Dirty money pushed, dirty money pulled. A gravity analysis of anomalous financial statistics

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Introduction

 Literature using gravity specifications to investigate dirty money flows (see, e.g., Walker 1999 and Walker and Unger, 2009) → several limitations both because of the lack of a solid theoretical underpinning and reliable data («high risk» money not included in official data sources)

•Goal: Develop a method to pinpoint origin-destination (country) pairs that may present an higher risk of dirty money flows

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•Goal: Develop a method to pinpoint origin-destination (country) pairs that may present an higher risk of dirty money flows

•How?

- Identify characteristics of territories making them "risky" (focusing on secrecy and corruption)
- Check correlation of the latters with anomalies in financial flows (the difference between the estimation of the "theoretical" flow and the actual flow).
- **Predict the probability** that financial flows between two territories are "anomalous" (i.e. contain dirty money) based on the presence of the above mentioned characteristics.

Major advances

- Instead of using semi-arbitrary pre-defined jurisdictional categories («offshore»/ tax havens) we look at impact of various factors on *patterns of anomalies in bilateral financial flows*
- •Question is whether "map" of global/local anomalies in financial statistics is correlated with illicit money flows
 - Develop methodology for isolating time-variant push and pull factors for dirty transactions.

Major advances

- Instead of using semi-arbitrary pre-defined jurisdictional categories («offshore»/ tax havens) we look at impact of various factors on *patterns of anomalies in bilateral financial flows*
- •Question is whether "map" of global/local anomalies in financial statistics is correlated with illicit money flows
 - Develop methodology for isolating time-variant push and pull factors for dirty transactions.
- Approach can be applied to any kind of economic flow (e.g. trade, FDI...) and to any dyadic dataset
- •Using of existing financial statistics partially bypasses the missing-data problem in dirty money flows' analysis

Previous gravity estimates of DM flows

• Walker (1999) model:

$$\frac{F_{ij}}{\sum_{i} F_{ij}} = \frac{\left(\left(\frac{GNP_{j}}{pop_{j}}\right)Attractiveness_{j}\right)}{distance_{ij}^{2}}$$

• Where:

$$Attractiveness_{j} = 3BS_{j} + GA_{j} + Swift_{j} - 3CF_{j} - CR_{j} + 15$$

 Limitations: lack of a solid theoretical underpinning in economic theory; weights constructed based on «educated guess», no data on F_{ij} (i.e. money laundered) - means no real empirical testability

Research questions

•To what extent are anomalies in official statistics on global investment flows explained by illicit financial activity?

•I.e., are offshoreness, financial secrecy, tax levels and corruption correlated with the above financial anomalies?

Methodology

• STEP 1

- Estimate generic, entirely fixed-effects-based Gravity Model of investment (Okawa and van Wincoop, 2013) to get expected flows. Full FE PPML (Santos Silva and Teneyro, 2006) → "clean" residuals
- Identification: *Dirty Flows* = difference between actual flows and predictions → evidence on which places attract more funds than expected and from where (i.e. pairs with higher residuals)

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• STEP 2

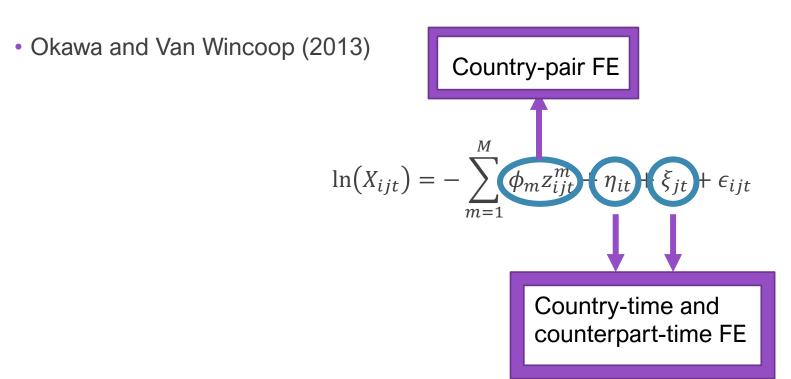
- Rank outliers \rightarrow what origins and destinations appear more often/on the top of outliers' list?
- Anomalies' analysis → are anomalies associated to «dirty flows» determinants? (e.g. financial secrecy, offshoreness, corruption, low/no taxes)

1° step: estimating equation

• Okawa and Van Wincoop (2013)

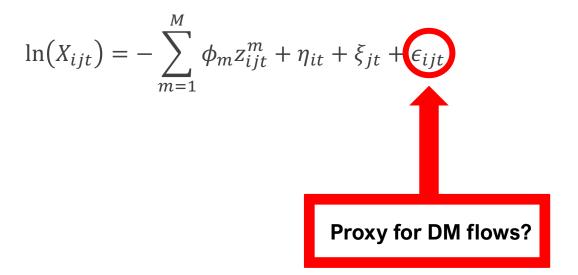
$$\ln(X_{ijt}) = -\sum_{m=1}^{M} \phi_m z_{ijt}^m + \eta_{it} + \xi_{jt} + \epsilon_{ijt}$$

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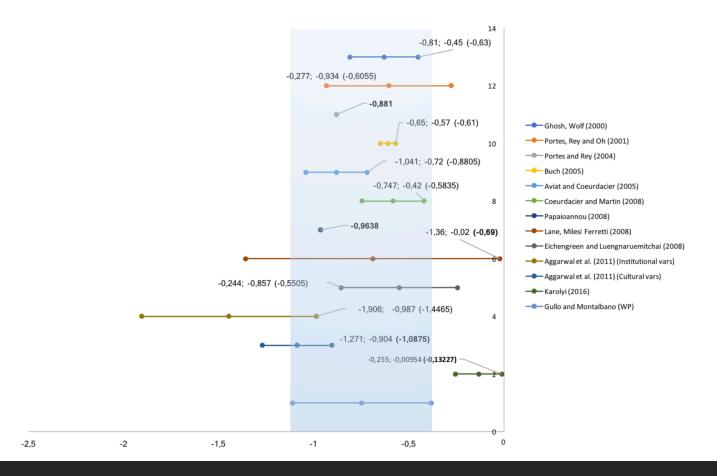
• Okawa and Van Wincoop (2013)



1° step: the data

- •Dirty Money often invested into financial assets to avoid holding large amounts of cash (layering phase) or to place money in its final spot (Unger, 2017)
- Diffificult sector to monitor and regulate → money can be hidden in anonymous accounts in OFCs: little or no tax on investment returns + privacy (Hines, 2010)
- Unbalanced panel merging CPIS data (Dep. Var.= Annual portfolio investment (2001-2015)) with CEPII gravity dataset.

Estimation of OW (2013) with traditional gravity variables (meta-analysis of distance coefficient)



1° step: Outliers identification

 Compute internally studentized residuals → difference between observed and fitted outcome divided by standard deviation (on country-pairs)

• Normalize on 0-1 scale to construct **anomaly index** (1 = most anomalous flow)

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 Compute internally studentized residuals → difference between observed and fitted outcome divided by standard deviation (on country-pairs)

• Normalize on 0-1 scale to construct **anomaly index** (1 = most anomalous flow)

• Observation commonly considered outlier if *Stud.Res.* \geq 2 or 3. For second step analysis:

• *OutLow* = 1 if *Stud.Res.* ≥ 2

• **OutHigh** = 1 if Stud.Res. \geq 3

2° step: Top 20 outliers

Rank	Country	Counterpart	Year
1	United States	Cayman Islands	2014
2	United States	Cayman Islands	2015
3	United States	Ireland	2015
4	United States	Cayman Islands	2012
5	United States	Cayman Islands	2013
6	Luxembourg	United States	2014
7	United States	Cayman Islands	2011
8	United States	Ireland	2014
9	United Kingdom	Germany	2014
10	United Kingdom	United States	2008
11	United Kingdom	Germany	2015
12	France	Luxembourg	2015
13	Luxembourg	United States	2013
14	Germany	Luxembourg	2008
15	United Kingdom	United States	2009
16	United States	United Kingdom	2003
17	United Kingdom	Germany	2012
18	Japan	Cayman Islands	2010
19	United States	France	2007
20	United Kingdom	United States	2010

2° step: outlier status determinants

Variable	Source	Description
SS	Tax Justice Network	Secrecy Score, data for every other year from 2008 to 2015 (gaps filled with mean between previous and following year)
CPI	Transparency International	Corruption perception index (yearly data from 2001)
OFC	Zoromè (2007), IMF and FSF	OFC = 1 if the country is listed as OFC by one of the three
TAX	KPMG	Corporate tax rates as percentage of GDP
EGMONT	Egmont Group	EGMONT=1 1 if the country's FIU is part of the Egmont group

2° step: outliers' probit analysis

• **Ordered probit** to check if studentized residuals' thresholds of 2 and 3 are significant (*not reported*): do coefficients vary depending on the "anomaly region» the observation belongs to?

• Both cut points highly significant → the presence of heterogeneity in the relationship between dirtymoney related covariates and the anomaly level of country-pairs

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• **Probit estimation** to check causal nexus of probability to be an outlier in global financial statistics with factors related to dirty money flows

Probit estimation results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
VARIABLES	OutLow	OutLow	OutLow	OutLow	OutLow	OutLow	OutLow	OutHigh	OutHigh	$\operatorname{OutHigh}$	OutHigh	OutHigh	$\operatorname{OutHigh}$	$\operatorname{OutHigh}$
CPI(o)			-0.000937	-0.000955	-0.000945	-0.000932	-0.000937			-0.00297***	-0.00299***	-0.00298***	-0.00297***	-0.00298***
			(0.000635)	(0.000783)	(0.000689)	(0.000775)	(0.000812)			(0.000580)	(0.000715)	(0.000718)	(0.000674)	(0.000803)
SS(o)	-0.00289***	-0.00371***						-0.00343***	-0.00462***					
	(0.000310)	(0.000487)						(0.000344)	(0.000433)					
SS(d)	0.000818**	0.00304***	0.00173***		0.000846*	0.00194***	0.000798**	0.000594*	0.00284***	0.00122***		0.000254	0.000973*	0.000241
	(0.000321)	(0.000402)	(0.000396)		(0.000440)	(0.000621)	(0.000403)	(0.000343)	(0.000443)	(0.000444)		(0.000592)	(0.000551)	(0.000524)
OFC(d)				0.217^{***}	0.194^{***}	0.290***	0.187***				0.215^{***}	0.208***	0.267***	0.206***
				(0.0304)	(0.0344)	(0.0513)	(0.0423)				(0.0390)	(0.0413)	(0.0578)	(0.0340)
OFC(d) = 1 * SS(d)						-0.00304***							-0.00192**	
						(0.00106)							(0.000901)	
TAX(o)		0.00164^{*}	0.00176	0.00172	0.00175^{*}	0.00177	0.00175		-0.000918	0.000269	0.000262	0.000271	0.000282	0.000271
		(0.000874)	(0.00110)	(0.00124)	(0.00104)	(0.00125)	(0.00128)		(0.000901)	(0.00131)	(0.00136)	(0.00126)	(0.00125)	(0.00136)
TAX(d)		0.00507***	0.00494***	0.00553***	0.00552***	0.00538^{***}	0.00533***		0.00199	0.00188**	0.00248**	0.00248^{**}	0.00240***	0.00243**
		(0.00108)	(0.00109)	(0.00113)	(0.000913)	(0.000960)	(0.00109)		(0.00126)	(0.000955)	(0.00112)	(0.00103)	(0.000902)	(0.00101)
EGMONT(d)							0.0465							0.0123
							(0.0381)							(0.0442)
Constant	-1.792***	-2.090***	-2.044***	-2.070***	-2.084***	-2.098***	-2.116***	-1.816***	-1.955^{***}	-1.836***	-1.875***	-1.879***	-1.888***	-1.887***
	(0.0101)	(0.0593)	(0.0683)	(0.0765)	(0.0495)	(0.0739)	(0.0760)	(0.0115)	(0.0528)	(0.0599)	(0.0664)	(0.0648)	(0.0684)	(0.0703)
Observations	72,433	33,606	29,580	29,580	29,580	29,580	29,580	72,433	33,606	29,580	29,580	29,580	29,580	29,580

*** p<0.01, ** p<0.05, * p<0.1

Probit estimation results

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			(0.000635)	(0.000783)	(0.000689)	(0.000775)	(0.000812)			(0.000580)	(0.000715)	(0.000718)	(0.000674)	(0.000803)
SS(o)	-0.00289***	-0.00371***						-0.00343***	-0.00462***					
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OFC(d) = 1 * SS(d)						-0.00304***							-0.00192**	
						(0.00106)							(0.000901)	
TAX(o)		0.00164*	0.00176	0.00172	0.00175^{*}	0.00177	0.00175		-0.000918	0.000269	0.000262	0.000271	0.000282	0.000271
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Standard errors in parentheses														

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Robustness tests

• Repeat 2° step estimates using the relative value of secrecy for each jurisdiction.

VARIABLES	(1) OutLow	(2) OutLow	(3) OutLow	(4) OutLow	(5) OutLow
$SS(o)_{rel}$	466.6 (2,998)	-2,690 (3,108)			
$SS(d)_{rel}$	-338.3	2,240	351.6***	355.8^{***}	338.2^{**}
	(2,064)	(2,141)	(110.3)	(110.6)	(148.6)
OFC(d)				0.280^{***}	0.271^{***}
				(0.0504)	(0.0429)
$OFC(d) = 1 * SS(d)_{rel}$				-629.2***	-609.3***
				(217.3)	(220.3)
TAX(o)		0.00158*	0.00176*	0.00176	0.00175
		(0.000894)	(0.00105)	(0.00118)	(0.00114)
TAX(d)		0.00482***	0.00492***	0.00541^{***}	0.00524***
		(0.000933)	(0.000974)	(0.00109)	(0.000906)
CPI(o)			-0.000962	-0.000950	-0.000942
			(0.000619)	(0.000668)	(0.000701)
EGMONT(d)					0.0415
_					(0.0391)
Constant	-1.831***	-2.118***	-2.034***	-2.088***	-2.116***
	(0.0100)	(0.0444)	(0.0518)	(0.0711)	(0.0626)
Observations	72,433	33,606	29,580	29,580	29,580
	Standa	rd errors in p	arentheses		
	*** p<	0.01, ** p < 0.0	05, * p < 0.1		

Robustness tests

- Repeat 1° step GM estimation only including GDPs to proxy for countries' dimension and physical distance to control for informational frictions → findings robust no matter the specific theoretical assumptions in the Okawa and VanWincoop's (2013) Gravity model (ranking of the anomalies does not vary much)
- May outliers have some hidden characteristics that would make them appear anomalous with any kind of flow? → Spearman test on anomaly indexes using other data

	Portfolio Investments	p-value
Direct Investments	0.0180	0.0020
Imports	0.0126	0.0280

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The importance of reputation: not to raise suspects when moving DM a secret onshore jurisdiction may be preferred to a secret OFC.

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What impact did transparencyrelated reforms have on financial flows to OFCs?

Does Transparency bring Cleanliness? Offshore Financial Secrecy Reform and Corruption Control

Daniel Haberly, University of Sussex

Alex Cobham, Tax Justice Network

Valentina Gullo, University of Sussex





UNIVERSITY OF SUSSEX

Anti-Corruption Evidence

Research Programme



Does Transparency bring Cleanliness? Offshore Financial Secrecy Reform and Corruption Control

Panel analysis of impact of changing jurisdiction-level policies on "high risk" offshore shell company formation & dissolution by client countries

Data:

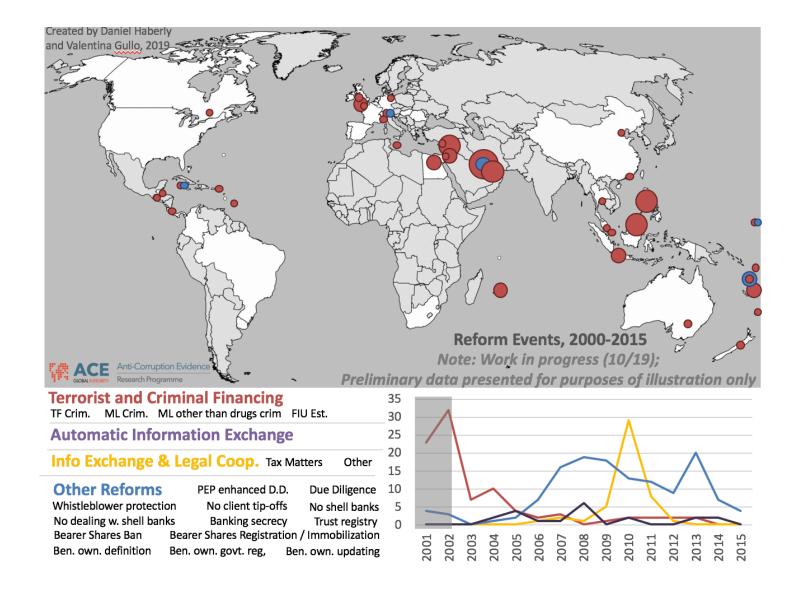
- **Dependent Variable:** "high risk" offshore financial flows / stocks
 - ICIJ data leaks shell company formation / dissolution (all client global sample, and PEP-focused sample for selected countries)
- Independent Variable: changing offshore secrecy policy landscape
 - New <u>Historical</u> Financial Secrecy Database (HFSD)

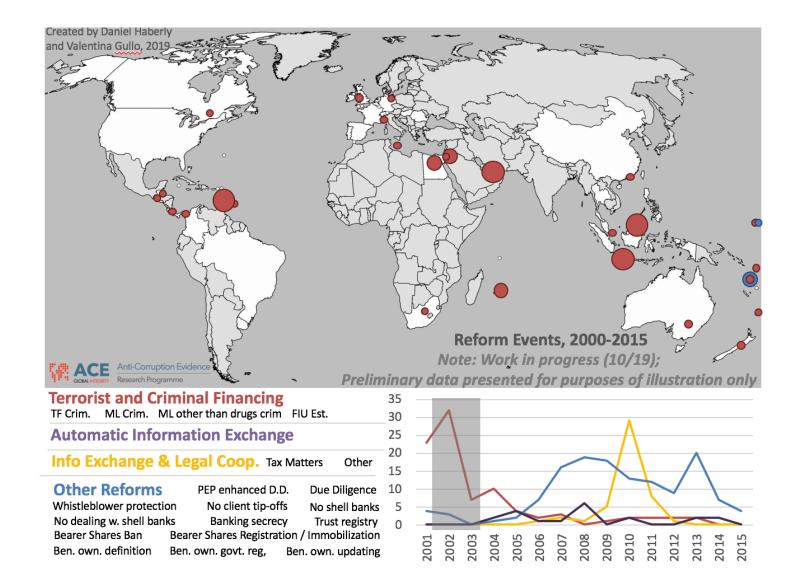


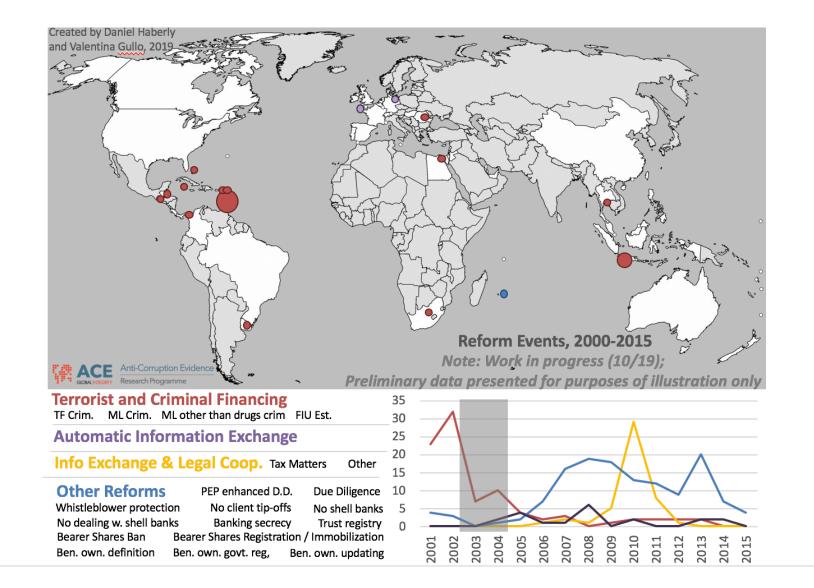
61 jurisdictions – prioritized based on combination of OFC / tax haven lists, TJN evaluations, importance in international financial markets, and importance in ICIJ data

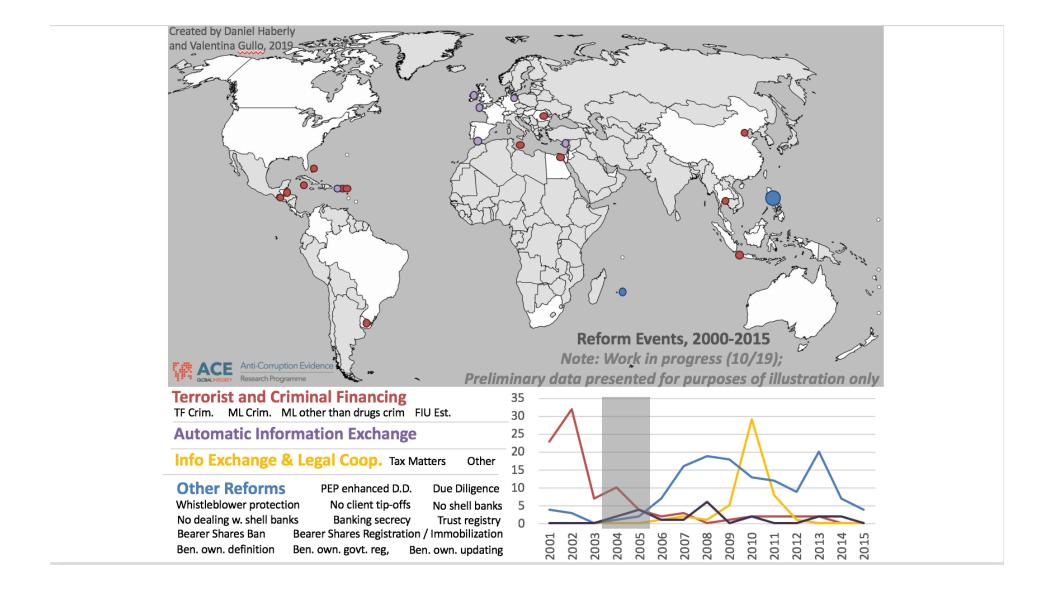
16 years (2000-2015) – based on combination of ICIJ coverage and policy data availability

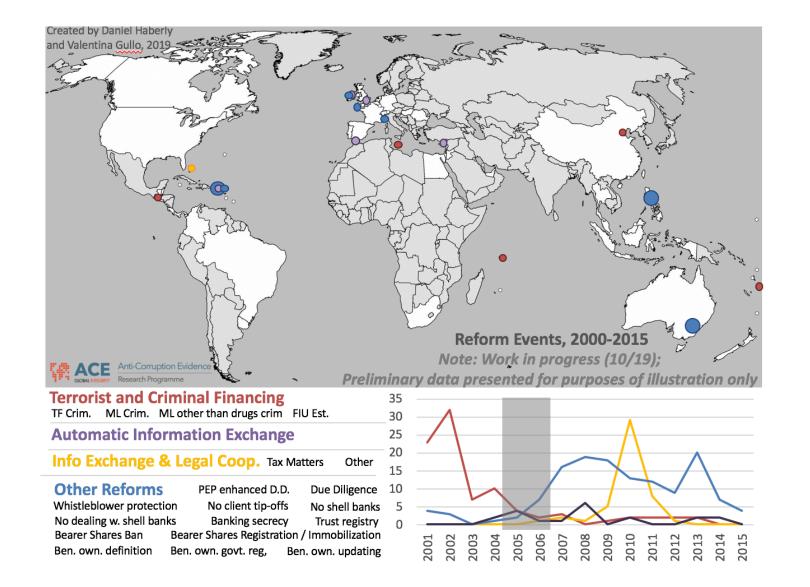
20 policy variables – defined based on combination of importance and data availability

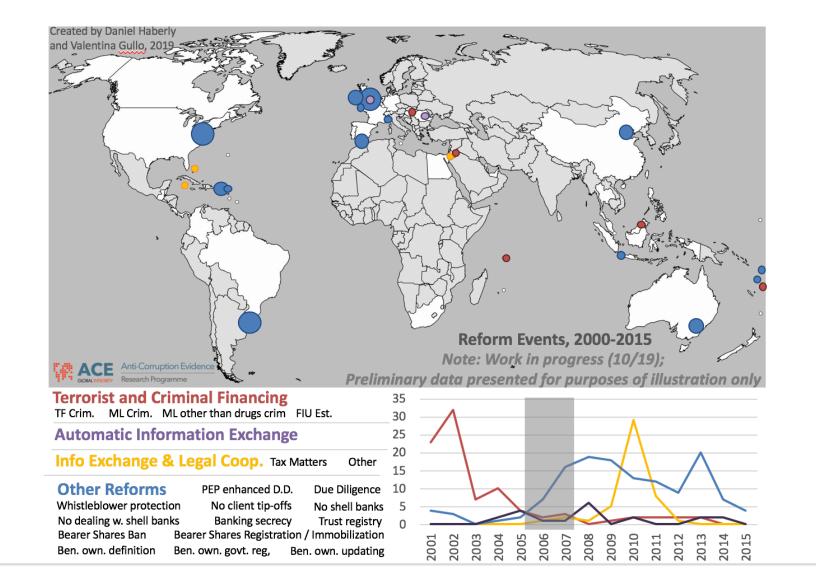


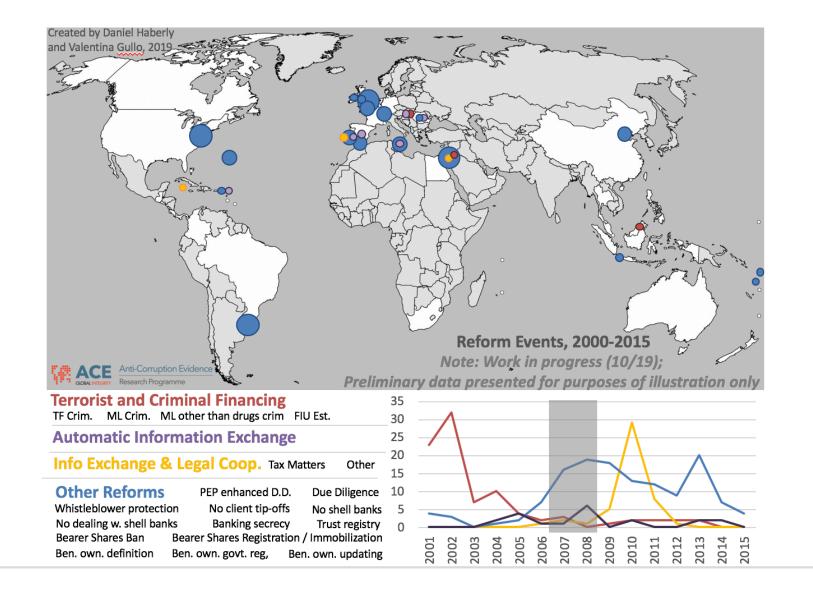


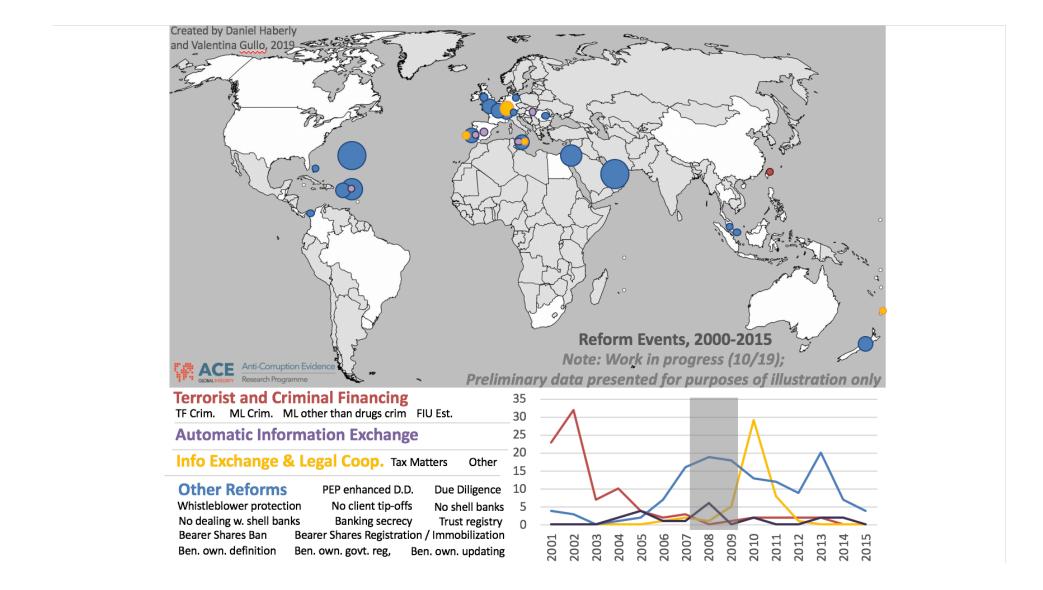


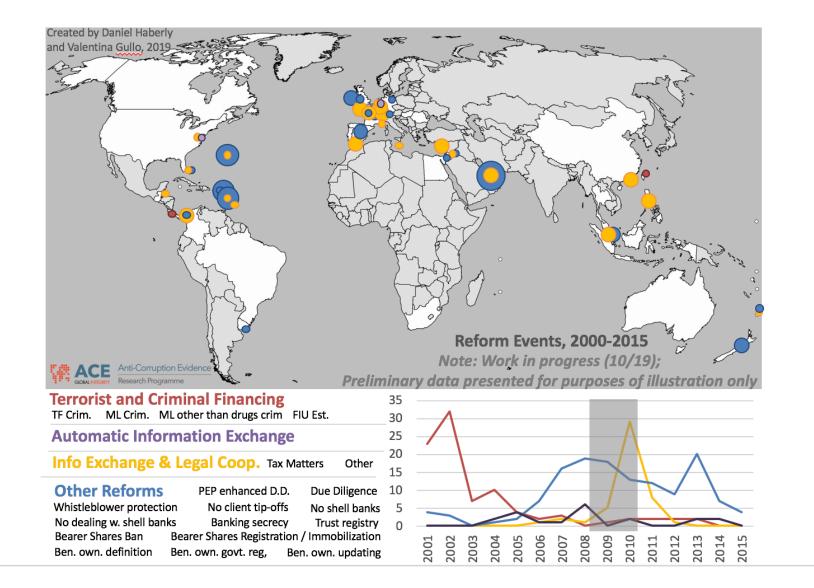


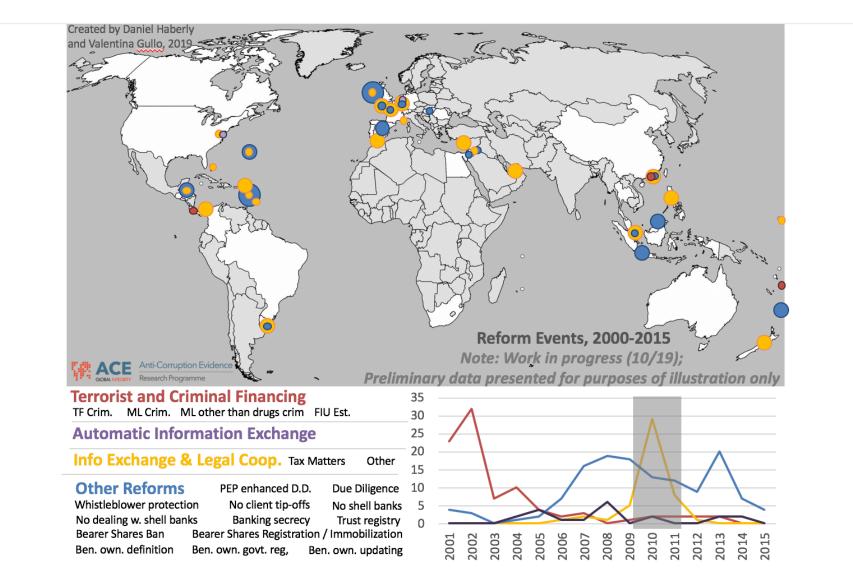


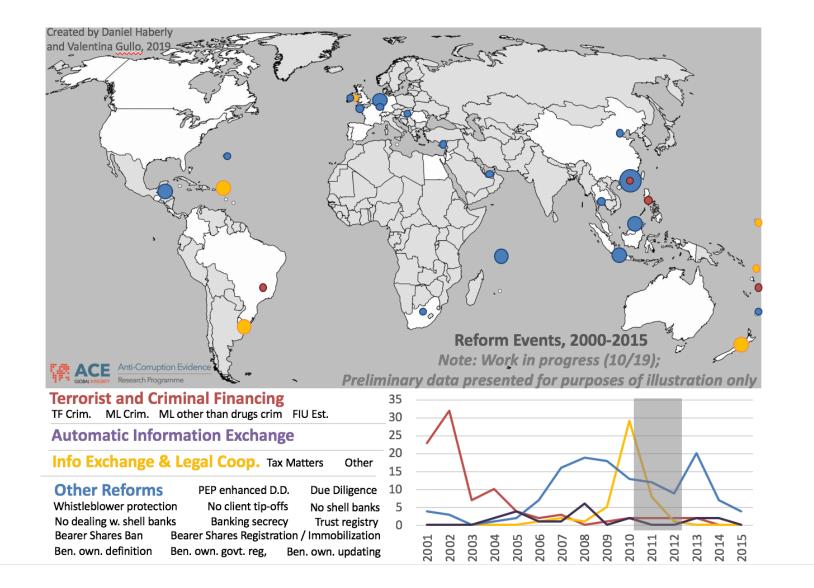


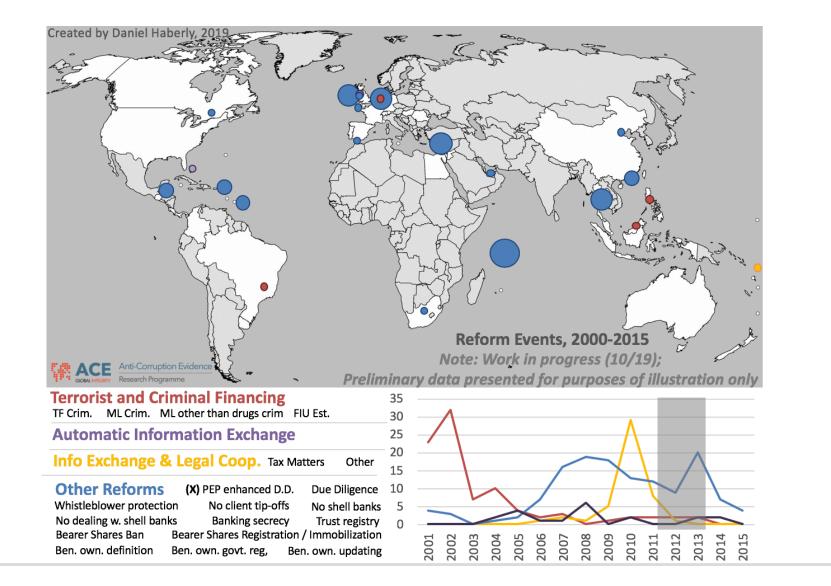


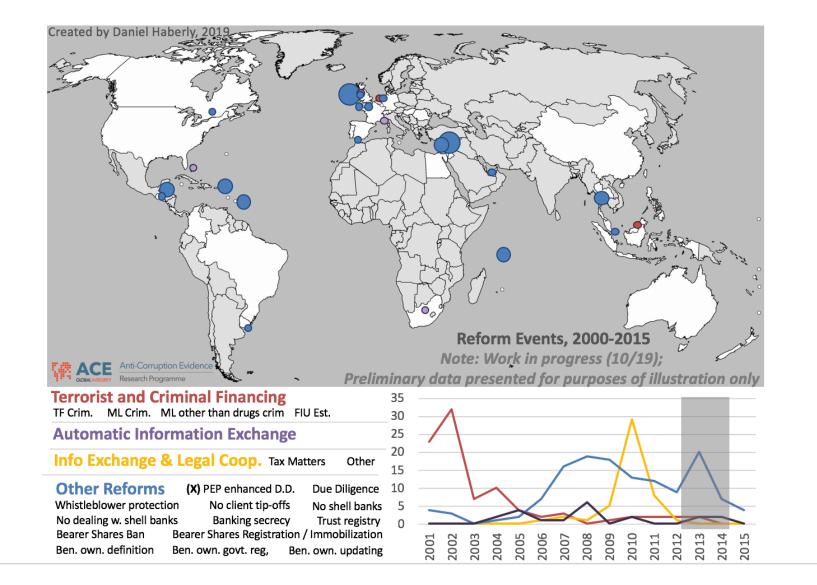


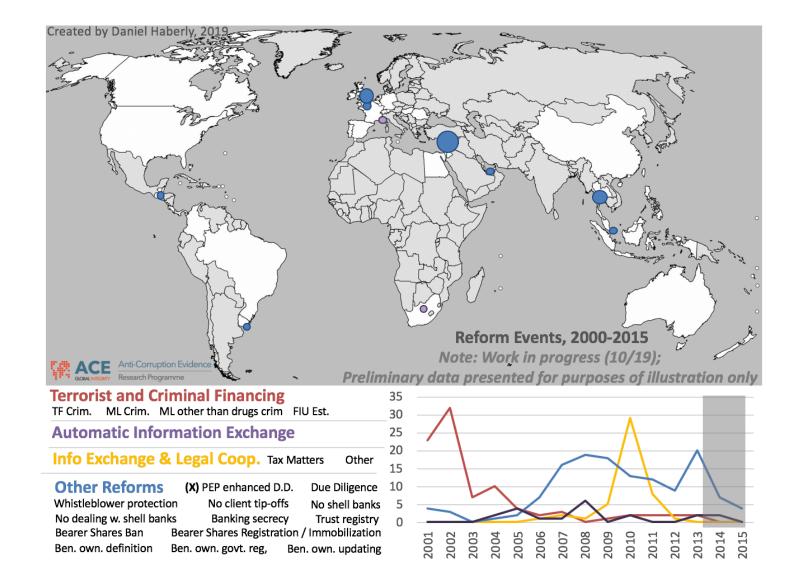












Thank you!

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