a given year. Figure 2 shows the averages for the period 2002-2013 for the sample countries. In the case of measles, Durrheim *et al.* (2014) noted that in order to ensure population immunity levels, in most settings each new birth cohort requires a coverage greater than 95% at every administrative level. On the other hand, given that, by construction, the quantity of IFFs in a country is related to the quantity of financial flows originating from trade, the indicator of the relative importance of the IFFs was calculated as a ratio of the IFFs to total trade. Figure 3 shows the averages by country for the period 2002-2013.

Insert Figures 2 and 3 here

Figure 3 also shows that some countries stand out in the ranking of countries according to the ratio of IFFs to total trade. These countries include Liberia and Togo and, to a lesser extent, Nicaragua, Costa Rica, Suriname, Zambia, Honduras, and Paraguay. However, there are large differences between the sample countries in the size of trade flows. For this reason, the following index has been calculated as an alternative indicator of the importance of IFFs for the sample countries, in order to obtain a relative measure of the weight of IFFs in a country in relation to total IFFs, while controlling for the participation of this country in total trade:

$$IFF\ Index = \left(\frac{IFF_{it} / Trade_{it}}{\sum_{i=1}^{56} IFF_{it} \Big/ \sum_{i=1}^{56} Trade_{it}} \right) = \left(\frac{IFF_{it} \Big/ \sum_{i=1}^{56} IFF_{it}}{Trade_{it} \Big/ \sum_{i=1}^{56} Trade_{it}} \right) \quad (1)$$

If the value of this index is greater than 1 for a specific country (i) in a year (t), then the IFF in this country as a share of total IFF is greater than its trade as a share of total trade. In other words, this result would indicate that, in this year, the country has experienced a particularly negative impact of IFF on its economy. Otherwise, if the value of this index is less than 1 for a specific country, then the share of total IFF in this country is lower than its corresponding share in total trade. This means that in this year the impact of IFFs in this country is lower than the mean corresponding to the 56 countries in the sample as a whole. Figure 4 shows the averages of the *IFF Index* by country for the period 2002-2013.

Insert Figure 4 here

For example, Figure 4 shows that in Liberia the average level of the *IFF Index* is 9.7. That is, its share to total IFF is 9.7 times greater than its share to total trade, indicating the huge impact of illicit financial outflows on this country over this period. In contrast, the average level of this index is 0.18 in Algeria, indicating that its share to total IFF is 18% of its share to total trade. However, the different sizes of the economies in the sample countries have to be taken into account when the index is used to compare the size of the flows. This aspect has been taken into account in Figures 5a, 5b, and 5c, which show both the relevance of IFFs in relation to trade and the size of the economy (also in terms of trade).

Insert Figures 5a, 5b, and 5c

The Russian Federation (Figure 5a) has an outstanding relative weight in the total IFF. Venezuela and Kazakhstan are also of relevance (Figure 5b). Due to their oil and gas industries, these three countries also generate the highest GDP. However, the case of Algeria is noteworthy. Although this economy is also reliant on the oil and gas industry, its share to total IFF is the lowest in the sample, which is related to the rigid capital controls in its state-dominated economy. In addition, Nicaragua and El Salvador in Latin America, and Ethiopia, Liberia, Togo, and Zambia in sub-Saharan Africa are among the smallest economies in which IFFs might have damaged the wellbeing of the population in these countries.

Empirical model and estimation strategy

In order to analyse the impact of the relative size of IFFs on child vaccination coverage, we used the following dynamic panel data model as a baseline specification:

$$\mathrm{Cov}_{it} = \mu_i + \eta_t + \lambda\ \mathrm{Cov}_{it\text{-}1} + \alpha\ \mathrm{IFFT}_{it\text{-}1} + \beta\ \mathrm{X}_{it} + \varepsilon_{it} \quad (2)$$

where t = 1, …, T are (12) time periods, and i = 1, …, N are (56) countries in the panel. Cov_{it} represents the average coverage rate (in percentages) of measles, polio, and DPT vaccines for country (i) in year (t). Given that within countries the level of coverage rate tends to persist over time, Cov_{it-1} is included in the model as an additional regressor to allow dynamic adjustment while controlling for the countries' initial coverage level. X_{it} represents a set of control variables. In the baseline model, this set includes $lnGDPpc_{it}$ (the level of GDP per capita in natural logs in constant 2010 US$,), which is a proxy for overall affluence in a country, and GIR_{it} (gross intake ratio to first-grade female primary education in percentages), which is a proxy for female educational level in the country. Education, and particularly female education, is an important control variable because low educational levels may hinder the acceptance of immunisation programs, which has had documented negative effects on vaccine coverage rates (Dietrich 2011). Other socio-economic variables can affect infant immunisation rates (e.g., indicators of health expenditure, urbanisation rate, and variables related to the control of corruption and the quality of governance). However, it is important to take into account that multicollinearity is an issue in most regression models which employ aggregate data, given that, for example, GDPpc is not only a proxy for overall affluence in a country, but is also associated with other socio-economic variables such as the resources invested in healthcare services, the quality of governance and institutions, and other income-related factors. Thus, to avoid multicollinearity and limit the "omitted variable bias", we included a vector of unobserved country-specific (fixed) effects (μ_i) and an additional vector of time-specific effects (η_t) in the baseline estimations. These country-specific dummy variables allow to control for the joint effect of the omitted time-invariant variables.

However, as stated before, it can be expected that the consequences of high IFFs worsen in high corruption contexts, given that a combination of high IFFs and high corruption not only reduces countries' fiscal space for health, due to insufficient domestic resource mobilisation, but also promotes wasteful public health expenditures, thus increasing the cost and reducing the quality (and scope) of the provision of public health services. Therefore, to obtain some evidence of these effects we finally estimated the model (2) considering two clusters of countries constructed in accordance with their average perceived corruption level in the period.

The parameter of interest in model (2) is (α). This coefficient indicates the short-run effect of the relative level of IFFs in a country (IFFs as a percentage of total trade) on the level of vaccination coverage, all other factors being equal. It is important to note that the variable *IFFT* included in equation (2) was lagged by one period, because it was assumed that it takes time (at least 1 year) before the change in the relative importance of illicit financial funds in a country has an impact on health output (i.e. vaccines coverage rate). It was expected that the estimated coefficient (α) would be negative and significant; this would show that a higher relative level of *IFFT* in year (t) would reduce the infant immunisation coverage rate over the next year (t+1).

The estimation strategy used was as follows. First, we employed OLS regression in equation (2). However, among other potential problems associated with the use of this initial naïve OLS regression, estimation biases may arise when using the OLS estimator in equation (2) because this estimator is inconsistent in dynamic panel data models (i.e. the well-known "dynamic panel bias" (Nickel 1981)). Thus, in a second step, we used the bias-corrected LSDV estimator (LSDVC), developed by Bruno (2005) in the Stata program 'xtlsdvc', to generate consistent estimates for equation (2). Nevertheless, the LSDVC may be the preferred estimator for dynamic panel-data models with few cross-sections (N) and strictly exogenous regressors. However, the properties of this estimator are not guaranteed in the presence of endogenous or even weakly exogenous regressors (Bruno 2005: 475). Thus, we included a third step in the estimation strategy, in which we controlled for endogeneity (eliminating country-specific effects) and used the OLS estimator for equation (2) in first differences and then used the Arellano and Bond (1991) GMM estimator (i.e., the "difference-GMM" estimator). The Stata program 'xtabond2' implemented by

Roodman (2009) was used to generate consistent and efficient estimates of the parameters in equation (2). Using the "cluster" and "robust" options, this package controls for autocorrelation and heteroscedasticity and obtains HAC-corrected standard errors in the estimation. In addition, the two-step GMM procedure in this program can implement the Windmeijer (2005) correction for "finite sample bias".

When endogeneity of the regressors is an issue, the available evidence can suggest which of the explanatory variables in the model could be endogenous, but it cannot indicate whether the correlation with the error term is sufficiently large as to invalidate the OLS estimation due to its inconsistency. One way to overcome this problem is to study the possible endogeneity of the regressors from an empirical perspective by using, for example, Wu-Hausman tests to test the null hypothesis of exogeneity of the regressors in the estimations (Wu 1973; Hausman 1978). If the results of these tests applied to the variables in first differences show that the hypothesis of exogeneity of the regressors cannot be rejected, then, in principle, these variables can be valid instruments for the estimation. In those cases in which the hypothesis of exogeneity can be rejected, in line with Arellano and Bond (1991) and Kiviet (1995), the levels of endogenous variables lagged by at least two periods could be used as instruments for the first difference. With this aim, the Wu-Hausman tests for exogeneity was computed for each independent variable in the GMM estimations using the two-step procedure described in Cameron and Trivedi (2005, p. 276).

Furthermore, consistent difference-GMM estimation should satisfy at least two conditions: there should be no serial correlation of order two in the residuals and the selected instruments should be jointly valid. To test whether the instruments employed in the estimation were jointly valid, we used the Hansen J test of over-identifying restrictions (which tests whether the instruments as a group are exogenous). The Arellano-Bond second-order autocorrelation test (m_2) for the error term were used to check for the presence of serial correlation of order two (by construction, residuals of the first-differenced equation can be correlated in first order).

Results and Discussion

Table 3 shows the descriptive statistics of the variables employed in the estimations and Table 4 shows the results for the baseline regression model. First, column [1] in Table 4 shows robust within-group OLS estimates as a benchmark for the alternative estimates. Second, column [2] shows the LSDVC dynamic regression with bias correction initialised by the Arellano and Bond estimator. Finally, columns [3] and [4] show the robust difference-OLS and difference-GMM results.

Insert Tables 3 and 4 here

Based on the results of Wu-Hausman test the null hypothesis of exogeneity can only be rejected for the variable ΔGIR_{it} (t-stat = 2.45, p-value = 0.015). Thus, in the case of column [4] in Table 4, lagged levels of the regressors of the model were selected as instruments for the exogenous first differenced variables. GMM-type instruments were used in the case of ΔGIR_{it}. The option "laglimits" available in this package was used to limit instrument proliferation and to avoid "over-fitting bias".

In relation to the GMM estimator, we used a Hansen J test statistic to test the validity of the overall over-identifying restrictions. We also estimated a difference-in-Hansen tests of exogeneity of instruments subsets (two for the GMM-type set of instruments and one for the IV-type set of instruments) as a more specific check of the validity of these extra moment conditions. The p-values obtained for these tests, which have chi-squared asymptotic distributions, do not permit the null hypothesis of the exogeneity of instruments subsets to be rejected. Also, Table 4 shows the p-values of the m_1 and m_2 tests for first-order and second-order serial correlation in the first-differenced residuals, asymptotically distributed as N(0, 1). In the case of GMM regression [4], the Hansen test and the difference-in-Hansen test do not permit the overall and extra over-identifying restrictions at the 10% level to be rejected, indicating that the assumption required for consistency of the GMM approach is not rejected. In addition, the rejection outcome of the m_1 test and the non-rejection of the m_2 test jointly indicate that the (level) disturbance term is not serially correlated, showing that the GMM estimations are consistent.

All estimated coefficients were significant and presented the expected signs in the four regressions. In particular, both the GDPpc level ($lnGDPpc_{it}$) and the relative number of new female entrants in the first grade of primary education (GIR_{it}) had a positive impact on infant vaccination coverage. Otherwise, in all estimations, the relative level of IFFs had a negative impact on vaccination coverage. Robustness checks for these results can be found in the online supplementary file.

Model (2) has been also estimated controlling for the level of countries' perceived level of corruption, as measured by the CPI. With this aim, based on the average level of perceived corruption in the period 2002-2013, we identified a cluster of the 25 most corrupt countries, for which the value of the average CPI level was less than 2.9. The remaining 31 countries belonged to the less corrupt cluster of countries. The criterion for the selection of the cut-off point was to have a balanced number of countries in each cluster. It is important to note that variations in the cut-off point did not affect the value and statistical significance of the estimated coefficients.

Thus, we first generated a dummy variable (HC_{it}) to control for those countries belonging to the highest corruption cluster. This variable was employed to estimate the coefficient resulting from the interaction term between this dummy and the variable of interest $IFFT_{it-1}$.

Insert Table 5

Table 5 shows the estimation results obtained using the dummy variable interaction term approach. It is clear that $IFFT_{it-1}$ only had a significant impact on the dependent variable for the most corrupt cluster of countries. When only the cluster of less corrupt countries was addressed, the coefficient estimated for this variable was no longer significant in all regressions. For this reason, the base model was finally estimated using data for the 25 countries belonging to the most corrupt cluster.

Insert Table 6

Table 6 shows the estimation results obtained for the most corrupt cluster of countries. In this case, most estimated coefficients were significant and presented the expected signs in the four regressions. In particular, the level and first differences of the variable $IFFT_{it-1}$ had a negative and significant impact on infant vaccination coverage (the values of the estimated coefficients were very similar, ranging from -0.057 to -0.079). Taking into account the results presented in Table 6 column [4], in the short run, a 1 p.p. increase in the ratio of IFFs to total trade accounts for an average decrease of 0.079 p.p. in the infant vaccination coverage rate in the following year. Moreover, in the long run, the total effect of an annual 1 p.p. increase in the ratio of IFFs to total trade on vaccination coverage rate over the coming years was -0.19 p.p. [= -0.079 / (1-0.575)]. At first sight, this effect may appear to be weak. However, if we consider that there was a 0.023 p.p. increase in the vaccination coverage rate between 2002 and 2013 in the Ukraine, which is easily the country in the sample that has undergone the greatest improvements, then a 0.19 p.p. increase in this rate would be 8.3 times greater than the increase over a similar period.

Conclusions

In recent years, IFFs have come under increased scrutiny by policy communities, including the OECD, G20, and the UN systems. The main focus has been the urgent need to reduce IFFs as part of development policy. The efforts by the international community to curb IFFs, especially in developing countries, are justified because these flows drain the scarce public resources available to finance the provision of public services and investments, especially those related to human development. As a first step in analysing the social costs of illicit capital flows in developing countries, this article analysed the impact of IFFs on a relevant basic health output: the infant immunisation coverage rate. We used data for 56 low- and middle-income countries for the period 2002-2013.

The main result of the empirical analysis was that the relative level of IFFs over this period was negatively associated with vaccination coverage levels, but only for the sample of countries with very high levels of perceived corruption. Specifically, the total effect of an annual 1 p.p. increase (decrease) in the ratio of IFFs to total trade would be a 0.19 p.p.

decrease (increase) in the level of the vaccination coverage rate over the coming years. Given that there was an annual average of 18 million infants in this cluster of 25 countries, this result suggests that at least 34,000 children may not receive this basic health care intervention in the future as a consequence of this increase in IFFT in any particular year. This research finding also suggests that it is not just the volume of IFFs that is curbing infant vaccination coverage; rather, what seems to harm this basic health output are periods when the increase in IFFs is greater than the observed increase in total trade.

Moreover, in countries with a high level of perceived corruption, such as Liberia, Togo, Zambia, or Chad, the public resources lost as a consequence of the huge IFFs would be a reasonable additional explanation for the low infant immunisation rate in these countries. However, the problem of high IFFs and relative low infant immunisation rates is not only pervasive in sub-Saharan Africa, but also in countries such as Azerbaijan and the Ukraine in Europe and Central Asia, in Venezuela, and Paraguay in South America, and Indonesia, Cambodia, and the Philippines in East Asia and the Pacific. In these countries, which have high levels of corruption and wasteful public health expenditures, two negative effects could be having an impact on the provision of infant immunisation programmes:

- Insufficient domestic resource mobilisation caused by reductions in tax revenues due to the existence of a high relative volume of illicit financial flows.
- The additional reduction of the fiscal space for the provision of basic health services due to shifts in the composition of public spending away from social sectors caused by corruption in governments and public institutions.

More research is needed in order to analyse these effects and to find alternative explanations for these findings.

Finally, as Stiglitz (2000) and Brada *et al.* (2013) pointed out, states, particularly emerging economies, have to "bridle" capital flows given their harmful effects on domestic liquidity and hence economic growth. As Stiglitz (2000: 1082) indicated: "Liberalisation required sufficiently strong and stable financial institutions, which in turn meant that a strong regulatory framework would have to be in place as a prerequisite". The findings of this study offered evidence showing that, in high corruption developing countries, this prerequisite might be also crucial in order to prevent the negative effects of capital flows on the health conditions of populations.

Nevertheless, it is important to note some limitations of the empirical analysis. On the one hand, further research is needed to study the effect of IFFs on other dimensions of human development, such as education and poverty. It would also be relevant to study the specific mechanisms by which increases IFFs can harm both the provision of different basic health care interventions and achievements in related health outcomes. On the other hand, the sample of countries included in the analysis should be enlarged in order to obtain more general results.

Notes

1. In addition to this, when analysing the effect of corruption on the provision of health services, it is important to note that the way corruption is organised and practised determines its effect on the provision of basic public services: some countries have similar corruption patterns but have very different public health performance. In other words, we should not ignore the fact that there are idiosyncratic historical and cultural factors that feed and shape the nature of corruption networks in countries. In this regard, Shleifer and Vishny (1993) show that when corruption networks are organised and managed by a strong centralised state, corruption is likely to be less harmful to societies than when it is organised by numerous government officials acting as independent

monopolists. In addition, Olson (1993) indicated that when these networks are managed by "rational stationary bandits", they may have incentives to even encourage the provision of public goods needed to promote economic growth (thus limiting embezzlement and bribery) in order to consolidate their political power and enrich themselves.

2. See http://www.who.int/gho/immunization/en/

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Table 1. *Variables employed in the estimations*

Measles	The percentage of children less than 1 year who have received at least one dose of measles-containing vaccine in a given year.	World Health Organization, World Bank
Polio	The percentage of one-year-olds who have received three doses of polio vaccine in a given year.	World Health Organization, World Bank
DPT	The percentage of one-year-olds who have received three doses of the combined diphtheria, tetanus toxoid and pertussis vaccine in a given year.	World Health Organization, World Bank
Cov	Average infant vaccination coverage rate (in %) calculated as: Cov = (Measles + Polio + DPT) / 3	Authors
GDPpc	GDP per capita, in constant 2010 US$.	World Bank
HEP	Health expenditure public, in % of total health expenditure.	World Bank
GE	Government Effectiveness Index, normalised values from 0 (weak) to 1 (strong).	Worldwide Governance Indicators, World Bank
CPI	Corruption Perception Index, with values from 0 (highly corrupt) to 10 (clean country).	Transparency International
UP	Urban population, as a % total population	World Bank
GIR	Gross intake ratio to first-grade female primary education (%). As this calculation includes all new entrants to first grade (regardless of age), the ratio can exceed 100% due to over-aged and under-aged children entering primary school for the first time. In the case of Russian Federation, the data available is for 2014. Female data series over the period 2002-2013 have been calculated for this country assuming that this series follows the available average annual growth rate for both sexes' series over the period.	World Bank, Authors
IFF	Illicit financial flows (in current US$).	Global Financial Integrity
Trade	Total trade in current US$.	World Bank, UN COMTRADE
IFFT	Ratio of illicit financial flows to total trade, in %. (IFFT = IFF/Trade · 100)	Authors
IFF Index	Share in total IFF as a ratio of the share in total trade. See equation (1).	Authors
IFFGDP	Ratio of illicit financial flows to GDP, in %. (IFFT = IFF/GDP · 100)	Authors
IFFpc	Illicit financial flows per capita (in constant 2010 US$ per inhabitant)	Authors

Table 2. *Low- and middle-income countries in the sample by region*

Sub-Saharan Africa	**Latin America & Caribbean**	**Middle East & North Africa**	**Europe & Central Asia**
Botswana	Argentina	Algeria	Armenia
Burkina Faso	Brazil	Morocco	*Azerbaijan*
Cameroon	Colombia	Tunisia	*Belarus*
Chad	Costa Rica	**South Asia**	Bulgaria
Congo, Republic of	Dominican Republic	*Bangladesh*	Georgia
Cote d'Ivoire	*Ecuador*	India	*Kazakhstan*
Ethiopia	El Salvador	*Maldives*	*Moldova*
Gambia	*Guatemala*	**East Asia & Pacific**	Romania
Lesotho	Honduras	*Cambodia*	*Russian Federation*
Liberia	Jamaica	China	Serbia
Madagascar	Mexico	*Indonesia*	*Ukraine*
Malawi	*Nicaragua*	*Philippines*	
Mali	Panama	*Thailand*	
Namibia	*Paraguay*		
Tanzania	Peru		
Togo	Suriname		
Zambia	*Venezuela*		

Note: countries have been selected according to World Bank classification by income levels in 2015. Countries belonging to the highest perceived corruption cluster are shown in italics.

Table 3. *Annual averages of pooled variables used in the estimations.*
(672 observations, 56 countries over the period 2002-2013)

Variables	Δ %	Mean	Max	Min
Infant vaccination coverage rate, % (Cov_{it})	0.86	86.48	99.00	22.67
GDP per capita, in constant 2010 US$, ($GDPpc_{it}$)	3.62	3,810.44	14,687.98	194.17
Health expenditure public, in % of total health expenditure (HEP_{it})	0.81	50.15	85.27	11.20
Government Effectiveness Index (GE_{it})	0.50	0.41	0.81	.00
Corruption Perception Index (CPI_{it})	1.25	3.08	8.00	1.20
Urban population, as a % total population (UP_{it})	1.03	52.24	91.45	14.79
Gross intake ratio to first-grade female primary education, % (GIR_{it})	0.28	107.92	186.35	43.80
Ratio of illicit financial flows to total trade, % ($IFFT_{it}$)	-0.66	14.63	272.01	0.13
Share in total IFF as a ratio of the share in total trade (IFF $Index_{it}$)	1.28	1.82	31.58	0.02
Ratio of illicit financial flows to GDP, in % ($IFFGDP_{it}$)	-0.10	13.17	260.97	0.05
Illicit financial flows per capita, in constant 2010 US$ ($IFFpc_{it}$)	-1.11	852.73	12,751.69	0.00

Note: the growth rates Δ% were estimated by regressing the natural log of the variable on a constant and a time trend. The average growth rate is the coefficient of the time trend.

Table 4. *Estimates of regression models*

Independent variables	Levels		First differences	
	FE	FE corrected	OLS	Two-step GMM
	[1]	[2]	[3]	[4]
$Cov_{i\ t-1}$	0.521*** (8.29)	0.615*** (19.84)	-0.139 (-1.52)	0.300*** (2.50)
$IFFT_{it-1}$	-0.051*** (-3.64)	-0.047*** (-4.05)	-0.053** (-2.68)	-0.075*** (-2.59)
Ln $GDPpc_{it}$	8.900*** (3.18)	8.612*** (3.22)	9.705 (1.51)	6.812** (2.20)
GIR_{it}	0.076*** (3.30)	0.066*** (2.96)	0.016 (0.60)	0.167* (1.87)
Adjusted R^2	0.897	-	0.086	-
Pesaran CD test (p-value)	-0.48 (0.64)	-	0.26 (0.80)	-
m_1 (p-value)	-0.44 (0.66)	-	0.22 (0.82)	-2.29** (0.02)
m_2 (p-value)	-1.14 (0.25)	-	-1.63* (0.10)	-1.41 (0.16)
Hansen J test (p-value)	-	-	-	51.40 (0.34)
# Instruments	-	-	-	52
# Countries	56	56	56	56
# Years	11	11	10	10
# Observations	616	616	560	560

Notes: *Cov_{it}* is the dependent variable. In the case of FE, FE corrected and OLS first differences regressions include year dummies as control variables. The standard errors and covariance are heteroscedasticity and autocorrelation consistent (HAC). The Windmeijer's finite-sample correction for the two-step covariance matrix was applied. The t-statistics (in regressions [1] and [3]) and z-statistics (in regressions [2]-[4]) of the coefficients are in parenthesis. *Pesaran CD test* is the residual cross-section dependence test. The null hypothesis is the absence of error cross-section dependence. The instruments employed for first-differences Arellano-Bond estimation [4] are: $lnGDPpc_{it-1}$ and $IFFT_{it-2}$ as standard instruments; and, in the case of the endogenous variables, both lagged levels (dated t-6 to t-10) of variable $Cov_{i\ t-1}$ and lagged levels (dated t-3 to t-7) of GIR_{it} as GMM-style instruments set. The difference-in-Hansen tests of exogeneity of instruments subsets do not reject the null hypothesis in any case.

* Denotes coefficient significant at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 5. *OLS estimates of regression models*

Independent variables	*Levels*		*First differences*
	FE	*FE corrected*	*OLS*
	[1]	[2]	[3]
$Cov_{i\ t-1}$	0.516*** (8.21)	0.608*** (19.58)	-0.137 (-1.50)
$IFFT_{it-1}$	0.054 (1.62)	0.044 (1.11)	0.048 (0.83)
$IFFT_{it-1}$ * HC_{it}	-0.112*** (-3.30)	-0.100** (-2.50)	-0.108* (-1.79)
Ln $GDPpc_{it}$	9.108*** (3.25)	8.783*** (3.32)	9.520 (1.49)
GIR_{it}	0.076*** (3.30)	0.066*** (2.95)	0.017 (0.64)
Adjusted R^2	0.899	-	0.092
Pesaran CD test (p-value)	-0.55 (0.58)	-	0.14 (0.89)
m_1 *(p-value)*	-0.46 (0.64)	-	0.16 (0.87)
m_2 *(p-value)*	-1.04 (0.30)	-	-1.65* (0.10)
# Countries	56	56	56
# Years	11	11	10
# Obs.	616	616	560

Notes: Cov_{it} is the dependent variable. *HC* is a dummy variable which takes the value 1 when the country has an average level of CPI less than 2.9 in the period 2002-2012 (i.e. this country has a very high level of perceived corruption). The standard errors and covariance are heteroscedasticity and autocorrelation consistent (HAC). The t-statistics of the coefficients are shown in parenthesis. Regressions include year dummies as control variables. *Pesaran CD test* is the residual cross-section dependence test. The null hypothesis is the absence of error cross-section dependence.
* Denotes coefficient significant at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 6. *Estimates of regression models.*
Cluster of countries with the highest level of perceived corruption

	Levels		*First differences*	
	FE	*FE corrected*	*OLS*	*Two-step GMM*
	[1]	[2]	[3]	[4]
$Cov_{i\ t-1}$	0.536*** (6.71)	0.631*** (10.92)	-0.160 (-1.38)	0.575*** (4.29)
$IFFT_{it-1}$	-0.061*** (-4.61)	-0.057*** (-3.76)	-0.061*** (-3.47)	-0.079** (-2.05)
Ln $GDPpc_{it}$	9.160** (2.13)	8.997** (2.30)	10.226 (0.98)	4.339 (0.79)
GIR_{it}	0.091*** (2.96)	0.083** (2.01)	-0.004 (-0.10)	-0.051 (-0.46)
Adjusted R^2	0.896	-	0.117	-
Pesaran CD test (p-value)	-0.68 (0.50)	-	-0.92 (0.36)	-
m_1 (p-value)	-0.52 (0.60)	-	0.36 (0.72)	-2.29** (0.02)
m_2 (p-value)	-0.41 (0.68)	-	-1.15 (0.25)	-0.55 (0.58)
Hansen J test (p-value)	-	-	-	20.37 (0.37)
# Instruments	-	-	-	23
# Countries	25	25	25	25
# Years	11	11	10	10
# Obs.	275	275	250	250

Notes: Cov_{it} is the dependent variable. In the case of FE, FE corrected and OLS first differences regressions include year dummies as control variables. The standard errors and covariance are heteroscedasticity and autocorrelation consistent (HAC). The t-statistics (in regressions [1] and [3]) and z-statistics (in regressions [2] and [4]) of the coefficients are shown in parenthesis. The Windmeijer's finite-sample correction for the two-step covariance matrix was applied. *Pesaran CD test* is the residual cross-section dependence test. The null hypothesis is the absence of error cross-section dependence. The instruments employed for first-differences Arellano-Bond estimation [4] are: $lnGDPpc_{it-1}$ and $IFFT_{it-2}$ as standard instruments; and lagged levels of variables $Cov_{i\ t-1}$ and GIR_{it} as the GMM-style instruments set, using the option "collapse" of xtabond2 software. The difference-in-Hansen tests of exogeneity of instruments subsets do not reject the null hypothesis in any case.
* Denotes coefficient significant at the 10% level, ** at the 5% level, and *** at the 1% level.

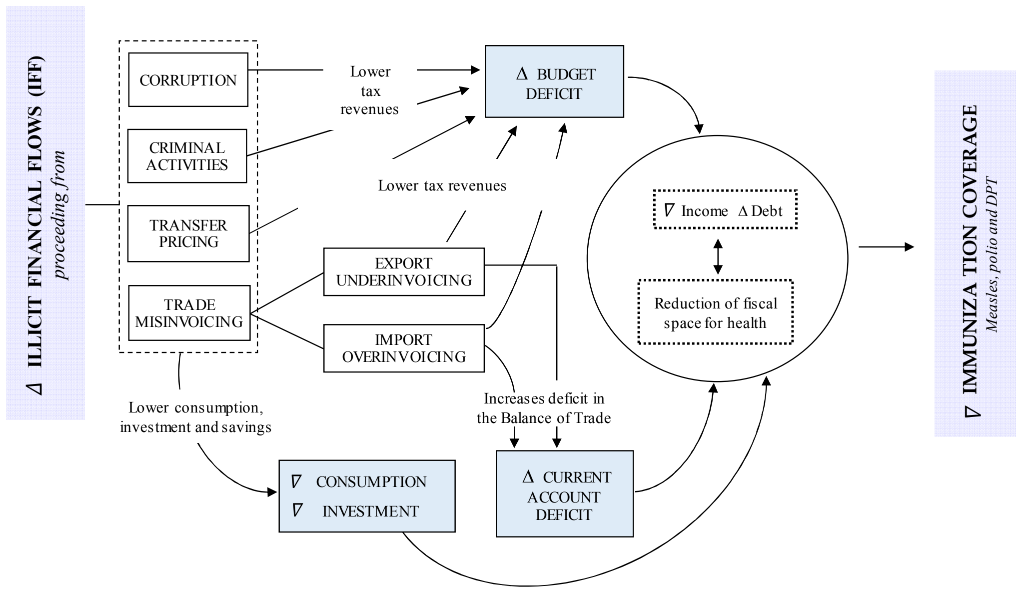

Figure 1. *The components of IFFs and their potential effects on countries' fiscal space for health and infant immunisation coverage*

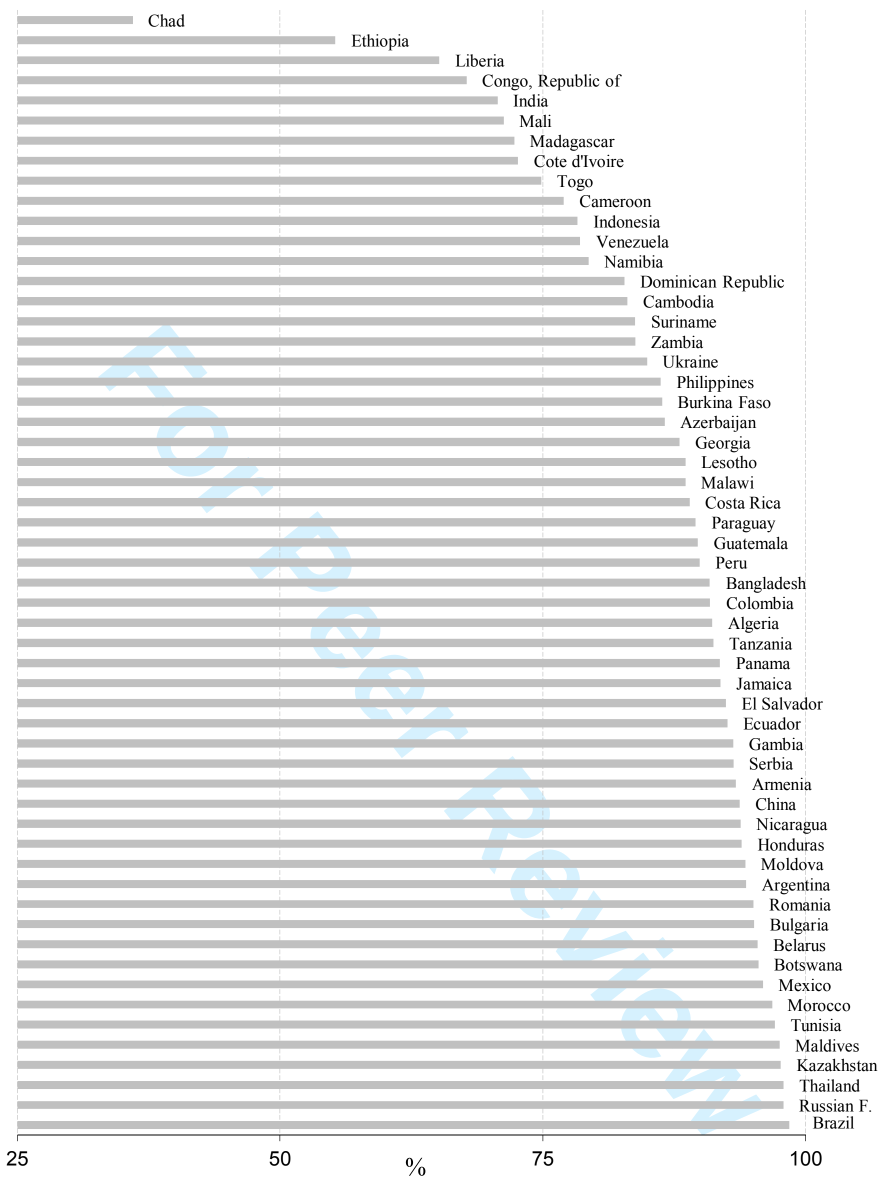

Figure 2. *Average infant vaccination coverage against measles, polio, and DPT in low- and middle-income countries. Averages for the period 2002-2013.*

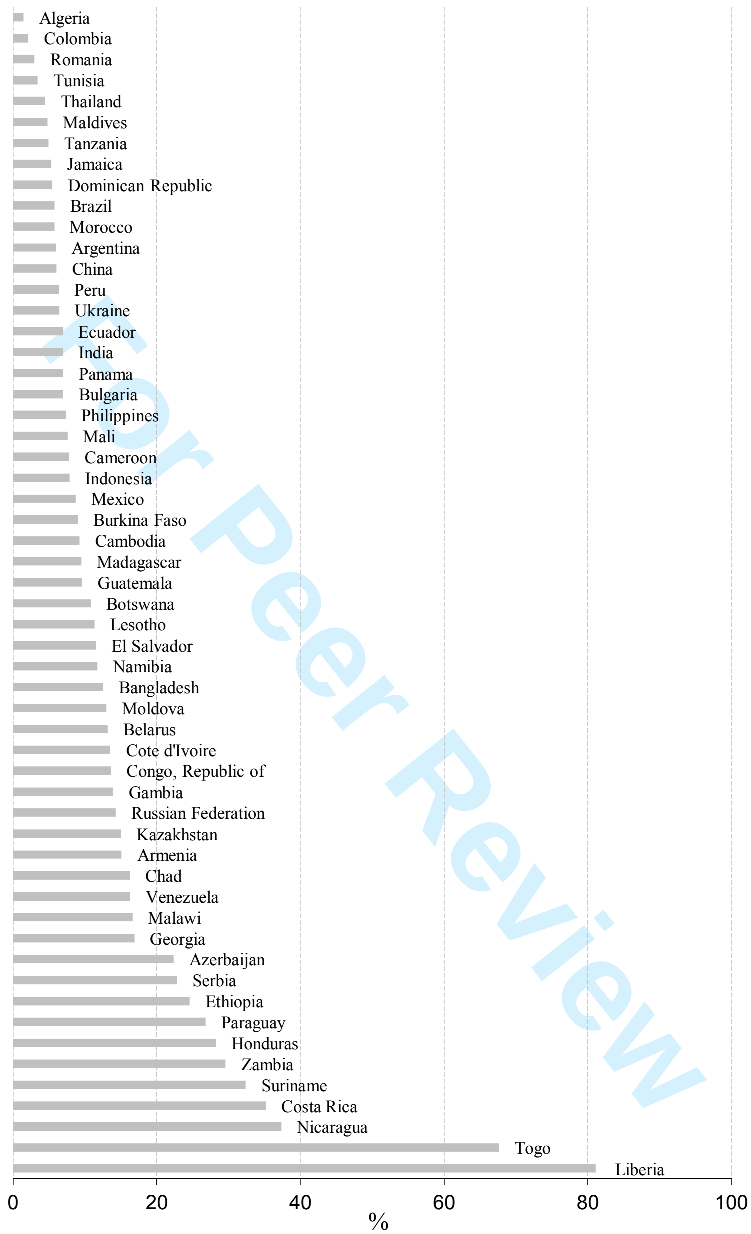

Figure 3. *The ratio of IFFs to total trade in low- and middle-income countries. Averages for the period 2002-2013.*

Figure 4. *IFF index in low- and middle-income countries. Averages for the period 2002-2013.*

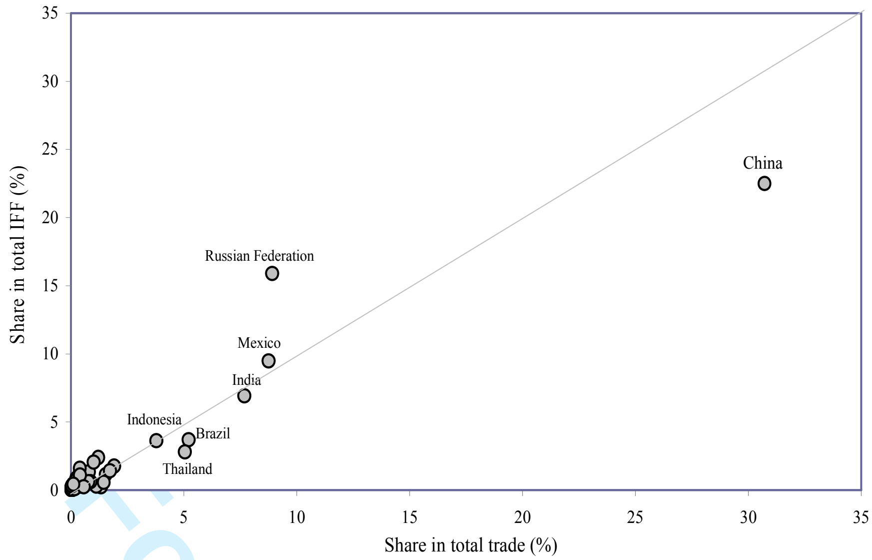

Figure 5a. *Relationship between the share to total trade and the share to total IFF. Averages for the period 2002-2013. All countries in the sample.*

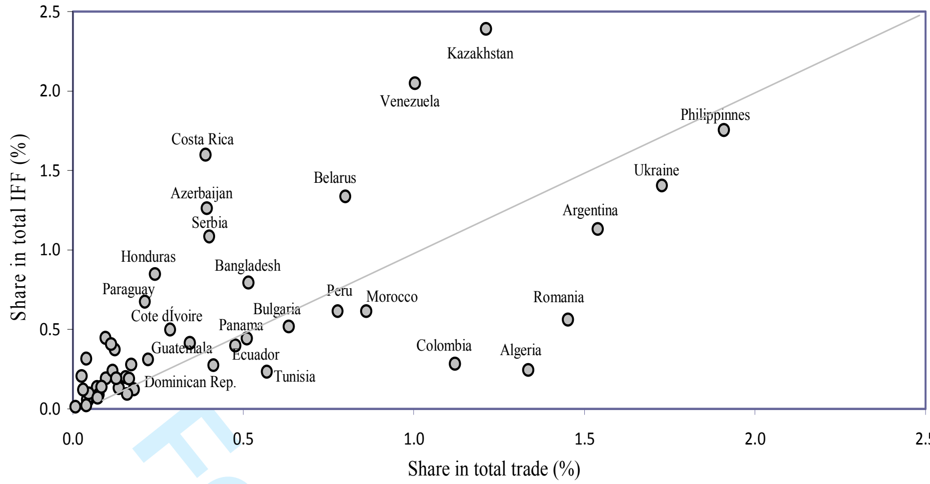

Figure 5b. *Relationship between the share to total trade and the share to total IFF. Averages for the period 2002-2013.*
All countries in the sample excluding those indicated in Figure 5a.

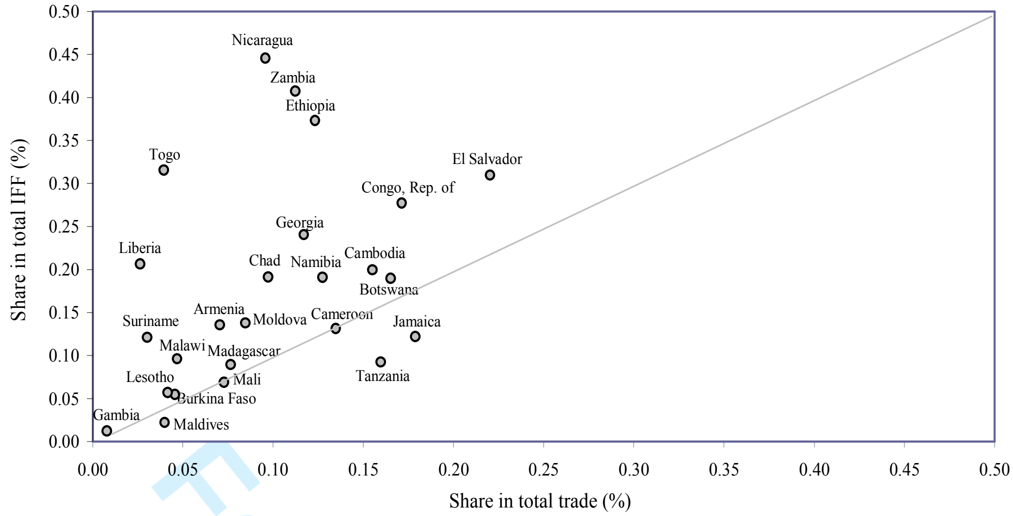

Figure 5c. *Relationship between the share to total trade and the share to total IFF. Averages for the period 2002-2013. All countries in the sample excluding those indicated in Figures 5a and 5b.*

Results and Discussion

Robustness checks

We performed two robustness checks to address the following questions: Are the results robust to omitted variable bias? Are the results robust to other measurements of IFFs?

Firstly, to test the robustness of the baseline estimation results and to assess the extent of the possible omitted variable bias in the baseline estimations, model (2) has been also specified and estimated controlling for a set of additional variables — suggested by the literature — that have an impact on immunisation coverage. The selected variables are as follows: public health expenditure (in % of total health expenditure, HEP); the *Government Effectiveness Index*[1] (GE); and an indicator of urbanisation (urban population (UP), as a % of total population).

Insert Table 7

As expected, these additional variables show a strong linear relationship with GDPpc (see Table 7). Other potential regressors, such as the *CPI*, are not included in the model because there is also a strong lineal association between *GE* and *CPI*. Table 8 shows the estimation results of the alternative specifications.

Insert Table 8

As shown in Table 8, column [2], when employing the fixed effects (FE) model, the omitted variables likelihood ratio (LR) test statistic rejects at a conventional significance level the null hypothesis that *HEP*, *GE*, and *UP* are jointly significant. When the model is specified in first differences, the omitted variables LR test statistic in column [4] does not reject the null hypothesis that *HEP*, *GE*, and *UP* are jointly significant (although, in this case, none of the corresponding estimated coefficients are statistically significant). However, it is important to note that the results shown in Table 8 confirm that the value and significance of the estimated coefficient for *IFFT* do not change when these additional variables are included, indicating that this estimation result is robust.

Secondly, in order to assess the sensitivity of the results to other measurements of IFFs, we considered alternative indicators, such as the following variables: Ratio of IFFs to total trade (in %) (*IFFT*); share in total IFF as a ratio of the share in total trade (*IFF Index*); ratio of IFFs to GDP (in %) (*IFF/GDP*); and IFF per capita (US$ per inhabitant) (*IFF/Population*).

Insert Table 9

Table 9 shows the FE estimation results obtained using these different indicators of the importance of IFFs in each country. This table shows that a significant negative effect of IFFs on Cov_{it} is only observed when the volume of IFFs in each country is expressed in relative terms and in relation to total trade (which is the case in both $IFF\ Index_{it-1}$ and $IFFT_{it-1}$). Although the sign is in the expected direction, no significant association was observed when this variable was expressed in per capita terms or in relation to GDP. It is also important to note that no significant changes were observed in the values of the remaining independent variables considered in the model. Thus, the research findings suggest that an increase in IFFs is not simply a factor which may damage infant vaccination coverage. What seems harmful to the provision of this health output are periods in which there is an increase in the volume of IFFs greater than the corresponding increase in total trade. As a result, this research finding implies that, in order to prevent the negative effects of illicit capital flight, it is not enough for countries to reduce IFFs in absolute terms or even in per capita terms; what might be effective is a reduction (increase) in the volume of IFFs greater (smaller) than the possible observed reduction (increase) in total trade.

Notes

1. Governance is a multidimensional concept that, in general, refers to the exercise of political, economic, and administrative capacity. The World Bank's Worldwide Governance Indicators (WGI) provide aggregate indicators that capture the different dimensions of governance. Specifically, the WGIs provide measures of the quality of governance, on a scale of scores from -2.5 to 2.5, for the six different dimensions considered: control of corruption; government effectiveness; political stability; regulatory quality; rule of law; and voice and accountability. A range of surveys conducted by institutes, non-governmental organizations, and international organizations are employed in the construction of these indexes. Among these indexes, the *Government Effectiveness Index* (GE) is used in this article as the indicator of governance. Among other aspects, it mainly measures perceptions regarding the quality of bureaucracy and public service delivery. This index could be considered a good proxy for the quality of public health service delivery, unlike other institutional quality measures (such as political stability, regulatory quality, rule of law, and voice and accountability) that are expected to have a weaker relationship with health outcomes.

Table 7. *Pearson's correlation matrix of the potential independent variables*

Variables	$IFFT_{it-1}$	Ln $GDPpc_{it}$	HEP_{it}	GE_{it}	CPI_{it}	UP_{it}	GIR_{it}
$IFFT_{it-1}$	1						
Ln $GDPpc_{it}$	-0.251	1					
HEP_{it}	-0.142	0.305	1				
GE_{it}	-0.318	0.512	0.320	1			
CPI_{it}	-0.127	0.305	0.342	0.681	1		
UP_{it}	-0.072	0.784	0.167	0.229	0.165	1	
GIR_{it}	0.095	-0.224	-0.007	-0.015	0.003	-0.155	1

Note: Coefficients of correlation computed using a common sample of 616 observations.

Table 8. *OLS estimates of alternative regression models*

Independent variables	Fixed Effects		First differences	
	[1]	[2]	[3]	[4]
$Cov_{i\,t-1}$	0.511*** (6.10)	0.521*** (6.04)	-0.137 (-1.50)	-0.139 (-1.52)
$IFFT_{it-1}$	-0.054*** (-2.93)	-0.051** (-2.58)	-0.055** (-2.73)	-0.053** (-2.68)
Ln $GDPpc_{it}$	8.642*** (3.23)	8.900*** (3.40)	9.929 (1.54)	9.705 (1.51)
HEP_{it}	0.045 (1.42)	-	0.068 (1.52)	-
GE_{it}	4.631 (1.02)	-	3.405 (0.61)	-
UP_{it}	0.227* (1.75)	-	0.394 (1.03)	-
GIR_{it}	0.074** (2.36)	0.076** (2.45)	0.013 (0.49)	0.016 (0.60)
Adjusted R^2	0.898	0.897	0.087	0.086
Pesaran CD test (p-value)	-0.50 (0.62)	-0.48 (0.64)	0.28 (0.78)	0.26 (0.80)
Omitted variables LR test (p-value)	-	7.63** (0.054)	-	3.47 (0.32)
m_1 (p-value)	-0.42 (0.67)	-0.44 (0.66)	0.17 (0.86)	0.22 (0.82)
m_2 (p-value)	-1.14 (0.25)	-1.14 (0.25)	-1.73* (0.08)	-1.63* (0.10)
# Countries	56	56	56	56
# Years	11	11	10	10
# Obs.	616	616	560	560

Notes: Cov_{it} is the dependent variable. The standard errors and covariance are heteroscedasticity and autocorrelation consistent (HAC). The t-statistics of the coefficients are shown in parenthesis. Regressions include year dummies as control variables. *Pesaran CD test* is the residual cross-section dependence test. The null hypothesis is the absence of error cross-section dependence.

* Denotes coefficient significant at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 9. *Fixed effects (FE) estimations using alternative measurements of IFFs*

Independent variables	[1]	[2]	[3]	[4]
Cov_{it-1}	0.511*** (6.10)	0.514*** (8.25)	0.526*** (8.13)	0.529*** (8.15)
$IFFT_{it-1}$	-0.054*** (-2.93)	-	-	-
IFF $Index_{it-1}$	-	-0.429*** (-3.74)	-	-
$(IFF/GDP)_{it-1}$	-	-	-0.016 (-0.91)	-
$(IFF/Population)_{it-1}$	-	-	-	-0.000 (-1.06)
Ln $GDPpc_{it}$	8.642*** (3.23)	8.515*** (2.89)	8.105** (2.69)	8.476** (2.77)
HEP_{it}	0.045 (1.42)	0.043 (1.42)	0.033 (1.02)	0.034 (1.06)
GE_{it}	4.631 (1.02)	5.036 (1.21)	5.659 (1.31)	5.394 (1.26)
UP_{it}	0.227* (1.75)	0.227* (1.93)	0.174 (1.49)	0.176 (1.49)
GIR_{it}	0.074** (2.36)	0.075*** (3.25)	0.071** (3.16)	0.071** (3.15)
Adjusted R^2	0.898	0.900	0.894	0.894
m_1 *(p-value)*	-0.42 (0.67)	-0.43 (0.66)	-0.54 (0.59)	-0.61 (0.54)
m_2 *(p-value)*	-1.14 (0.25)	-1.14 (0.25)	-1.21 (0.23)	-1.22 (0.22)
# Countries	56	56	56	56
# Years	11	11	11	11
# Obs.	616	616	616	616

Notes: Cov_{it} is the dependent variable. The standard errors and covariance are heteroscedasticity and autocorrelation consistent (HAC). The t-statistics of the coefficients are shown in parenthesis. Regressions include year dummies as control variables.
* Denotes coefficient significant at the 10% level, ** at the 5% level, and *** at the 1% level.