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## The Impact of Gray-Listing on Capital Flows: An Analysis Using Machine Learning

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# The Impact of Gray-Listing on Capital Flows: An Analysis Using Machine Learning

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**Abstract**

The Financial Action Task Force's gray list publicly identifies countries with strategic deficiencies in their AML/CFT regimes (i.e., in their policies to prevent money laundering and the financing of terrorism). How much gray-listing affects a country's capital flows is of interest to policy makers, investors, and the Fund. This paper estimates the magnitude of the effect using an inferential machine learning technique. It finds that gray-listing results in a large and statistically significant reduction in capital inflows.

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# Contents

# 1 Introduction

This paper examines what happens to a country's capital flows after it is identified in the Financial Action Task Force (FATF)'s list of countries or jurisdictions with strategic deficiencies in their framework for Anti-Money Laundering/Combating the Financing of Terrorism (AML/CFT). The list of countries with such deficiencies is known as the gray list. How much gray-listing affects a country's capital flows is of interest to policy makers and investors. It is also of interest to the Fund in relation to country surveillance, prioritizing capacity development effort, and in relation to forecasts of demand for Fund-supported programs and estimates of capacity to repay.

The FATF maintains two public lists of countries with weak AML/CFT regimes: "jurisdictions under increased monitoring" that "are actively working with the FATF to address strategic deficiencies in their regimes"[1] and "high-risk jurisdictions subject to a call for action" that are not actively engaging with FATF to address these deficiencies.[2] The former is known as the gray list and the latter as the blacklist.

As of now there are only two countries on the blacklist—Iran and North Korea—whereas there are nineteen on the gray list—Albania, Barbados, Botswana, Burkina Faso, Cambodia, Cayman Islands, Ghana, Jamaica, Mauritius, Morocco, Myanmar, Nicaragua, Pakistan, Panama, Senegal, Syria, Uganda, Yemen, and Zimbabwe.[3] Countries that are not currently on the gray list could be gray-listed in the future as the process is ongoing and the FATF standards are periodically updated. Appendix A describes the gray-listing process.

For a country on the blacklist, FATF calls on other countries to apply enhanced due diligence and countermeasures, increasing the cost of doing business with the country and in some cases severing business relations altogether. Even countries placed on the gray list could experience a disruption

[1] http://www.fatf-gafi.org/publications/high-risk-and-other-monitored-jurisdictions/documents/increased-monitoring-february-2021.html.

[2] http://www.fatf-gafi.org/publications/high-risk-and-other-monitored-jurisdictions/documents/call-for-action-february-2021.html.

[3] Based on the FATF announcement in February 2021.

in capital flows. One possible mechanism is de-risking, whereby banks exit relationships with customers that are based in high-risk countries to reduce compliance costs (Alleyne et al., 2017; Collin, Cook, and Soramaki, 2016). Another is market enforcement, whereby investors use gray-listing as a heuristic for evaluating the risk of doing business with a country, and therefore reallocate resources to reduce their exposure to the country (Morse, 2019).

Nevertheless, the empirical evidence for these effects is weak. There have only been a few studies, some of which found little or no effect.

Kudrle (2009) searches for the impact of gray-listing on cross-border bank flows in 38 tax havens over the period 2000 to 2007. Using the jurisdiction's share in the total value of the corresponding Bank for International Settlements (BIS) category for Offshore Centers as a dependent variable, he finds little systematic effect of gray-listing.

Farias and de Almeida (2014) examine the impact of gray-listing on the ability to attract and retain FDI in a sample of 36 Latin America and Caribbean countries (of which 7 were gray-listed) over the period 2000 to 2006. They find a significant but small reduction in the ratio of FDI to GDP (on average, 0.3–0.4 percentage points).

Balakina, D'Andrea, and Masciandaro (2016) examine how cross-border bank flows respond to gray-listing in a sample of 126 countries (of which 29 have been gray-listed) over the period 2000 to 2015. Using annual growth of total foreign claims (i.e., net bank flows) from BIS data, they find no consistent effect of gray-listing. However, when total foreign claims are split between bank outflows (growth in total foreign assets) and inflows (growth in total foreign liabilities), they find a small but statistically significant increase in outflows (about 23 percent a year on average while on the gray list) but not in inflows.

Collin, Cook, and Soramaki (2016) examine the effect of gray-listing on cross-border payments to and from countries. Using SWIFT monthly numbers of cross-border payments between customers in every country connected to the SWIFT network between 2004 and 2014 and linking these numbers with data on the timing of gray-listing, they find that being added to the gray list results in a 7–10 percent reduction in the number of payments sent to an affected country by the rest of the world. But they find that it has no consistent effect on the number of payments sent from an affected country. They also find no evidence of reduction in bilateral payments between gray-listed countries.

Finally, Morse (2019) analyzes the effect of gray-listing on bank inflows (growth in cross-border liabilities) for 39 countries (10 of which were gray listed) in 2010–2015 and finds a large significant impact on the bank inflows of around 15–16 percent.

This paper contributes to the literature on the effect on gray-listing on capital flows in three ways. First, to the best of our knowledge, this is the first study that looks at the impact of gray-listing on all components of capital flows: FDI, portfolio flows, and banking and other flows. Second, it uses more recent data on gray-listing and includes a larger sample of gray-listed countries. Third, to the best of our knowledge, this is also the first study that studies the problem using machine learning.

More specifically, the paper analyzes the impact of gray-listing on capital flows in a sample of 89 emerging and developing countries in 2000–2017. We use quarterly data on capital flows from the IMF Financial Flows Analytics (FFA) database. The data on gray-listing come from FATF public statements, which are issued three times a year (February, June, and October) and FATF annual reports. During this period, 78 countries have been gray-listed at least once (not all of them remain in the estimation sample due to missing values). For empirical execution, we use a machine learning technique known as lasso.

The paper finds a large, significant negative effect of gray-listing on capital inflows. The empirical results suggest that capital inflows decline on average by 7.6 percent of GDP when the country is gray-listed. The results also suggest that FDI inflows decline on average by $-3.0$ percent of GDP, portfolio inflows decline on average by $-2.9$ percent of GDP, and other investment inflows decline on average by $-3.6$ percent of GDP. The estimated impacts are all statistically significant.

The remainder of the paper is organized as follows. Section 2 presents stylized facts, using an event study approach to describe how capital flows evolved around the time of gray-listing. Section 3 discusses the intuition behind the lasso technique and applies it to the estimation of the impact of gray-listing on capital flows. Section 4 presents robustness checks. Section 5 concludes.

## 2 Event Analysis

We use an event history analysis (e.g., see Gourinchas and Obstfeld, 2012) to explore the evolution of capital flows around the time of gray-listing in affected countries. Formally, we estimate the following fixed-effect panel regression:

$$y_{i,t} = \alpha_i + \gamma\lambda_t + \sum_s \beta_s \delta_{s,t} + \varepsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is capital flows for country $i$ in time $t$; $\alpha_i$ is a country fixed effect, $\lambda_t$ is a dummy variable that equals 1 in each quarter during the global financial crisis (GFC) and 0 otherwise, and $\delta_{s,t}$ is a dummy variable that equals 1 when a country $i$ is $s$ periods away from gray-listing in time $t$. We set $s$ to nine quarters (four quarters before, four quarters after) to see how capital flows evolve before and after gray-listing. The country fixed effect ($\alpha_i$) measures the average capital flow for a country $i$ in periods outside the GFC and the gray-listing event ("tranquil times"). The coefficient $\gamma$ measures the average deviation of capital flows in country $i$ in each quarter during the GFC. The coefficient $\beta_s$ captures how capital flows evolved within an $s$-quarter window surrounding gray-listing. The error $\varepsilon_{i,t}$ captures all the remaining variation in the capital flows.

The data on capital flows come from the IMF's FFA database, which provide quarterly data on FDI, portfolio flows (debt and equity), and other investments (private, official, bank, and non-bank) on a gross basis (inflows and outflows) and a net basis. The data are available in both nominal terms (i.e., in millions of USD) and as a share of (quarterly) GDP. We use the latter for this analysis. Our focus is on the sample of 89 emerging and developing countries (EMDCs) for which the data are available for the period between

2000q1 and 2017q4.[4] See appendix B for the list of countries. The list of EMDCs is taken from the World Economic Outlook (WEO) in 2000, to which we add nine EMDCs not included at the time (Afghanistan, Brunei Darussalam, Iraq, Korea, Kosovo, Liberia, Montenegro, Serbia, and Timor-Leste) and six advanced economies (Greece, Hong Kong, Iceland, Ireland, Israel, and Singapore) mainly for the purpose of maintaining a reasonable sample size.[5] We exclude China from the analysis because of its unique characteristics including its size. Extreme values in capital flows are also excluded from the data before running the model in equation (1).[6]

The dates of gray-listing come from FATF public statements, issued three times a year (currently in February, June, and October) and FATF annual reports, and are provided in Appendix A. As explained in the appendix, the timing of the news does not necessarily follow an automatic calendar because gray-listing is an outcome of a case-by-case evaluation process that is subject to debate and repeated extensions. Moreover, some types of capital flows may respond to the announcements more quickly than others (Becker and Noone, 2008).

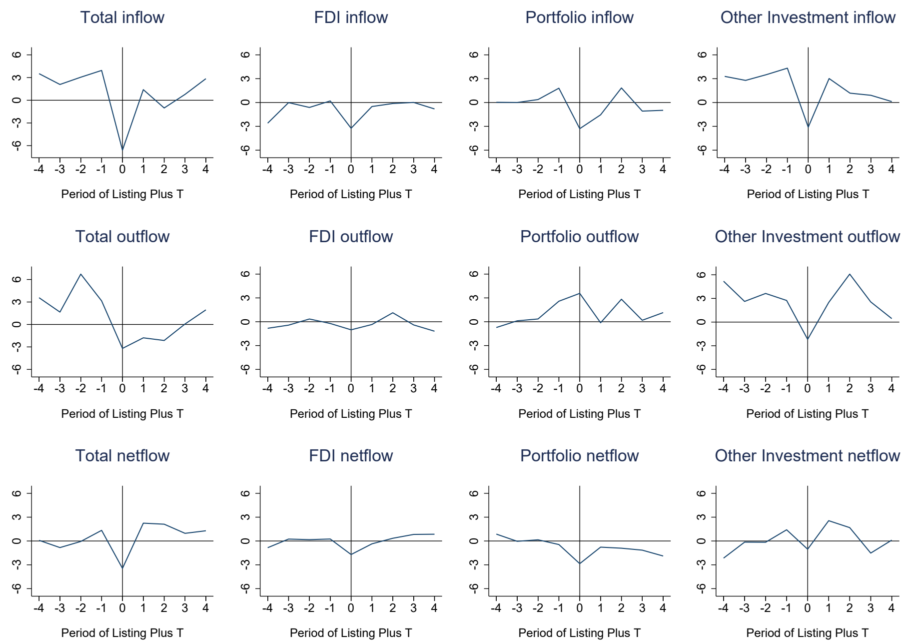
To capture responses of capital flows to an event, the exact timing of which is uncertain, we follow the approach in the literature (e.g., Bussiere and Fratzscher, 2006, Gourinchas and Obstfeld, 2012, and more recently, Choi and Hashimoto, 2017) and define the event as a window $[t_0 - k, t_0 + k]$, where $t_0$ is a date of the FATF announcement and $k$ is allowed to vary

[4]Unavailability of quarterly data on GDP constrains the sample size. In the FFA, the data on quarterly capital flows are available for 121 EMDCs but the data on quarterly GDP are available only for 81, of which 34 have been gray-listed. We therefore supplement the quarterly GDP data for 8 more gray-listed countries using data from the IFS and Haver: for Tajikistan using the available quarterly GDP data from Haver; for Angola, Bangladesh, Nepal, and Trinidad and Tobago using estimated quarterly GDP based on the quarterly industrial production data from the IFS; and for Pakistan, Panama, and Venezuela using estimated quarterly GDP based on the quarterly industrial production data from Haver. The estimation of quarterly GDP follows the Chow-Lin method (see Chow and Lin, 1971).

[5]Given their size or their economic structure, capital flows in these countries can be influenced to a greater degree by similar forces as those in EMDCs.

[6]Detection of extreme values are based on the fixed-effect (within) transformation, $\ddot{y}_{it} = (y_{it} - \bar{y}_{it})$, where $\bar{y}_{it} = \frac{1}{T}\sum_{t=1}^{T} y_{it}$, and defined as those that lie outside the whiskers of the generalized box plot that adjusts for asymmetry and skewness in the distribution of $\ddot{y}_{it}$. See Bruffaerts et al (2014).

Figure 1: Evolution of Capital Flows Around Gray-Listing (Percent of GDP)




The figure presents results from estimation of the fixed-effect panel regression in equation (1) on quarterly data between 2000q1 and 2017q4. Each heading corresponds to the dependent variable in the model. The estimates of conditional means of each variable are reported on the vertical axis. The horizontal axis represents the number of quarters before (negative sign) and after a shock. Excludes extreme values. See text for detail.

between 1 and 3 quarters.[7] Figures 1 and 2 plot the estimates of $\beta_s$ in equation (1) for each type of capital flow.

Capital inflow declines sharply at time of gray-listing (Figure 1). Gross inflow is on average over 6 percentage points of GDP lower compared to the historical norms. All components of capital inflow experience a decline at the time of gray-listing. FDI inflow, on average, declines by 3.2 percent of GDP, portfolio inflow by 3.3 percent of GDP, and other inflow by 3.1 percent

[7] For example, Gourinchas and Obstfeld (2012) define the timing of banking, currency, and financial crisis using a window, where $k$ is allowed to vary between 1 to 3 years; Choi and Hashimoto (2017) define the timing of data transparency policy reform using an event window in which $k$ is allowed to vary between 1 to 4 quarters.

of GDP. Although the magnitude of the decline is similar for both FDI and portfolio inflows, dynamics around the time of gray-listing show that portfolio flows tend to be more sensitive and prone to reversal after a shock, which is in line with the conventional wisdom (Becker and Noone, 2008).

Looking at the behavior of capital outflows, gross outflow declines, on average by around 3 percentage points at the time of gray-listing, which partially offsets the drop in gross infows.[8] However, there is a surge in capital outflow a few quarters ahead of the announcement. Such behavior is well-documented in the literature and consistent with information asymmetry, where domestic investors know more about the country than foreign investors.[9]

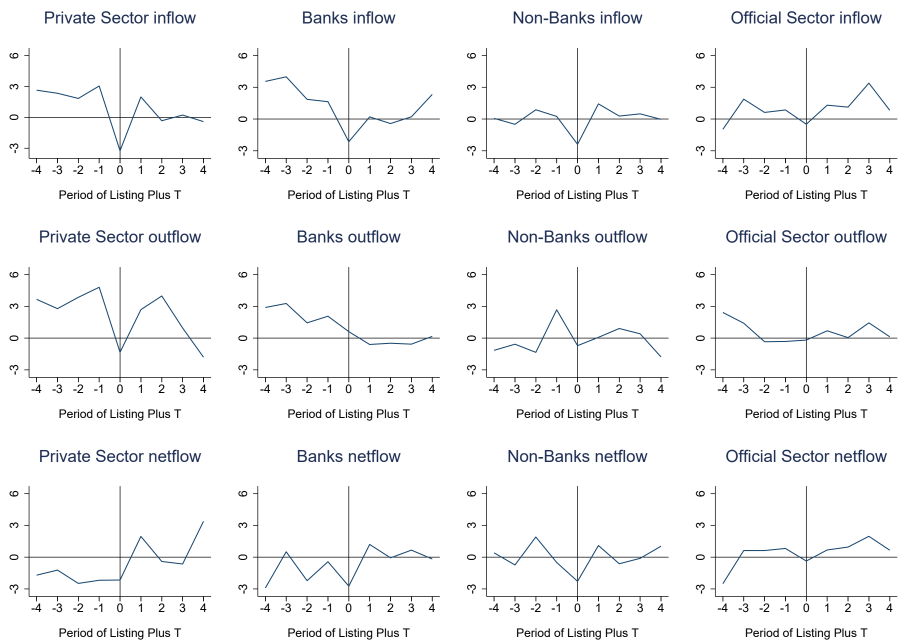
Figure 2 shows components of "other" investment flows, which consist of interbank loans, suppliers' credits, trade credits, and other more difficult to classify items. On average, their inflows decline by 2 to 3 percent of GDP (Figure 2). Inflows in the private sector are more severely affected (−3.3 percent of GDP) than those in the official sector (−0.5 percent); bank flows are somewhat less affected (−2.1 percent) than nonbank flows (−2.4 percent). We, again, observe the anticipatory behavior in the outflows, which seem to increase few periods ahead of the announcement of gray-listing, especially among private sector flows (both bank and non-bank).

What explains the V-shaped recovery after the initial fall in capital inflow? A possible explanation is that the initial decline in capital flow represents an "overshooting" and is followed by a period of large volatility because of incomplete information and learning by foreign investors (Bacchetta and van Wincoop, 2000). Gray-listing creates a large degree of uncertainty, especially in the early period, when foreign investors are unsure about how domestic firms will cope and how other investors will respond in the new environment. Using a theoretical model and simulations, Bacchetta and

[8] Such offsetting behavior is well-documented in the literature. See for example, Broner et al. (2013) and Forbes and Warnock (2012).

[9] A substantial literature has documented such information differences between domestic and foreign agents. See, for example, Tille and van Wincoop (2014) and IMF (2013). Broner et al. (2013) also report similar empirical evidence showing that gross capital outflows start rising ahead of a crisis when the crisis originates domestically.

Figure 2: Evolution of Components of Other Flows Around Gray-Listing (Percent of GDP)




The figure presents results from estimation of the fixed-effect panel regression in equation (1) on quarterly data between 2000q1 and 2017q4. Each heading corresponds to the dependent variable in the model. The estimates of conditional means of each variable are reported on the vertical axis. The horizontal axis represents the number of quarters before (negative sign) and after a shock. Excludes extreme values. See text for detail.

van Wincoop (2000) show that in such an environment capital flow could overshoot in response to news and then fluctuate widely in early periods as investors update their perceptions.

Another question is whether the decline in capital flow is genuine or if it merely reflects migration of capital to informal channels? To see this we re-run the equation (1) using net errors and omissions as the dependent variable. The result is reported in Appendix C. Net errors and omissions show a slight increase at time of gray-listing, but not as much to fully explain the extent of declines in capital inflow, suggesting that while some of the declines are explained by diversion of the inflow to shadow (informal) flows, much of the declines in capital inflows are a genuine decline.

# 3 Econometric Analysis

The event history analysis in the previous section shows that gray-listing is associated with a sharp decline in capital inflow. While suggestive, the analysis does not allow us to attribute all or even most of the decline to gray-listing, because other factors may also be driving the results. That is, there are many possible confounding factors. In order to isolate and estimate the treatment effect of gray-listing, we need to use a regression analysis to control for the confounding factors.

## 3.1 Methodology

We estimate a simple model of capital flow:

$$y_{i,t} = \alpha d_{i,t} + \mathbf{x'}_{i,t}\beta + \mu_i + \varepsilon_{i,t}, \quad i = 1, \ldots, n; \; t = 1, \ldots, T \qquad (2)$$

where $d_{i,t}$ is the causal variable of interest or treatment effect, $\mathbf{x}_{i,t}$ is the set of controls or confounding factors, $\mu_i$ is a country fixed effect, and $\varepsilon_{i,t}$ is the error.

There is potentially a large number of confounding factors. According to the literature on the determinants of capital flows (including sudden stops or capital reversals), there are two broad categories of factors that need to be accounted for—global and domestic. The global factors are included to account for important co-movements in capital flows across emerging and developing economies. Commonly used variables for this purpose include VIX (as a proxy for global risk aversion), changes in money supply of major advanced economies (as a proxy for global liquidity), growth rates of major advanced economies (as a proxy for the strength of the global economy and perhaps investors' risk appetite), and the Federal Funds Rate (to account for the special role of the U.S. dollar as a source of liquidity to the global financial system). The domestic factors are country-specific factors that may explain differences across countries in capital inflows. Commonly used variables for this purpose include the level of per capita income, real GDP growth, trade openness, financial openness, the exchange rate regime, exchange rates, foreign reserves, current account balances, bank credit, and sovereign credit ratings.

The large number of potential confounding variables poses a challenge to model selection and estimation. First, where there are many potential confounding variables, it is likely that only some of them are relevant, but empirical studies often do not agree because of their differences in data, models, methodology, as well as researchers' preoccupations. Second, there is a problem of estimation. Including too many variables in the regression leads to inefficiency; because variables tend to be highly correlated with each other, they need to be included parsimoniously (Eichengreen and Gupta, 2016). Yet failing to control for key confounders leads to omitted variable bias. Third and finally, there is a problem of saturation (or "high dimensionality"). It is possible that the influence of these variables is nonlinear and that there are important interactions effects. But using several permutations of each variable—such as levels, lags, differences at various horizons, and polynomials—or including all pairwise interactions and temporal and spatial effects would be infeasible as it would quickly run into a problem of degrees of freedom.

Faced with these dilemmas, economists are increasingly using machine learning for model selection and estimation. The proposed estimation strategy in this paper is lasso.[10] Lasso is probably the most familiar machine learning technique among economists (Mullainathan and Spiess, 2017). As such, it has a relatively well-developed literature on the statistical properties of its estimates. In the current context, it has the following attractive properties.

First, it is a straightforward extension of linear regression but is good at dealing with the dimensionality problem. Just like ordinary least squares (OLS), lasso minimizes the sum of squared deviations between observed and model predicted values. Unlike OLS, to achieve a dimension reduction, lasso imposes a penalty on model complexity by limiting the sum of the absolute values of the coefficients and forces all but the most important ones to zero. Simply put, lasso does the model selection for us by systematically selecting the most important features and throwing out others that contribute little to the model's fit (Ahrens, Hansen, and Schaffer, 2019).

Second, it allows causal interpretation of the estimated coefficients for a subset of variables. Since the primary purpose of most supervised machine learning techniques is prediction, the techniques usually do not produce estimates that can be interpreted as causal (Tiffin, 2019). Similarly, lasso, in general, does not produce unbiased estimates of coefficients and standard errors required to perform valid inference.[11] However, an extension of lasso, known as double-selection lasso (Belloni, Chernozhukov, and Hansen, 2014a; Urminsky, Hansen, and Chernozhukov, 2016), addresses the problem by adopting a modified estimation procedure and generates unbiased coefficients and standard errors for a subset of variables that are suitable for making causal inferences.

[10] Developed by Frank and Friedman (1993) and Tibshirani (1996). While lasso originally stood for least absolute shrinkage and selection operator, today it is considered a word and not an acronym and encompasses other machine learning algorithms based on similar principles, such as ridge and elastic-net.

[11] This is because lasso, by selecting the covariates based on their ability to predict the outcome subject to constraints on model complexity as described above, may not select the "true" model (i.e., the data-generating process or DGP). And there is a possibility that the regularization excludes some variables that belong in the DGP and a correlation between them and variables included in the model can create bias in the estimated coefficients (i.e., omitted variable bias).

Finally, a recent paper by Belloni, Chernozhukov, and Hansen (2014a) provides a panel data extension of double-selection lasso, accommodating common forms of within-group correlation and heteroskedasticity in errors expected in a panel data context.

### 3.2 Model

Formally, for the general model

$$y_i = \mathbf{x'}_i\beta + \varepsilon_i, \quad i = 1, \ldots, n \tag{3}$$

lasso finds a vector of coefficients, $\beta$, such that

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \mathbf{x'}_i\beta)^2 + \lambda\sum_{j=1}^{p}|\beta_j| \tag{4}$$

is minimized for a given value of $\lambda$. The last term distinguishes lasso from OLS: there is a cost to including many regressors and we can reduce the objective function by setting $\beta_j = 0$ for variables that contribute little to the fit. Thus, lasso does the model selection for us.[12] The parameter $\lambda$ is called a tuning parameter, which controls the overall penalty level. The larger is $\lambda$, the more coefficients are shrunk to zero. If $\lambda = 0$ we have an

[12] How does lasso's feature reduction compare with successively reducing the number of insignificant controls using OLS (i.e., the general-to-specific approach)? Ahrens, Hansen, and Schaffer (2018) note that the latter approach tends to be more vulnerable to "pre-test bias", "researcher degrees of freedom", and "p-hacking". Pre-test bias refers to nonindependence of successive test statistics in sequential hypothesis testing in econometric modeling (Giles and Giles, 1993); researcher degrees of freedom refers to many decisions available to researchers in model selection (e.g., which variables to include or exclude, whether to combine or transform variables, which alternative specifications to be compared and tested, etc.); and p-hacking refers to researchers exploring various analytical alternatives to search for a combination that yields significant results and to report only what worked (Simmons, Nelson, and Simonsohn, 2011). Ahrens, Hansen, and Schaffer (2018) also compare model-selection and performance of lasso against a "kitchen sink" OLS (includes all regressors) and a "step-wise" OLS (begin with general model and drop if p-value below 0.05). They found that the kitchen-sink OLS suffered from "classical" symptoms of overfitting, with lowest in-sample RMSE (root-mean-square errors) and worst out-of-sample prediction; and the step-wise OLS suffered from biased (over-sized) coefficients, inflated R-squared, and invalid p-values; while lasso-based models, in contrast, had generally superior in-sample and out-of-sample performance.

OLS regression (Ahrens, Hansen, and Schaffer, 2019 and Fonti and Belitser, 2017).

Lasso estimator can also be written as

$$\hat{\beta}_{\text{lasso}}(\lambda) = \arg\min_{\beta} \frac{1}{n} \sum_{i=1}^{n} (y_i - \mathbf{x'}_i \beta)^2 + \frac{\lambda}{n} \sum_{i=1}^{p} \psi_j |\beta_j| \tag{5}$$

where $\lambda$ is the tuning parameter that controls the overall penalty level as before and $\psi_j$ are predictor-specific penalty loadings. The latter are predictor-specific to account for the fact that the predictors $x_j$ are not of equal variance. Under a homoskedasticity assumption, lasso sets the penalty loading to

$$\psi_j = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_{i,j}^2} \tag{6}$$

In order to allow for valid inference on the coefficient of a variable of interest (in our case, the dummy variable for gray-listing), we follow the double-selection approach developed by Belloni, Chernozhukov, and Hansen (2014a). Rewriting equation (3), we split the vector $\mathbf{x_i}$ into a variable of interest, $d_i$, and other controls:

$$y_i = \beta_0 d_i + \beta_1 x_{i,1} + \cdots + \beta_p x_{i,p} + \varepsilon_i \tag{7}$$

We want to be able make a valid inference on the parameter $\beta_0$. The double-selection approach estimates the equation (7) in three steps:

1. Use lasso to estimate $y_i$ on $x$'s without $d_i$. Denote the set of lasso-selected controls by A.

2. Use lasso to estimate $d_i$ on $x$'s. Denote the set of lasso-selected controls by B.

3. Estimate the following equation using OLS:

$$y_i = \beta_0 d_i + \mathbf{w}_i' \beta + \varepsilon_i \tag{8}$$

where $\mathbf{w}_i = A \cup B$, i.e., the union of the selected controls from Steps 1 and 2 (Ahrens, Hansen, and Schaffer, 2018). Thus, the double-selection approach first uses lasso to select covariates correlated with the outcome ($y_i$), and second, uses lasso to select covariates correlated with the treatment ($d_i$). By taking the union of both sets of covariates and including them as controls in a standard OLS regression (in the third stage), it takes account of the joint association that is the source of bias for the treatment effect (Belloni, Chernozhukov, and Hansen, 2014a.)

Finally, the panel data extension of double-selection lasso developed by Belloni et al. (2014b) extends the general model to the panel framework:[13]

$$y_{i,t} = x_{i,t}'\beta + \alpha_i + \varepsilon_{i,t}, \quad i = 1, \ldots, n; \; t = 1, \ldots, T \tag{9}$$

Eliminating the fixed effects by subtracting the individual specific intercept leads to the "within model":

$$\ddot{y}_{i,t} = \ddot{x}_{i,t}'\beta + \ddot{\varepsilon}_{i,t} \tag{10}$$

where $\ddot{x}_{i,t} = x_{i,t} - \frac{1}{T}\sum_{t=1}^{T} x_{i,t}$. The coefficient estimate is defined by the solution to the penalized minimization problem of the within model:

$$\hat{\beta}_{\text{lasso}}(\lambda) = \arg\min_{\beta} \frac{1}{nT} \sum_{i=1}^{n} \sum_{t=1}^{T} (\ddot{y}_{i,t} - \ddot{x}_{i,t}'\beta)^2 + \frac{\lambda}{nT} \sum_{i=1}^{p} \psi_j |\beta_j| \tag{11}$$

The approach by Belloni et al. (2014b) to accommodate the non-homoskedastic errors, according to Ahrens, Hansen, and Schaffer (2019), is similar to standard clustered-error adjustments used in OLS models, whereby "observations within clusters are aggregated to create 'super-observations,' which are assumed independent, and . . . are treated similarly to cross-sectional observations in the non-clustered case" (p. 21). Accordingly, the penalty loading $\psi_j$ is given by

$$\psi_j = \sqrt{\frac{1}{nT} \sum_{i}^{n} u_{ij}^2} \tag{12}$$

[13]Following exposition comes from Ahrens, Hansen, and Schaffer (2019).

where $u_{ij}$ is the "super-observation", defined as $u_{ij} = \sum_t x_{ijt}\varepsilon_{it}$ for the $i$th cluster and $j$th regressor.

### 3.3 Data

For the empirical implementation of the model in equation (10), the dependent variables are gross capital inflow, FDI inflow, portfolio inflow, and other inflows, all as a share of GDP. The data on capital flows come from the FFA database, as before. We supplement the data on quarterly GDP where it is possible using the data from the IFS and Haver, and exclude extreme values from the data before running the model in equation (10) (see Section 2 for detail).

The explanatory variable of interest is an indicator variable $d_{it}$ (= 1 for gray-listing), defined over a window $[t_0 - k, t_0 + k]$, where $t_0$ is the date of the FATF announcement and $k$ is varied between 1 and 3 quarters (see Section 2). Following a standard practice in the literature, we drop post-gray-listing observations for four quarters, so as to avoid the post-gray-listing dynamics in capital flow biasing our estimation of $\beta_0$.[14]

With regard to control variables $\mathbf{x}_{i,t}$, there are 15 domestic primary variables: six exchange rate variables (exchange rate vis-a-vis the SDR, nominal effective exchange rate, real effective exchange rate, all for period average and end of period); two official reserves variables (in U.S. dollars and as a share of GDP); two current account balance variables (in U.S. dollars and as a share of GDP); one-year ahead forecast of real GDP growth rate; a measure of capital account openness; a measure of exchange rate flexibility; and credit ratings. Because of endogeneity concerns, all domestic variables are included in the model with four-quarter lags. Missing values in the primary domestic variables reduce the sample size to 81 countries, of which 28 have been gray-listed. See Appendix B for the list of countries. The domestic variables are complemented by 22 international variables: VIX, the U.S. short-term rate, the U.S. 10-year rate, the U.S. Federal Funds rate, two commodity price indexes (one including and one excluding gold), the

[14] For example, see Detragiache and Demirguc-Kunt (1998), Eichengreen and Gupta (2016), and Gourinchas and Obstfeld (2012).

real GDP growth rate of G4 countries (the U.S., the Euro Area, the U.K., and Japan) in total and individually, the money supply of G4 countries as a share of GDP in total and individually, the growth rate of the money supply of G4 countries in total and individually, and a dummy variable for the GFC. Furthermore, the analysis uses several permutations of each variable—such as levels and differences—as well as interaction effects of each variable with the three categorical variables in the model (a measure of exchange rate flexibility, credit ratings, and the dummy variable for the GFC). Finally, the model includes a full set of year fixed effects. Overall, this yields 2,842 variables. Appendix D describes the variables and sources.

### 3.4 Results

Table 1 reports the estimates of the impact of gray-listing on capital inflow, with results for different types of capital inflow presented across the columns. With double-selection lasso, the estimates of the coefficient of the variable of interest ($\beta_0$) can be interpreted just as they are in a standard linear regression. However, the coefficients of the control variables cannot and therefore are not reported here.[15]

Table 1: Effect of Gray-Listing on Capital Inflows

| | Total | FDI | Portfolio | Other |
|---|---|---|---|---|
| Coefficient | $-7.550^{***}$ | $-3.034^{***}$ | $-2.926^{***}$ | $-3.551^{***}$ |
| Standard Errors | (1.522) | (1.016) | (0.981) | (0.685) |
| Conf. Intervals | [-10.53, -4.57] | [-5.02, -1.04] | [-4.85, -1.00] | [-4.89, -2.21] |

The table presents estimates of the effect of gray-listing on the type of capital flow, in percent of GDP. Each specification includes additional controls as described in the text and Appendix D and a full set of year and country fixed effects. Robust standard errors clustered by country are in parentheses. Confidence intervals are at the 95 percent confidence level. *, **, *** mean, respectively, significant at the 10, 5, and 1 percent level.

Our point estimate for the effect of gray-listing on total capital inflow is $-7.6$, meaning that we expect a country's capital inflow to decline by

[15] This is because lasso, in general, does not produce unbiased estimates of coefficients and standard errors (see Section 3.1). The double-selection lasso eliminates the source of the bias for estimating the variable of interest (Section 3.2). But estimates of other controls remain open to the potential bias.

7.6 percent of GDP when the country is gray-listed. The coefficient estimate is statistically significant at the 1 percent level based on the robust standard errors. The 95 percent confidence interval is between $-10.6$ percent of GDP and $-4.6$ percent of GDP, meaning that most countries experience a decline within this range when gray-listed.[16]

Moving on to different components of capital flows, the effect of gray-listing on FDI inflow is estimated to be $-3.0$ percent of GDP and the effect on portfolio flow is estimated to be $-2.9$ percent of GDP, both are significant at the 1 percent confidence level (Table 1, columns 2 and 3). The relative magnitude of the coefficients is thus similar for FDI and portfolio inflows–consistent with the finding in the event analysis–although it is possible that dynamics around the time of gray-listing could show different sensitivity both before and after the event (see Section 2).

Looking at different categories of other flows (Table 2), the estimated impact of gray-listing is largest for non-official sector flows ($-3.8$ percent of GDP). Banking sector flows are somewhat less negatively affected than other (non-bank) private flows ($-2.0$ percent of GDP and $-2.4$ percent of GDP). Official sector flows are the least severely affected ($-0.9$ percent of GDP). All estimates are significant at the 5 percent level or better.

[16] The impact of $-7.6$ percent of GDP seems large, although not unseen during previous crises (see e.g., Broner et al., 2013). To put it into perspective, using the FFA data, a decline of this magnitude corresponds to about the 25th percentile of the distribution of quarterly declines in gross capital inflow for EMDCs during the GFC (which means that 25 percent of EMDCs in the sample had a larger quarterly decline), or corresponds to about the 45th percentile of the distribution of quarterly declines for countries affected by the Asian Crisis in 1997–98.

Table 2: Effect of Gray-Listing on Categories of Other Inflows

| | Official | Non-Official | Banks | Other Private |
|---|---|---|---|---|
| Coefficient | $-0.925^{**}$ | $-3.796^{***}$ | $-1.964^{***}$ | $-2.372^{***}$ |
| Standard Errors | (0.393) | (0.755) | (0.667) | (0.443) |
| Conf. Intervals | [-1.70, 0.15] | [-5.28, -2.32] | [-3.27, -0.66] | [-3.24, -1.50] |

The table presents estimates of the effect of gray-listing on the components of other investment flows, in percent of GDP. Each specification includes additional controls as described in the text and Appendix D and a full set of year and country fixed effects. Robust standard errors clustered by country are in parentheses. Confidence intervals are at the 95 percent confidence level. *, **, *** mean, respectively, significant at the 10, 5, and 1 percent level.

# 4 Robustness

## 4.1 Event Window

Our analysis focuses on the response of capital flows in a period around gray-listing, and to capture the response, we define gray-listing as an event with widow $[t_0 - k, t_0 + k]$ where $t_0$ is the date of the FATF public announcement and $k$ is varied between 1 and 3 quarters, allowing for the possibility that gray-listing may be foreseen by market participants and that some investors may delay their response due to uncertainty (see Section 2). The size of the window in an event study is an open choice (Choi and Hashimoto, 2017). If the window is too narrow, it may preclude any proper identification of the effect of an event that takes time to materialize. If the window is too wide, other confounding factors may affect the dependent variable. In the baseline, we use $k = 3$. To check robustness of our estimates reported in Table 1, we re-estimate the model using $k = 1$, 2, and 4. Results are reported in Table 3.

For all values of $k$, we consistently find negative and statistically significant effects of gray-listing on capital inflows. The absolute size of the coefficient is larger when using a wider event window ($k = 4$), perhaps as expected. The coefficient becomes smaller in absolute value using a narrower window ($k = 2$ or $k = 1$) but remains negative and significant. It is possible that the larger impact we find using the wider window reflects influences of confounding factors; it is also possible that we may not see the

Table 3: Robustness: Effect of Gray-Listing using Different Event Windows

| | $k$=4 | $k$=3 | $k$=2 | $k$=1 |
|---|---|---|---|---|
| Coefficient | $-8.203^{***}$ | $-7.550^{***}$ | $-5.789^{***}$ | $-4.836^{***}$ |
| (Standard Errors) | (1.524) | (1.522) | (1.649) | (1.683) |
| Conf. Intervals | [-11.19, -5.22] | [-10.53, -4.57] | [-9.02, -2.56] | [-8.14, -1.54] |

The table presents estimates of the effect of gray-listing on total capital inflow, in percent of GDP. Each column corresponds to the size of $k$ in an event window $[t_0 - k, t_0 + k]$. The column $k$=3 corresponds to the baseline results in the column "Total" in Table 1. Each specification includes additional controls as described in the text and Appendix D and a full set of year and country fixed effects. Robust standard errors clustered by country are in parentheses. Confidence intervals are at the 95 percent confidence level. *, **, *** mean, respectively, significant at the 10, 5, and 1 percent level.

full extent of impact on capital inflow using a narrower window, for example, because gray-listing is foreseen by market participants and they adjust their behavior earlier or, conversely, because gray-listing does not initially trigger de-risking among the investors in sufficient numbers within the first few months.

## 4.2 Small Number of Gray-Listing Observations

In our data, gray-listing observations are a small minority of the sample—about 0.7 percent—and this reduces the model's accuracy for estimating the impact of gray-listing on capital flows. To check robustness of our estimates reported in Table 1, we re-estimate the model using different resampling techniques to increase the share of gray-listing observations in our sample. The techniques we used are oversampling, which involves adding more observations of the minority class sample; undersampling, which involves removing the majority class observations; and using a combination of the two. In all cases, we boost the share of gray-listing observations up to about 2 percent of the data (for example, see Tiffin, 2019).

The simplest oversampling technique would involve replicating the existing minority class observations (i.e., gray-listing=1) until the desired mix of majority and minority class in the sample is achieved. However, we use an alternative technique known as SMOTE (Synthetic Minority Oversampling

Technique).[17] Instead of replicating exact copies of the existing minority class observations, SMOTE creates synthetic copies that are similar to, but not exactly the same as, the existing minority class observations (see Fernandez et al., 2018 for details).

Next, we use random undersampling (RU), which involves randomly selecting and deleting the majority class observations, until the share of gray-listing observations in the data reaches 2 percent.[18]

Finally, we use a combination of SMOTE and random undersampling. According to the machine learning literature, the combined approach often results in the model with better out-of-sample performance (Brownlee, 2020).

The results are reported in Table 4. The estimated coefficients of gray-listing remain negative and similar in size to that obtained in the baseline. The standard errors become smaller where a number of the minority-class observations are substantially increased (i.e., under SMOTE) as expected but not where only the share of the minority-class observations is increased (i.e., under random undersampling or a combination of SMOTE and random undersampling). The 95 percent confidence intervals are therefore smaller under SMOTE, ranging from $-9$ to $-4$ percent of GDP, but remains similar to the baseline in others ($-11$ to $-4$ percent of GDP).

# 5 Concluding Remarks

How much gray-listing affects a country's capital flows is of interest to policy makers, investors, and the Fund. It tells the policy makers about potential

[17] The technique is originally developed by Chawla et al. (2002), and since has become *de facto* standard in the machine learning literature for dealing with imbalanced data (Fernandez et al., 2018). In this literature, SMOTE is often used for resampling the minority class observations based on outcome (dependent) variables. Here, we apply SMOTE for resampling the minority class based on the predictor (independent) variable (i.e., gray-listing), as done in, for example, Torgo et al. (2013) and Tiffin (2019).

[18] Random undersampling, although simple and effective, has a limitation that samples are removed "without any concern for how useful or important they might be in determining the decision boundary between the classes. This means it is possible, or even likely, that useful information will be deleted" (Brownlee, 2020).

Table 4: Robustness: Effect of Gray-Listing using Different Event Windows

| | Baseline | SMOTE | RU | SMOTE & RU |
|---|---|---|---|---|
| Coefficient | $-7.550^{***}$ | $-6.316^{***}$ | $-7.245^{***}$ | $-7.504^{***}$ |
| Standard Errors | (1.522) | (1.320) | (1.535) | (1.599) |
| Conf. Intervals | [-10.53, -4.57] | [-8.90, -3.73] | [-10.25, -4.24] | [-10.64, -4.37] |

The table presents estimates of the effect of gray-listing on total capital inflow, in percent of GDP. Each column corresponds to the re-sampling method used to increase the share of minority class data (gray-listing=1). Each specification includes additional controls as described in the text and Appendix D and a full set of year and country fixed effects. Robust standard errors clustered by country are in parentheses. Confidence intervals are at the 95 percent confidence level. *, **, *** mean, respectively, significant at the 10, 5, and 1 percent level.

economic costs of gray-listing and may encourage them to make appropriate investments to address gaps in their countries' AML/CFT regimes. It tells investors how others may respond to the gray-listing of countries of interest. It is of interest to the Fund in relation to country surveillance, capacity development, forecasts of demand for Fund programs, and estimates of capacity to repay. For example, a sudden loss of capital inflows after gray-listing could lead to loss of external reserves, and for vulnerable countries, it could mean a Balance of Payments crisis and demand for an IMF program; if the country already has a Fund program, it could mean delays in implementing agreed reforms, or a need to recalibrate policy targets and timeline for achieving them; if a country has only recently completed the Fund program, a sudden loss of capital inflows or external reserves could signal risk to capacity to repay the Fund and call for a closer monitoring.

The paper presents a relatively novel approach—machine learning—to estimating the effect of gray-listing on capital flows, where there is a large number of potentially confounding factors. The particular machine learning technique used, lasso, provides a systematic approach to model selection and estimation while still allowing for causal inference on the estimated coefficient of the treatment effect.

The paper finds that gray-listing has a significant negative impact on a country's capital flows. The magnitude of the negative effect is large—on average $-7.6$ percent of GDP. It varies, however, by type of capital flow. The results are robust despite the small number of gray-listings in the sample and are robust to a narrower definition of the timing of gray-listing.

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# Appendices

## A FATF Gray-Listing

The Financial Action Task Force (FATF), established in 1989 by the G-7, is an intergovernmental body that develops and promotes policies to protect the global financial system against money laundering and terrorist financing (https://www.fatf-gafi.org/about/). It has issued 40 recommendations on how states should combat the problems of money laundering, terrorist financing, and proliferation financing through legal and regulatory action. Since 2000, it has periodically issued lists of countries and jurisdictions that it judges to have strategic AML/CFT deficiencies.[19]

The FATF uses a mutual evaluation model. The evaluations are carried out by the FATF and nine FATF-style regional bodies, and occasionally, by the IMF or World Bank. Each body forms a small team consisting of legal, law enforcement, and financial experts. The assessment team conducts two to three on-site visits and rates the level of technical compliance of a country's legal and regulatory framework on each recommendation as compliant, largely compliant, partially compliant, or noncompliant. It also rates the effectiveness of the AML/CFT system on 11 "immediate outcomes" as low, moderate, substantial, or high. "The evaluation process is lengthy, often taking more than a year" (Morse, 2019, p.10).[20] The mutual evaluation reports are discussed and adopted in plenary meetings of the relevant assessor body. FATF mutual evaluations are adopted at tri-annual meetings (currently in February, June, and October). "During these meetings, evaluated countries may argue against portions of the draft report or advocate rating changes" (Morse, 2019, p.10).[21]

[19] In the early 2000s, the FATF mainly assessed countries for technical compliance, whereas the FATF revised its standards and assessment methodology in 2012–13 to focus on evaluating the effectiveness of AML/CFT systems. This meant that countries removed from the gray list on account of legal reforms may have ended up back on the list for lack of effective implementation.

[20] For more detail, see https://www.fatf-gafi.org/media/fatf/documents/methodology/FATF-4th-Round-Procedures.pdf.

[21] More specifically, during the meetings, FATF members, observers, assessors, and the

There are several ways a country can become subject to review by the International Cooperation Review Group (ICRG): it does not allow timely publication of the mutual evaluation report or does not participate in as a member in the FATF's Global Network, the result of its assessment shows a significant number of key deficiencies, or it is nominated for the ICRG review by one or more other countries for specified and substantiated reasons.[22] The country that enters the ICRG review process as a result of poor performance on its mutual evaluation has one year to address its key deficiencies to avoid listing. If deficiencies are not sufficiently addressed, the FATF works with the country to develop an action plan. Once the plan is adopted by the FATF and committed to by the country, the FATF includes the country in the gray list. If no action plan is agreed with the FATF or high-level political commitment is not given, the FATF includes the country in the black list. Countries on the gray list that fail to make sufficient progress on their action plans within one year are also subject to blacklisting.

The decisions of FATF or outcomes of the plenary meetings involve a complex case-by-case assessment and do not follow an automatic timetable. Each assessed country can argue or dispute the findings of the mutual evaluation report and its ratings. Moreover, the FATF can extend the previously agreed deadlines for taking actions, further prolonging the gray-listing process.

Table A1 provides a list of gray-listed countries with dates of announcements.

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assessed countries consider issues where there is significant debate over the interpretation of a FATF Standard or the application of the methodology. These issues are raised by delegations (including the assessed country) that have an analytical concern. This vetting process may result in changes in ratings, analysis, conclusions, or recommendations.

[22]Entries to the ICRG review process through the last mechanism are rare, however, and require the consensus of the FATF membership. There are also mechanisms in the ICRGs procedures to ensure that the FATF does not review small countries with a potentially insignificant impact on the financial system.

Table A1. Gray-listed countries, 2000–17

| Country | First Listing | First Delisting | Second Listing | Second Delisting |
|---|---|---|---|---|
| Afghanistan | Jun-12 | Jun-17 | | |
| Albania | Jun-12 | Feb-15 | | |
| Algeria | Oct-11 | Feb-16 | | |
| Angola | Feb-10 | Feb-16 | | |
| Antigua and Barbuda | Feb-10 | Feb-14 | | |
| Argentina | Jun-11 | Oct-14 | | |
| Azerbaijan | Feb-10 | Oct-10 | | |
| Bahamas[1/] | Jun-00 | Jun-01 | | |
| Bangladesh | Oct-10 | Feb-14 | | |
| Bolivia | Feb-10 | Jun-13 | | |
| Bosnia and Herzegovina | Jun-15 | Feb-18 | | |
| Brunei Darussalam | Jun-11 | Jun-13 | | |
| Cambodia | Jun-11 | Feb-15 | | |
| Cayman Islands[1/] | Jun-00 | Jun-01 | | |
| Cook Islands[1/] | Jun-00 | Feb-05 | | |
| Cuba | Jun-11 | Oct-14 | | |
| Cyprus (Northern Part) | Feb-08 | Oct-08 | | |
| Dominica[1/] | Jun-00 | Oct-02 | | |
| Ecuador | Feb-10 | Oct-15 | | |
| Egypt[1/] | Jun-01 | Feb-04 | | |
| Ethiopia | Feb-10 | Oct-14 | Feb-17 | Oct-19 |
| Ghana | Oct-10 | Feb-13 | | |
| Greece | Feb-10 | Jun-11 | | |
| Grenada[1/] | Sep-01 | Feb-03 | | |
| Guatemala[1/] | Jun-01 | Jul-04 | | |
| Guyana | Oct-14 | Oct-16 | | |
| Honduras | Oct-10 | Feb-12 | | |
| Hungary[1/] | Jun-01 | Jun-02 | | |
| Indonesia[1/] | Jun-01 | Feb-05 | Feb-10 | Jun-15 |
| Iraq | Oct-13 | Jun-18 | | |
| Israel[1/] | Jun-00 | Jun-02 | | |
| Kenya | Feb-10 | Jun-14 | | |
| Kuwait | Jun-12 | Feb-15 | | |
| Kyrgyz Republic | Oct-11 | Jun-14 | | |
| Lao PDR | Jun-13 | Jun-17 | | |
| Lebanon[1/] | Jun-00 | Jun-02 | | |
| Liechtenstein[1/] | Jun-00 | Jun-01 | | |
| Marshall Islands[1/] | Jun-00 | Oct-02 | | |
| Mongolia | Jun-11 | Jun-14 | | |
| Morocco | Feb-10 | Oct-13 | | |
| Myanmar[1/] | Jun-01 | Oct-06 | Feb-10 | Jun-16 |
| Namibia | Jun-11 | Feb-15 | | |
| Nauru[1/] | Jun-00 | Oct-05 | | |
| Nigeria[1/] | Jun-01 | Jun-06 | Feb-10 | Oct-13 |
| Nepal | Feb-10 | Jun-14 | | |
| Nicaragua | Jun-11 | Feb-15 | | |
| Niue[1/] | Jun-00 | Oct-02 | | |

Table A1. Gray-listed countries, 2000–17 (continued)

| Country | First Listing | First Delisting | Second Listing | Second Delisting |
|---|---|---|---|---|
| Pakistan | Feb-08 | Feb-15 | | |
| Panama[1/] | Jun-00 | Jun-01 | Jun-14 | Feb-16 |
| Papua New Guinea | Feb-14 | Jun-16 | | |
| Paraguay | Feb-10 | Feb-12 | | |
| Philippines[1/] | Jun-00 | Feb-05 | Oct-10 | Jun-13 |
| Qatar | Feb-10 | Oct-10 | | |
| Russia[1/] | Jun-00 | Oct-02 | | |
| São-Tomé and Príncipe | Feb-08 | Oct-13 | | |
| Sri Lanka | Feb-10 | Jun-13 | Nov-17 | Oct-19 |
| St. Kitts and Nevis[1/] | Jun-00 | Jun-02 | | |
| St. Vincent and the Grenadines[1/] | Jun-00 | Jun-03 | | |
| Sudan | Feb-10 | Oct-15 | | |
| Syria | Feb-10 | | | |
| Tanzania | Oct-10 | Jun-14 | | |
| Tajikistan | Jun-11 | Oct-14 | | |
| Thailand | Feb-10 | Jun-13 | | |
| Trinidad and Tobago | Feb-10 | Oct-12 | Nov-17 | Feb-20 |
| Tunisia | Nov-17 | Oct-19 | | |
| Turkey | Feb-10 | Oct-14 | | |
| Turkmenistan | Feb-08 | Jun-12 | | |
| Uganda | Feb-14 | Nov-17 | | |
| Ukraine[1/] | Sep-01 | Feb-04 | Feb-10 | Oct-11 |
| Uzbekistan | Feb-08 | Feb-10 | | |
| Vanuatu | Feb-16 | Jun-18 | | |
| Venezuela | Oct-10 | Feb-13 | | |
| Vietnam | Oct-10 | Feb-14 | | |
| Yemen | Feb-10 | | | |
| Zimbabwe | Jun-11 | Feb-15 | | |

[1/]Listed under the NCCT (non-co-operative countries and territories process) (2000–2006) before it was replaced by the ICRG process (since 2007). See FATF website for detail.

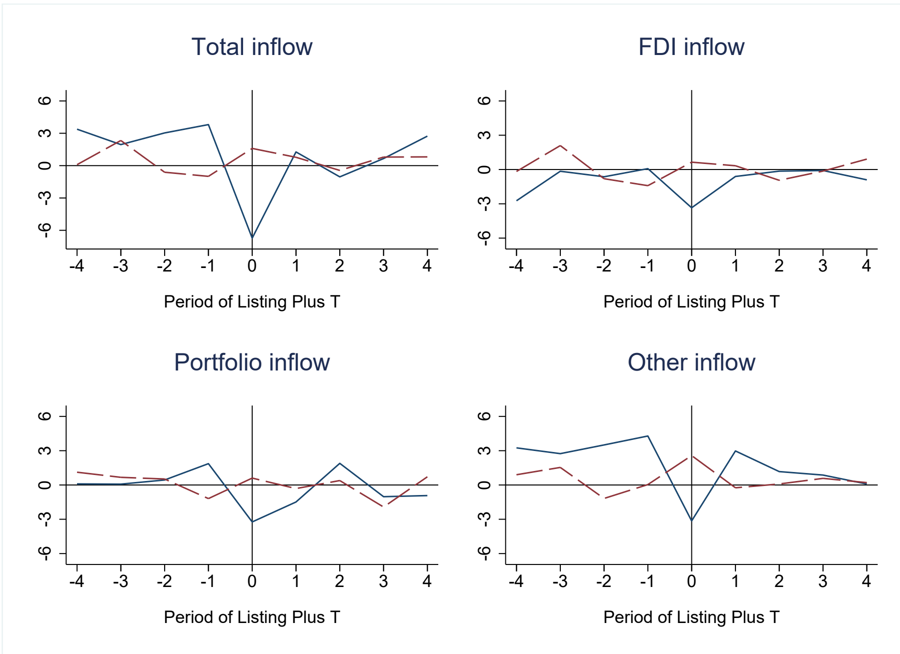
# B Estimation Sample: 2000q1–2017q4

| Country | Have Been Gray-Listed?[1/] | Country | Have Been Gray-Listed?[1/] |
|---|---|---|---|
| Albania | Yes | Latvia | |
| Angola[2/] | Yes | Lithuania | |
| Argentina | Yes | North Macedonia[2/] | |
| Armenia | | Malaysia | |
| Azerbaijan | Yes | Malta | |
| Bahrain[2/] | | Mauritius | |
| Bangladesh | Yes | Mexico | |
| Belarus | | Moldova | |
| Bolivia | Yes | Mongolia | Yes |
| Bosnia and Herzegovina | Yes | Montenegro, Rep. of[2/] | |
| Brazil | | Morocco | Yes |
| Brunei Darussalam | Yes | Namibia[3/] | Yes |
| Bulgaria | | Nepal[3/] | Yes |
| Cabo Verde | | Nicaragua | Yes |
| Cambodia[3/] | Yes | Pakistan[3/] | Yes |
| Chile | | Panama[3/] | Yes |
| Colombia | | Paraguay | Yes |
| Costa Rica | | Peru | |
| Croatia | | Philippines | Yes |
| Cyprus (Northern Part) | Yes | Poland | |
| Czech Republic | | Qatar[3/] | Yes |
| Dominican Republic | | Romania | |
| Ecuador | Yes | Russia | Yes |
| Egypt[3/] | Yes | Samoa | |
| El Salvador | | Saudi Arabia | |
| Estonia | | Serbia[2/] | |
| Georgia | | Seychelles | |
| Ghana[3/] | Yes | Singapore | |
| Greece[3/] | Yes | Slovak Republic | |
| Guatemala[3/] | Yes | Slovenia | |
| Honduras | Yes | South Africa | |
| Hong Kong SAR[2/] | | Sri Lanka | Yes |
| Hungary | Yes | Taiwan Province of China[2/] | |
| Iceland | | Tajikistan | Yes |
| India | | Tanzania[3/] | Yes |
| Indonesia | Yes | Thailand | Yes |
| Ireland[2/] | | Trinidad and Tobago[3/] | Yes |
| Israel | Yes | Turkey | Yes |
| Jamaica | | Uganda | Yes |
| Jordan | | Ukraine[3/] | Yes |
| Kazakhstan | | Uruguay | |
| Korea | | Venezuela | Yes |
| Kosovo[2/] | | Vietnam | Yes |
| Kuwait[3/] | Yes | Zambia | |
| Kyrgyz Republic[3/] | Yes | | |

[1/] At any time during the sample period 2000–2017. [2/] Not in the sample for lasso. [3/] Not in the sample in some specification for lasso.

# C Gray-Listing and Net Errors and Omissions

Figure 3: Evolution of Capital Flows and Net Errors and Omissions Around Gray-Listing (Percent of GDP)




Source: IFS, FFA, and authors' calculations. Based on estimation of equation (1) using quarterly data of total capital inflow to GDP and net errors and omissions to GDP between 2000q1 and 2017q4. Each panel reports the estimates of conditional means of each variable relative to "tranquil times" around the time of gray-listing. See Section 2 for detail.

# D Variables and Data Sources

Table D1. Variables and Data Sources

| Variable | Source | Permutation |
|---|---|---|
| **Global variables** | | |
| VIX | CBOE | level, squared |
| US 3-month T-bill rate | FRED | level, squared |
| US 10-year rate | FRED | level, squared |
| US Federal Funds rate | FRED | level, squared |
| Commodity price indexes | WEO | level, squared |
| Commodity price indexes, excluding gold | WEO | level, squared |
| G4 GDP (sum of US, Euro Area, UK, and Japan) | WEO | level, squared |
| GDP of US | WEO | level, squared |
| GDP of Euro Area | WEO | level, squared |
| GDP of UK | WEO | level, squared |
| GDP of Japan | WEO | level, squared |
| Real GDP growth rate of G4 countries | WEO | qoq, yoy, level, squared |
| Real GDP growth rate of US | WEO | qoq, yoy, level, squared |
| Real GDP growth rate of Euro Area | WEO | qoq, yoy, level, squared |
| Real GDP growth rate of UK | WEO | qoq, yoy, level, squared |
| Real GDP growth rate of Japan | WEO | qoq, yoy, level, squared |
| Money supply of G4 countries | IFS | level, squared |
| Money supply of US | IFS | level, squared |
| Money supply of Euro Area | IFS | level, squared |
| Money supply of UK | IFS | level, squared |
| Money supply of Japan | IFS | level, squared |
| Growth rate of G4 money supply | IFS | qoq, yoy, level, squared |
| Growth rate of money supply of US | IFS | qoq, yoy, level, squared |
| Growth rate of money supply of Euro Area | IFS | qoq, yoy, level, squared |
| Growth rate of money supply of UK | IFS | qoq, yoy, level, squared |
| Growth rate of money supply of Japan | IFS | qoq, yoy, level, squared |
| Money supply of G4 countries as a share of G4 GDP | IFS | level, squared |
| Money supply of US as a share of GDP | IFS | level, squared |
| Money supply of Euro Area as a share of GDP | IFS | level, squared |
| Money supply of UK as a share of GDP | IFS | level, squared |
| Money supply of Japan as a share of GDP | IFS | level, squared |
| **Domestic variables** | | |
| Exchange rates SDR, period average | IFS, WEO | qoq, yoy, squared |
| Exchange rates SDR, end of period | IFS, WEO | qoq, yoy, squared |
| Nominal Effective Exchange Rate, period average | IFS, WEO | qoq, yoy, squared |

Table D1. Variables and Data Sources (continued)

| Variable | Source | Permutation |
|---|---|---|
| Nominal Effective Exchange Rate, end of period | IFS, WEO | qoq, yoy, squared |
| Real Effective Exchange Rate, period average | IFS, WEO | qoq, yoy, squared |
| Real Effective Exchange Rate, end of period | IFS, WEO | qoq, yoy, squared |
| Official reserves in USD | IFS, WEO | level, qoq, yoy, squared |
| Official reserves as a share of GDP | IFS, WEO | level, qoq, yoy, squared |
| One-year ahead forecast of real GDP growth rate | WEO | yoy, squared |
| Current account balance in USD | IFS, WEO | level, qoq, yoy, squared |
| Current account balance as a share of GDP | IFS, WEO | level, qoq, yoy, squared |
| Capital account openness | Chinn and Ito (2006) | |
| Exchange rate flexibility | Ilzetzki et al (2019) | |
| Credit ratings | S&P Ratings | |

Note: CBOE = Chicago Board of Options Exchange; FRED = Federal Reserve Economic Data; IFS = International Financial Statistics; WEO = World Economic Outlook.