BANCA D'ITALIA

EUROSISTEMA

Questioni di Economia e Finanza

(Occasional Papers)

The gravity of Offshore Financial Centers: estimating real FDIs using a binary choice model

by Marco Albori, Alessio Anzuini, Fabrizio Ferriani and Luca Rossi

October 2023

Number 805

BANCA D'ITALIA
EUROSISTEMA

Questioni di Economia e Finanza

(Occasional Papers)

The gravity of Offshore Financial Centers: estimating real FDIs using a binary choice model

by Marco Albori, Alessio Anzuini, Fabrizio Ferriani and Luca Rossi

Number 805 – October 2023

The series Occasional Papers *presents studies and documents on issues pertaining to the institutional tasks of the Bank of Italy and the Eurosystem. The* Occasional Papers *appear alongside the* Working Papers *series which are specifically aimed at providing original contributions to economic research.*

The Occasional Papers *include studies conducted within the Bank of Italy, sometimes in cooperation with the Eurosystem or other institutions. The views expressed in the studies are those of the authors and do not involve the responsibility of the institutions to which they belong.*

The series is available online at www.bancaditalia.it .

ISSN 1972-6643 (online)

Designed by the Printing and Publishing Division of the Bank of Italy

THE GRAVITY OF OFFSHORE FINANCIAL CENTERS: ESTIMATING REAL FDIS USING A BINARY CHOICE MODEL

by Marco Albori*°, Alessio Anzuini*+, Fabrizio Ferriani*° and Luca Rossi*°

Abstract

Offshore Financial Centers (OFCs) exert a profound distortion on economic analyses based on cross-border capital flows reported in official statistics, as a large share of those investments is known to be solely due to tax and regulatory avoidance purposes. Notwithstanding the importance of this phenomenon, scant information is available concerning its actual magnitude. This paper focuses on Foreign Direct Investments (FDIs) and fills this gap by using an extensive list of FDI determinants and estimating a gravity-like binary choice specification to assess how much bilateral FDIs are driven by economic integration motives versus profit shifting opportunities. We find that the share of so-called phantom FDIs, after rising in 2010-15, stabilized at around 40% of total FDIs in recent years and that this share is systematically larger in OFCs, reconciling available evidence on the abnormal amount of recorded FDIs in OFCs.

JEL Classification: C33, F21, F23.
Keywords: Foreign Direct Investments, FDI network, tax havens, gravity models.
DOI: 10.32057/0.QEF.2023.0805

Contents

* Bank of Italy, Directorate General of Economics, Statistics and Research.

° International Economics Directorate.

+ Financial Stability Directorate.

1 Introduction[1]

The existence of tax havens and Offshore Financial Centers (OFCs) within the global financial system not only erodes countries' tax bases through jurisdictional arbitrage (Hines, 2010, Bolwijn et al. (2018), Tørsløv et al., 2022, Wier and Zucman, 2022), but also results in a significant unintended consequence: the distortion, sometimes to an extreme extent, of the international geographical distribution of capital and investment and the assessment of the real and financial integration between countries that can be inferred from official statistics. The role of OFCs in distorting official statistics is known since the seminal works of Lane and Milesi-Ferretti (2001, 2007, 2018) in which they use mirror statistics to estimate the foreign assets and liabilities positions for some of the most important OFCs.[2]

Consider the twenty countries with the largest stocks of inward FDIs in 2019 (Figure 1): as expected, the two largest economies in the world, United States and China, rank high, being respectively the first and fourth in the list; however, some countries such as the Netherlands, Luxembourg, British Virgin Islands, the Cayman Islands or Bermuda attract a disproportionate amount of foreign investment as compared to the size of their economies. One can reasonably suspect that some of these investments have little to do with financial and real integration reflecting macroeconomic fundamentals.

To understand why this happens, it is helpful to take a step back: what makes OFCs different from other countries? How does their presence influence gross capital flows? The International Monetary Fund (IMF) refers to OFCs as: (a) jurisdictions that have relatively large numbers of financial institutions engaged primarily in business with nonresidents; (b) financial systems with abnormal external assets and liabilities relative to the domestic financial intermediation sector; and (c) centres that provide some or all of the following services: low or zero taxation; moderate

[1]We thank Marco Taboga, Fabrizio Venditti and seminar participants at Banca d'Italia for useful suggestions. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of Italy. All remaining errors are ours.

[2]With the term "distortion" we solely mean a biased representation of the true underlying real integration between countries that is driven by economic fundamentals. This bias is generally driven by multinationals' tax and regulatory avoidance strategies.

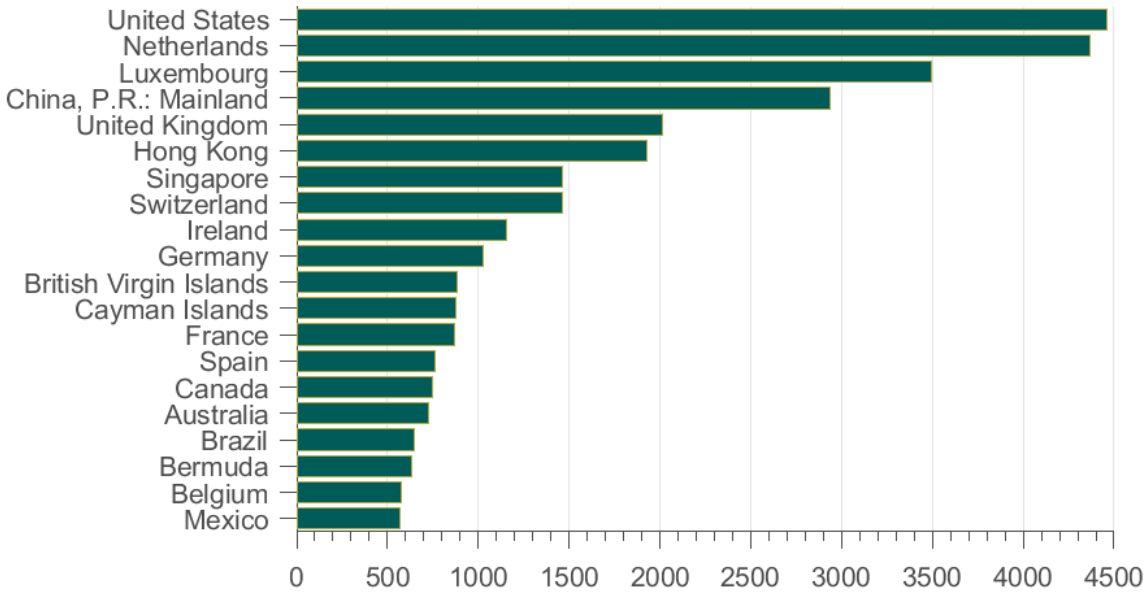

Figure 1: Total inward FDI by country in 2019, twenty economies with the largest stock; millions of dollars.

or light financial regulation; banking secrecy and anonymity. [3]

Multinationals take advantage of these services and favourable regulations using complex systems of intra-group operations that entail very large cross-border flows of financial and intangible capital, as well as capital income, all of which as of today are reported in the bilateral positions of the Balance of Payments (BoP), resulting in double counting and the multiplication of bilateral linkages. To make a practical example, suppose that a multinational company residing in country A sets up a subsidiary in an OFC, country B, to invests in a third country C. Aggregate official statistics based on the residency principle will display twice the invested amount and show that country A is integrated with country B and country B is integrated with country C, while from an economic perspective we can say it is country A (meaning, the economy of the ultimate investor) to be integrated with country C, with B being an intermediary exerting little or no influence on the investment decision.

Depending on the question at hand, economists might need data that better reflect investment links between the ultimate origin and destination countries. For istance, Damgaard et al.

[3] Admittedly, some of these distortions are neither due to profit shifting tout court nor to illegitimate transactions, but to the role of OFCs in intermediating capitals in compliance with national and international regulations.

(2019) shows that, in gravity regressions for FDIs, including the characteristics of the ultimate investor economy rather than those of the immediate one yields larger coefficients on real explanatory variables such as market size and distance, and improves the overall fit of the model.[4] These problems are pervasive also for capital flows other than FDI and our understanding of several related issues in international macroeconomics and finance. Recently, the availability of detailed commercial data has made possible reassessing international investment positions data; using security-level data, Coppola et al. (2021) reconstructed the network of ultimate investors for portfolio investment revealing that developed markets hold larger bilateral debt investments towards emerging markets, including China, and standard datasets overstate the importance of sovereign relative to corporate bonds and understate the foreign currency share in the external liabilities of large emerging markets. Building on the same methodology, Beck et al. (2023) restate the pattern of Euro Area portfolio investment positions by linking fund sector investments to the ultimate investors and by associating security issuance with the ultimate parent firms to look through the intermediation activities of Luxembourg, Ireland and the Netherlands, finding that Euro Area financial integration is quantitatively and qualitatively different from what implied by official data. Their estimates show indeed that the Euro Area is less financially integrated with the rest of the world and exhibits more *home-* and *home-currency bias*.

Still, and despite policy efforts, official statistics mostly record investment flows on a residency basis and most available BoP statistics do not disentangle or reallocate flows that are solely driven by the existence of profit shifting opportunities from those that are triggered by countries truly investing in each others' economic and financial environments. The fourth edition of the OECD's Benchmark Definition of Foreign Direct Investment makes an effort in this direction, by recommending to compile investment positions by ultimate investor economy and distinguishing investment into Special Purpose Entities (SPEs) from that in resident operating units, but only a

[4]To be precise, this result is based on "real" FDIs estimated using the methodology discussed later on in this Section; if anything, it confirms that even after purging investment data of the part due to financial/arbitraging motives, it is important to distinguish the ultimate origin and destination of flows when assessing the strenght of economic ties.

few countries provide such information.[5]

This paper fills the gap in the measurement of such distortions for FDIs: we fit a model that estimates the probability that the bilateral FDI stock received by a given host country is real. We rely on a simple binary choice specification and assume that all FDIs involving pairs of non-OFCs are real, whereas all FDIs between pairs of OFCs are *phantom*, i.e. they do not reflect effective investment intentions in real terms. Our regression controls for a large set of variables that may well explain the real or phantom nature of direct investments in a gravity-like framework, and we show the model is capable of successfully classifying the two types of capital flows. Crucially, we use the estimated coefficients to compute the probability that FDIs in bilateral stocks between OFCs and non-OFCs are real, and we interpret those estimates as the share of real FDIs in existing investment stocks. By aggregating them, we obtain estimates for the amount of global real and phantom FDIs; using bootstrapping techniques, we are also able to explicitly illustrate the uncertainty surrounding our global phantom FDIs estimates.

Our results suggest that the share of phantom FDIs, after rising in 2010-15, stabilized at about 40% of total FDIs in recent years and that the share of phantom FDIs is systematically larger in OFCs, reconciling the evidence on the abnormal amount of FDIs recorded in these countries. For the subset of European countries reporting data on investment into SPEs to the OECD, we find that estimated and declared real FDIs are positively correlated, suggesting that our estimates are on average effective in capturing real economic integration across countries.

Our work relates strictly to the scant existing literature trying to estimate the amount of FDIs related to financial intermediation and regulatory arbitrage. Analogously to Damgaard et al. (2019), we reconstruct the network of global real FDIs. In their work, the authors exploit a clear relationship between the share of FDIs invested in SPEs - which they name phantom FDI - and the ratio of total FDIs on GDP in a subset of sixteen countries reporting the former distinction to the OECD. They then extrapolate the same relationship to the rest of the economies for which

[5]SPEs are identified as legal entities with no or few employees, no production in the host economy, little or no physical capital presence, their ultimate owners are foreign resident, their asset and liabilities are mostly vis-à-vis non resident and their core business consists of group financing or holding activities.

FDIs are available in the IMF Coordinated Direct Investment Survey (CDIS), estimating the global amount of real and phantom FDIs and relocate the former by the ultimate owner using the Orbis database when this information is absent in the OECD statistics.

Differently from Damgaard et al. (2019), instead of relying on a linear relationship documented for only a few countries, we take advantage of the full information retrievable from bilateral FDI positions reported to the CDIS and their determinants. It is in this spirit that we employ a gravity framework similarly to Delatte et al. (2022); in their paper, the authors quantify what they call abnormal FDI as the unexplained component of bilateral FDI stocks modelled in a two-steps gravity regression. The methodology allows them to disentangle artificial activity driven by country-specific factors (e.g. lenient tax and transparency environment) from unobserved determinants of bilateral stocks related to historical, geographic or institutional proximity between any pair of investing and investor countries (e.g. historical relationships beyond former colonial links). The key diffence between our approach and theirs stands in the way we treat the explanatory variable in the gravity model. By imposing our assumptions on the quality of FDI among different kind of country pairs (OFCs and non-OFCs), we aim to estimate the share of real (phantom) FDI directly instead of assuming a multiplicative relationship between real and phantom FDI (in dollars) as they do.[6] Despite the differences in the method, our estimate of the amount of global phantom FDI based on a simpler methodology and an extensive set of FDI determinants deliver results that are not substantially dissimilar to those of both Damgaard et al. (2019) and Delatte et al. (2022).

The rest of the paper is structured as follows: Section 2 briefly describes the dataset, Section 3 introduces our methodological approach, and Section 4 presents the main empirical results. Finally, Section 5 offers some conclusion and policy remarks.

[6] A third approach, based on the similarity between reconstructing ownership linkages in the presence of conduit jurisdictions and the theory of absorbing Markov chains, relies on a probabilistic-based methodology to reallocate FDI to ultimate investors in Casella (2019) and to ultimate hosting economies in Accoto et al. (2023).

2 Data

The data used in this paper consist of two main blocks. The first one includes statistics on bilateral FDI positions and is obtained from the Coordinated Direct Investment Survey (CDIS) of the IMF over the period 2009-2019. The CDIS provides information on inward FDI by country of origin and outward FDI by recipient country; the coverage of FDI positions in the CDIS is ample but limited to an average of around 110 countries per year, which nevertheless account for a very large share of the world GDP, approximately 95% at the end of 2019. Consistent with the empirical literature in this field, we improve the overall country coverage by using mirror statistics, i.e. for countries not reporting the FDI data we associate the specular value declared by the partner countries. As an example, Germany reports as confidential the 2019 inward FDI data from Indonesia, whereas Indonesia reports a 12 USD millions outward FDI to Germany; we therefore assume 12 USD millions to be the figure of the FDI flows from Indonesia to Germany.[7] The second block of data contains an extensive list of variables that can be reasonably adopted to disentangle FDI data into real and phantom components. To this purpose we resort to multiple sources and obtain a set of variables covering, among the others, macroeconomic conditions (e.g. gross debt positions to GDP, inflation rate, unemployment rate, exchange rate), trade agreements, corporate tax rates, as well as several social and institutional indicators (e.g. governance, rule of law, political stability, corruption). In our baseline model the total number of observations (i.e. cross-country and year combinations) is 83,293, while the number of regressors is 91; the full list of variables with the corresponding sources are reported in Table 1.

3 Methodology

Our empirical study fits in the gravity literature, but it is based on methodological assumptions that are different from the ones described in Delatte et al. (2022). There, the authors use a two-step model where they assume that the *logarithm* of FDIs equals the sum of a real component r, a

[7] We also provide further adjustments as suggested in Damgaard et al. (2019).

Table 1: Data and sources

Determinants	Source
Bureaucracy quality, civil disorder, civil war, composite risk rating, consumer confidence, contract viability, corruption, cross border conflicts, democracy accountability, economic risk taking, ethnic tensions, external conflict, financial risk rating, foreign pressures, government cohesion, government stability, internal conflict, investment profile, law & order, legislative strength, military in politics, payment delays, political risk rating, popular support, poverty, religious tensions, repatriation, socioeconomic conditions, terrorism, war	International country risk guide (ICRG) data
Governance indicators	World Bank
FX rates vs US$	Refinitiv
Corporate tax rates	Tax foundation available at https://taxfoundation.org/
Government overall balance (%GDP), gross debt (%GDP)	IMF Fiscal monitor database
Economic policy uncertainty (EPU) index	EPU website available at www.policyuncertainty.com
GATT membership, WTO membership, EU membership, existence of a regional trade agreement (RTA) between any pair of countries, type of RTA	CEPII dataset
Bilateral imports and exports	CEPII
Average tariff rate on manufactured goods	UNCTADSTAT

We use World Bank statistics on profit tax (% of commercial profits) for countries where the corporate tax rate is not available from the Tax foundation database. The exact definition of each variable is available from the authors upon request.

phantom component p, and a residual term to obtain estimates of country-and-time fixed effects for origin and destination countries (first step estimation); then, they use these fixed effects as dependent variables in a second step estimation to obtain country specific residuals that can be

used to retrieve shares of phantom FDI.[8]

On the contrary, our empirical strategy relies on simple specific assumptions about the characteristics of FDIs occurring across OFCs and non-OFCs. More precisely, we first acknowledge that bilateral stocks involving two OFCs have little chance to entail significant amounts of investment in the real economy. The opposite is true for pairs of non-OFCs, where little FDIs can be expected to stem from profit-shifting-related activities.[9] By imposing this assumption on our data, we define the following indicator:

$$y_{odt} = \begin{cases} 0 \text{ if both } o \text{ and } d \text{ are OFCs,} \\ \\ 1 \text{ if neither } o \text{ nor } d \text{ are OFCs.} \end{cases} \tag{1}$$

where y_{odt} is a dummy equal to 0 if both the origin *(o)* and the destination *(d)* countries are classified as OFCs and equal to 1 in the opposite case, i.e. when both outward and inward countries are non-OFCs. This allows to recast the problem of isolating the phantom and real component of total FDIs into a predictive binary choice model of the form:

$$\log \frac{P(y_{odt} = 0|\mathbf{X}_{odt})}{P(y_{odt} = 1|\mathbf{X}_{odt})} = \beta_0 + \boldsymbol{\beta}'\mathbf{X}_{odt}. \tag{2}$$

where $\mathbf{X}$ is the matrix of macroeconomic, social, and istitutional characteristics described in Section 2, including variables for both origin and destination countries and bilateral ones; in other words, we let the model learn from the underlying patterns that lead to a bilateral stock being real or phantom based on the type of interconnection across countries. Once we obtain parameter estimates, we can use them in a predictive exercise by applying the estimated coefficients on pairs of one OFC and one non-OFC, which incidentally are those where it is less clear whether and by

[8] In addition, Delatte et al. (2022) retrieve the dollar amount of phantom FDI by transforming the logarithm of FDI, assuming a multiplicative structure between the real and phantom FDI components in the exponential transformation, rather than an additive one.

[9] Although based on aggregate country-level data, there are plausible reasons to suspect that investment in OFCs and non-OFCs behave differently: the correlation between FDI liabilities and external financial assets in OFCs is about 6 times larger than in non OFC, and the correlation between FDI liabilities and assets is more than twice as large in the first group of countries than in the latter.

how much one should consider FDIs to be real or phantom. We then use those out-of-sample estimates as weights to be applied to the corresponding dollar amounts of FDIs, thereby obtaining estimates of real and phantom FDIs for all pairs for which we do have a complete set of regressors available.

Our data-rich framework allows us to obtain a very good classification of bilateral positions, but requires that for a country-time data-point to be included in the model, the whole set of regressors needs to be available, something that is not always warranted. In order to cover the largest share of observations and FDIs, we therefore implement additional steps. First, in all cases where a prediction $\hat{y}_{od,t-1}$ is not available while $\hat{y}_{odt}$ exists, we assume that $\hat{y}_{od,t-1} = \hat{y}_{odt}$ and apply this scheme recursively backwards. As an example, if the first available prediction dates back to 2014, we assume all previous phantom FDI probabilities to be the same as the one estimated for 2014.[10] Second, whenever no prediction is available for a given pair of countries where both are either OFCs or non-OFCs, we simply impose our modeling hypothesis and set the share equal to 0 and 1 respectively. Finally, we complement with Damgaard et al. (2019) estimates to fill in the remaining missing bilater FDIs. Once we obtain our set of predictions, we simply compute Real and Phantom FDIs as

$$\begin{aligned} \mathrm{R}_{odt} &= \hat{y}_{odt} \cdot \mathrm{FDI}_{odt}, \\ \mathrm{P}_{odt} &= (1 - \hat{y}_{odt}) \cdot \mathrm{FDI}_{odt}. \end{aligned} \tag{3}$$

Table 2 summarizes the steps of our empirical strategy and shows both the share of observations and FDIs that are covered after each step. As one can see, our model is fitted on almost 13% of observations which account for almost 28% of global FDIs, while out-of-sample estimates cover approximately a similar additional amount of FDIs; further assumptions to deal with country-time data gaps allow to complete the coverage of FDIs.

An important pre-requisite of our framework is the classification of countries as OFCs or non-OFCs. This is a crucial piece of information to distinguish between real and phantom FDIs,

[10] Conditional on a pair of countries, standard deviations of our predictions are extremely low (indeed, almost negligible) meaning estimated probabilities are very stable over time. This is reassuring as it means that using the first available estimate as compared to alternatives such as time-averages leads to almost identical results.

Table 2: Observations and FDIs covered

Steps	Description	Observations	FDIs
First	Model estimation	12.5	27.9
Second	Out-of-sample probability estimates	16.3	52.5
Third	Carry-back	27.6	60.0
Fourth	Missing pairs of OFCs/non-OFCs	68.8	75.4
Fifth	Damgaard et al. (2019)	71.8	100.0

The Table displays the shares of observations and total FDI covered at each step of the estimation; data are in percentage.

but relies on a country classification that is not univocal as the literature has proposed different taxonomies. Our choice is to define a country as OFC if it falls into at least one of the lists compiled by the OECD, the IMF, or Hines Jr and Rice (1994), with the exception of Israel and Japan which are listed as OFCs by the IMF but that we prefer to include into the non-OFCs; the resulting set of countries is reported in Table 3.

Table 3: List of countries treated as Offshore Financial Centers

Andorra	Gibraltar	Maldives	Saint Kitts and Nevis
Anguilla	Grenada	Malta	Saint Lucia
Antigua and Barbuda	Guam	Marshall Islands	Saint Vincent and the Grenadines
Aruba	Guernsey	Mauritius	Sainte-Lucie
Bahamas	Hong Kong	Micronesia	Samoa
Bahrain	Ireland	Monaco	San Marino
Barbados	Isle of Man	Montserrat	Seychelles
Belize	Jersey	Nauru	Singapore
Bermuda	Jordan	Netherlands	Switzerland
British Virgin Islands	Lebanon	Netherlands Antilles	Thailand
Cayman Islands	Liberia	Niue	Tonga
Cook Islands	Liechtenstein	Northern Mariana Islands	Turks and Caicos Islands
Curacao	Luxembourg	Palau	Uruguay
Cyprus	Macao	Panama	US Virgin Islands
Dominica	Malaysia	Philippines	Vanuatu

Figure 2 displays the evolution of the shares of FDI involving different country pairs and distinguishes across four different groups of host-investor combinations: $O - O$ (blue line) where

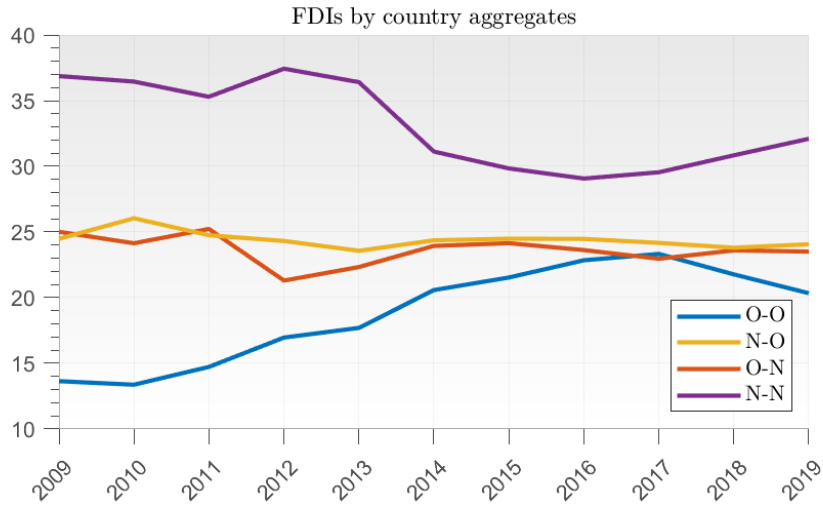

Figure 2: FDI by country groups. The Figure displays the shares of total inward FDI in country pairs o, d where both countries o (origin) and d (destination) can be either O (OFC) or N (non-OFC).

both the host and investor country are OFCs; $N-O$ (orange line), in which the host economy is a non-OFC while the investing one is an OFC and $O-N$ (red line) where the contrary is true, and $N-N$ (purple line) in which both countries are non-OFC.

The blue line shows that the share of investment between OFC has increased over time, rising from 13.6% in 2009 to above 20% in the most recent available years. During the same period, the share of what we assume being the most genuine form of investment, i.e. the one between countries that are not OFCs, has declined from 36.9% to 32.1%, but remains the largest component of the overall amount of FDIs. On the contrary, the share of FDI concerning pairs where a country is an OFC and the other is not, either on the investing or receiving side, has remained much more stable, at around 50%.[11]

4 Results

In this section, we present the main results of the methodological framework described in Section 3, and we particularly focus on the magnitude and dynamics of the phantom component of total

[11]For an extensive discussion of profit shifting practices that require the generation of FDIs to and from OFCs, see e.g. Anzuini et al. (2023).

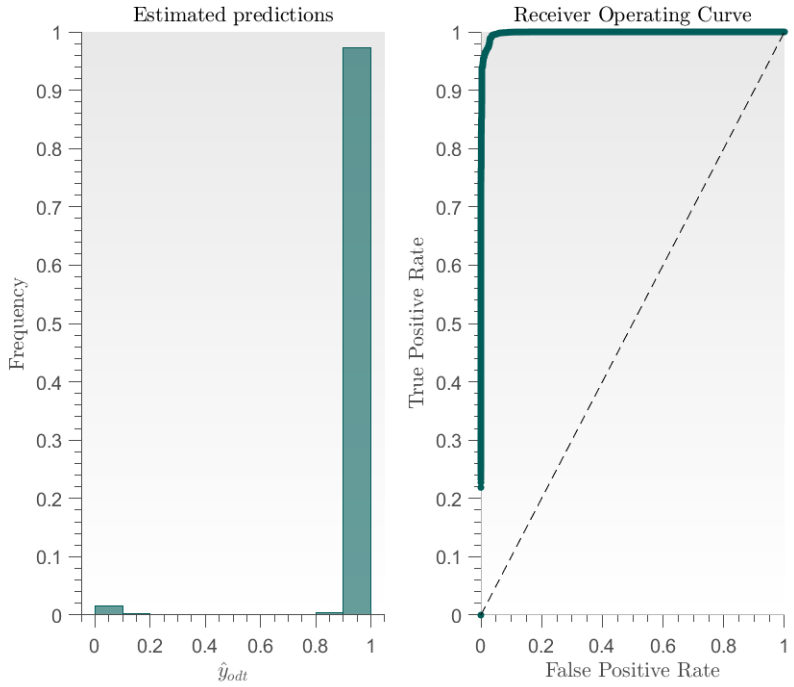

Figure 3: Model discrimination between OFC and non-OFC. The left plot displays the results of model classification between OFC and non-OFC, the right plot displays model performance in terms of ROC curve.

FDIs as is the one that is mainly responsible for distortions in the assessment of the extent of real integration across countries.

As we said, our approach relies on an extensive list of explanatory variables to characterize the traits of FDI flows across different country pairs, and we first display in Figure 3 some diagnostics on the ability of our model to correctly identify OFC vs non-OFCs. The left plot shows the performance of our model in terms of countries' binary classification and shows that the model has a clear gauge of which pairs of countries are OFCs and which are not. Most importantly, the right panel of Figure 3 plots the ROC curve and shows that this classification is most of the times starkingly correct as the farther the ROC curve is from the 45-degree line, the better the model performs with respect to a purely random classification. As is evident from the graph, the false positive rate is extremely low and our model is very effective in detecting OFCs.[12]

[12] As a robustness check we also estimate the model via elastic nets which should account for possible overfitting issues related to model over-parametrization. However, being the results with a penalized regression virtually indistinguishable from our baseline, we prefer reporting empirical findings obtained via a standard logit model which is an extremely simpler method and nevertheless ensures an exceptional performance in our setting.

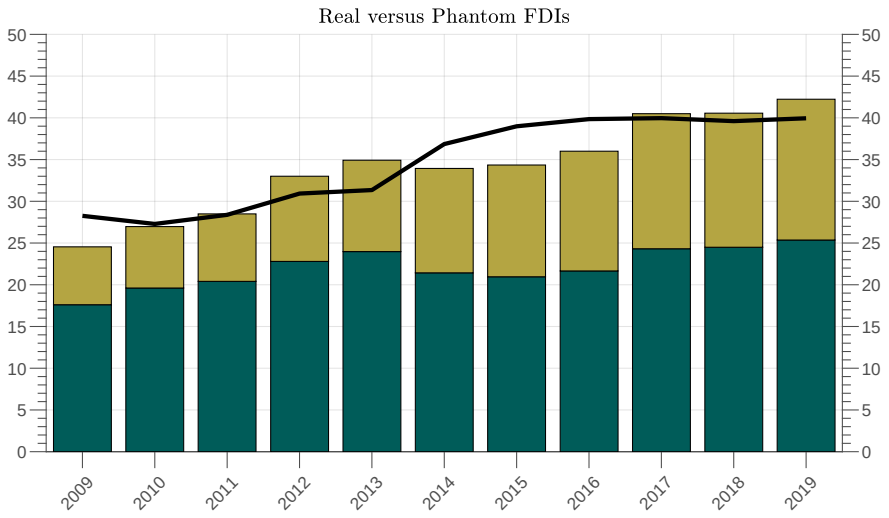

Figure 4: Real vs phantom FDI: time series dynamics. The Figure displays the breakdown of total FDI into real (green bars) and phantom (yellow bars) subcomponents measured in US$ trillions on the left axis. The black line depicts the dynamics of the share of phantom FDI (right axis).

Figure 4 displays the breakdown of global FDI into real and phantom subcomponents which is obtained by applying Equation 3 to model predictions. According to our estimates, global FDI amounted to $24.5 trillion in 2009 and gradually increased by 72% up to $42.2 trillion at the end of our sample. In 2009 the phantom component was $6.9 trillion and accounted for 28.2% of global FDI; the amount of phantom FDI nevertheless experienced a remarkable growth over time, reaching $16.9 trillion at the end of the sample (+143%). The share of phantom FDI moderately increased up to almost 40% in 2015, then stabilized around that value. The dynamics of the real component, our proxy of real economic integration, was much more subdued: from $17.6 trillion in 2009 to $25.4 trillion in 2019 (+44%). All in all, these findings corroborate our claim that the overall growth in global intermediated FDI should not be naively interpreted as an increase in cross-country real economic linkages. The period interested by the stabilization of the share of phantom FDI corresponds to a time during which policies aiming at contrasting profit shifting activies were implemented, like the OECD/G20 Base Erosion and Profit Shifting (BEPS) process and the 2017 Tax Cuts and Jobs Act in the United States. Interestingly, Garcia-Bernardo et al. (2022) and Wier and Zucman (2022) show that, despite these initiatives, global profit shifting did not decline between 2015 and 2019; the latter do not claim these measures were ineffective, but rather

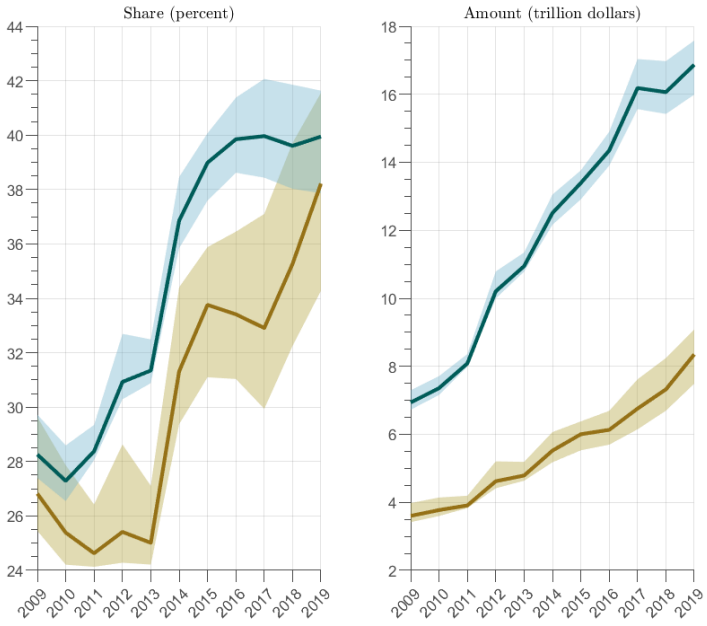

Figure 5: Phantom FDI. The left panel displays the dynamics of the global share of phantom FDIs (blue line) and the share of phantom FDIs involving exactly one OFC and one non-OFC (brown line). The right panel shows dollar amounts. Confidence intervals at 95% are displayed in shaded areas.

that, considering the growth of profit shifting in the preceding years, such policies might have at least stopped it.[13] Although it is outside the goal of this paper to establish any causal relation between the mentioned measures and FDI, it could be that our estimate of global phantom FDIs behaved analogously.[14]

In particular, the importance of OFCs in channeling phantom FDIs is displayed in Figure 5, both in terms of share (left plot) and overall amount (right plot); the blue line in the left plot reports the same percent estimate as the one in the previous figure but is also surrounded by a confidence interval, whereas the brown one provides estimated phantom FDIs existing between pairs of countries where one is an OFC while the other is not, as a share of total FDIs between the

[13] While Wier and Zucman (2022), building on the methodology developed in Tørsløv et al. (2022), focus more broadly on global profit shifting, Garcia-Bernardo et al. (2022) studies the effects of the Tax Cuts and Jobs Act on profit shifting by US companies using data up to 2020. Their results suggest that there was a small decline in the share of profits booked outside of the United States, largely driven by the repatriation of intellectual property to the United States by few large companies, and the Act did not affect the global allocation of profits by US firms, as the share of foreign profit booked in tax havens slightly fell but remained at a historically high level.

[14] As of June 2023, most of the countries we include in the list of OFCs participate in the OECD/G20 Inclusive Framework on BEPS.

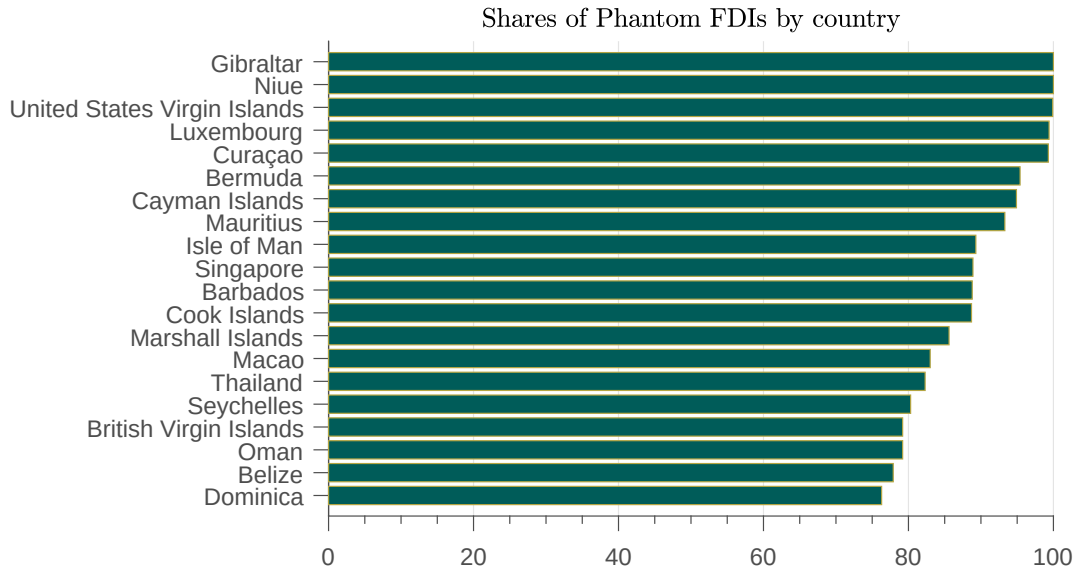

Figure 6: Top 20 countries in terms of share of phantom FDI. The Figure displays the top 20 countries in terms of phantom FDI.

same pairs of countries. The latter is interesting as bilateral FDIs between an OFC and a non-OFC are those which are not clearly a-priori real or phantom, and for which we indeed use our model to provide an answer. Our estimates thus suggest that the increase in phantom FDIs observed in the blue line is not solely driven by bilateral FDIs between OFCs, but also involves an increasingly higher share of investments featuring non-OFCs. Although the difference between the two shares has gone decreasing over time, the right panel shows that OFC intermediation with other OFCs has seen a steeper rise than the one related to OFC intermediation with non-OFCs.

A further evidence on the importance of OFCs for the network of global phantom FDI is displayed in Figure 6 where we present the top 20 countries in terms of share of phantom FDIs (%). Two results are worth emphasizing: first, all these countries are classified as OFC, according to at least one of the classifications adopted in this paper. Second, and possibly more interestingly, phantom FDI account for the largest part of total FDIs (on average 89.1% for countries in this graph), ultimately reconciling the evidence on the abnormal amount of recorded FDIs in some jurisdictions.

Figure 7 presents a scatter plot comparing estimated and declared real FDIs for a sample of

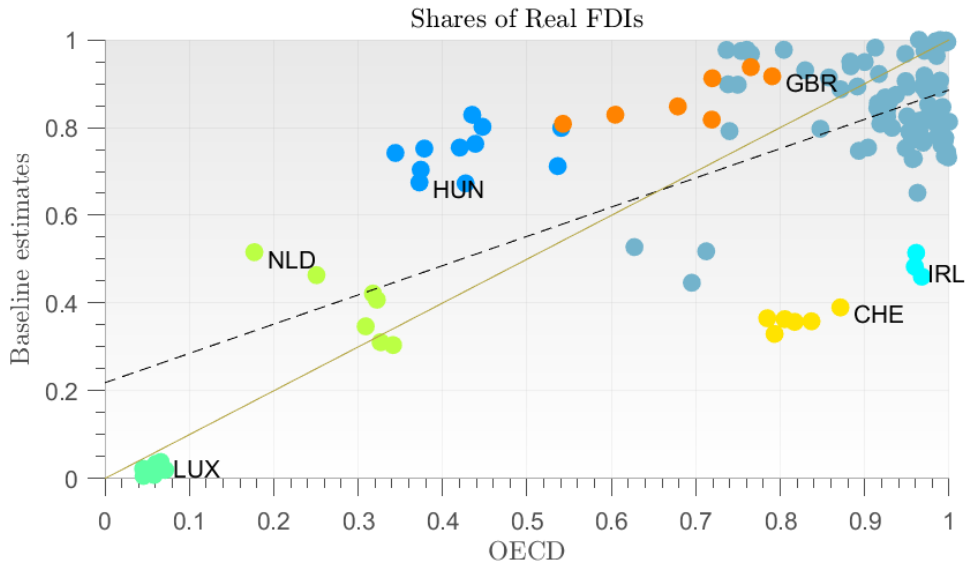

Figure 7: Real FDI: estimated vs declared. The Figure displays the comparison between estimated and declared real FDI for the sample of 18 (mostly European) OECD reporting countries; declared real FDI corresponds to FDIs in resident operating units (non-SPEs). Each dot on the scatter plot corresponds to a country/year observation. CHE=Switzerland, GBR=United Kingdom, HUN=Hungary, IRL=Ireland, LUX=Luxembourg, NLD=Netherlands. The brown line is the 45ï¿œ line, the dashed black line is a fitted linear regression.

OECD countries, i.e. for those countries for which a declared share of real FDIs, as proxied by investment in resident operating units - as opposed to SPEs, is available. The fitted regression line (dashed line in the graph) generally identifies a positive relationship between self-declared and estimated real FDIs; its slope is nevertheless smaller compared to the 45 degree line where all scatter points should ideally lie in case no phantom FDIs were in place. In turn, for some jurisdictions (e.g. Ireland and Switzerland) the graph emphasizes a remarkable larger amount of declared real FDIs compared to the corresponding share estimated by our model, whereas the opposite holds for Hungary and to a lesser extent for the United Kingdom and the Netherlands.

Finally, Figure 8 plots phantom-FDI-corrected estimates of inward FDIs from Figure 1. One can see that the role of OFCs in the real integration of economies is drastically reduced (with Luxembourg, Bermuda, British Virgin Islands, Cayman Islands and Singapore leaving the top positions), whereas countries that are better known to attract global investments emerge from previously-lower ranks (like Germany, India and Mexico).

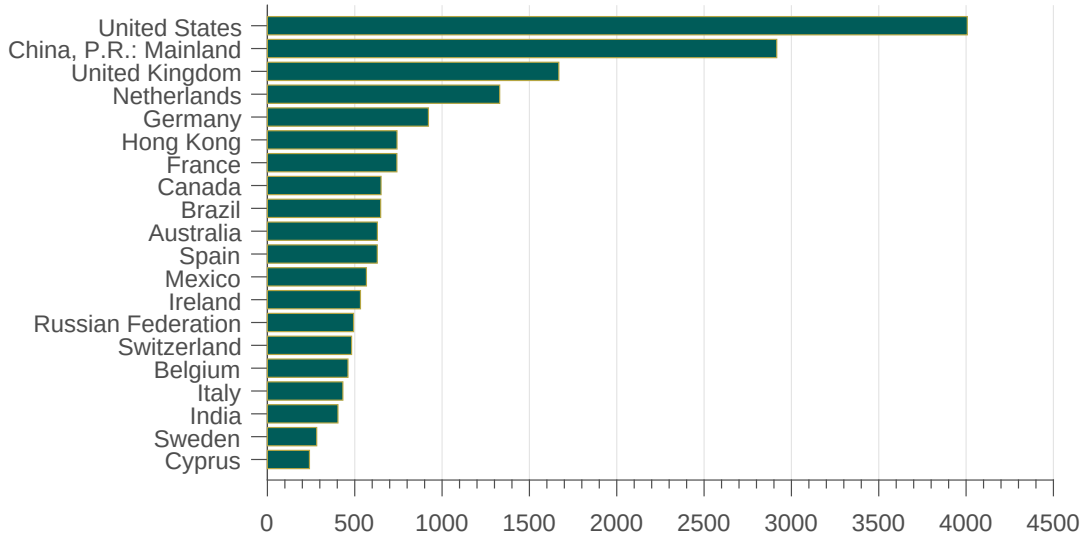

Figure 8: Real FDI by country. The Figure shows our estimates of real FDIs ranked according to our model, for the twenty economies with the largest stock as of 2019; millions of dollars.

5 Concluding remarks and policy implications

The availability of accurate and comparable FDI statistics is essential to reflect the true nature of investment flows. However, most available BoP statistics do not disentangle or reallocate flows that are solely driven by the existence of profit shifting opportunities from those that are triggered by countries truly investing in each others' economic and financial environments. In this paper, we explicitly tackle this issue by estimating a gravity-like binary model and retrieve an assessment of how much FDIs among OFCs and non-OFCs is real. Our estimates suggest that the share of phantom FDIs, after rising in 2010-15, stabilized at about 40% of total FDIs in recent years and that the share of phantom FDIs is systematically larger in OFCs, reconciling the evidence on the abnormal amount of FDIs recorded in these countries.

Our study confirms the anecdotal evidence on how cross-border investments can be largely inflated by fiscal and regulatory arbitrage opportunities and puts forward several policy implications. First, policymakers should promote greater transparency and the adoption of common standards in reporting financial data, as current practices may result in figures that do not accurately

tell apart the true nature of investment flows. Second, policymakers should focus on addressing the challenges posed by OFCs as these jurisdictions are found to account for the largest shares of phantom FDIs. This entails international cooperation efforts to overcome the lack of transparency and regulatory oversight, not only considering the activities of financial institutions, but also the role of non-financial actors such as multinational corporations as they can be largely responsible for complicated chains of cross-border investments. Lastly, policy strategies to boost FDI flows should enable conditions that promote stable and sustainable investments based on economic considerations rather than simply targeting total FDI flows, as this could underestimate the risk of volatile investment approaches.

References

ACCOTO, N., V. ASTUTI, AND C. CATALANO (2023): "A probabilistic method for reconstructing the foreign direct investments network in search of ultimate host economies," *Bank of Italy Occasional Papers n. 760*.

ANZUINI, A., E. PISANO, L. ROSSI, A. SANELLI, AND E. TOSTI (2023): "Clever Planning or Unfair Play? Exploring the Economic and Statistical Impacts of Tax Avoidance by Multinationals," *Bank of Italy Occasional Papers n. 799*.

BECK, R., A. COPPOLA, A. LEWIS, M. MAGGIORI, M. SCHMITZ, AND J. SCHREGER (2023): "The Geography of Capital Allocation in the Euro Area," Tech. rep.

BOLWIJN, R., B. CASELLA, AND D. RIGO (2018): "An FDI-driven approach to measuring the scale and economic impact of BEPS," *UNCTAD Transnational Corporations Journal*.

CASELLA, B. (2019): "Looking through conduit FDI in search of ultimate investors–a probabilistic approach," *Transnational Corporations*, 26, 109–146.

COPPOLA, A., M. MAGGIORI, B. NEIMAN, AND J. SCHREGER (2021): "Redrawing the Map of Global Capital Flows: The Role of Cross-Border Financing and Tax Havens," *The Quarterly Journal of Economics*, 136, 1499–1556.

DAMGAARD, J., T. ELKJAER, AND N. JOHANNESEN (2019): "What is Real and What is Not in the Global FDI Network?" *IMF Working Paper N. 19/74*.

DELATTE, A.-L., A. GUILLIN, AND V. VICARD (2022): "Grey zones in global finance: The distorted geography of cross-border investments," *Journal of International Money and Finance*, 120.

GARCIA-BERNARDO, J., P. JANSKÃŒ, AND G. ZUCMAN (2022): "Did the Tax Cuts and Jobs Act Reduce Profit Shifting by US Multinational Companies?" NBER Working Papers 30086, National Bureau of Economic Research, Inc.

HINES, J. R. (2010): "Treasure Islands," *Journal of Economic Perspectives*, 24, 103–126.

HINES JR, J. R. AND E. M. RICE (1994): "Fiscal paradise: Foreign tax havens and American business," *The Quarterly Journal of Economics*, 109, 149–182.

LANE, P. AND G. M. MILESI-FERRETTI (2001): "The external wealth of nations: measures of foreign assets and liabilities for industrial and developing countries," *Journal of International Economics*, 55, 263–294.

——— (2007): "The external wealth of nations mark II: Revised and extended estimates of foreign assets and liabilities, 1970-2004," *Journal of International Economics*, 73, 223–250.

——— (2018): "The External Wealth of Nations Revisited: International Financial Integration in the Aftermath of the Global Financial Crisis," *IMF Economic Review*, 66, 189–222.

TØRSLØV, T. R., L. S. WIER, AND G. ZUCMAN (2022): "The Missing Profits of Nations," Tech. rep.

WIER, L. AND G. ZUCMAN (2022): "Global profit shifting, 1975–2019," *NBER working paper*, 2022.