The elusive banker:

Using hurricanes to uncover (non-)activity in offshore financial centers

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Abstract: A number of small islands in the Caribbean and the Pacific are accumulating billions of dollars in international capital. Are these positions attracted by specialized human capital and innovative financial services, as such Offshore Financial Centers (OFCs) claim? Or are they the result of regulatory arbitrage as some economists assume, pointing to financial stability and effective taxation concerns? Based on several novel data sources, this study exploits the natural experiment of re-occurring hurricanes to test for reactions in financial service activity of OFCs. I find that local activity, captured by geospatial satellite data on nightlight intensity, decreases by 30-50% for at least 6 months. However, in OFCs neither the interbank market nor international investors react, while non-OFC islands do show strong negative reactions. Only local company incorporations decline in OFCs after hurricanes hit and this activity can be linked to financial hubs such as London. These results suggests that the high-powered financial service activities leading to the large international capital positions of OFCs take place elsewhere and that OFCs do not create value by providing human capital or financial services locally.

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1 Introduction

Few aspects of the international financial system are as opaque as offshore financial centers (OFCs) but the disproportionately high international capital positions they attract have led to increasing scrutiny. Banks and Non-Bank Financial Institutions (NBFIs) with a presence in OFCs argue to be providing skilled human capital and innovative legal and financial services that attract international capital. Also, companies, fund managers, and even official government aid institutions[1] argue that OFCs play a vital role in their international investment strategies, providing a set of unique skills and services supporting their activities. Such services include wealth management services, fund incorporation and management, single point of entry solutions, and the setting up of sophisticated corporate structures involving multiple entities and jurisdictions.

The empirical economic literature, on the other hand, usually operates under an assumption that few if any economic activities take place on OFCs. Instead, ownership structures are assumed to show passive deposits or assignment of ownership and OFCs are accused of merely providing opportunities for regulatory arbitrage (Garcia-Bernardo et al., 2017; Zucman, 2013). If these opportunities are used to circumvent bank regulation, they raise financial stability concerns (Haberly and Wójcik, 2017); if they are used for tax noncompliance, they can be damaging to the tax systems of other countries Zucman (2014). With the data sources employed here, this assumption becomes testable against the assertions mentioned above. Two hypotheses emerge: First, some correlation between financial and local economic activity should be observable if local human capital is involved on OFCs. Second, if financial service activity takes place in the OFC, it should react to exogenous shocks that affect it. Here, re-occurring natural disasters in the form of hurricanes are introduced as a natural experiment providing such a shock on the small Caribbean and Pacific islands engaged in offshore finance.

Despite several 'crackdowns on tax havens,' many of OFC islands continue to maintain high secrecy rules, low to zero tax rates, low to no reporting requirements, and light regulation of financial institutions. They have other things in common that point toward an advantage in providing financial services: they are economically open, provide a sophisticated communications infrastructure, and perform well on governance indicators measuring political and legal stability as well as corruption (Dharmapala, 2008; Dharmapala and Hines, 2009). This supports the interpretations of OFCs as contributors to the functioning of international capital markets through a comparative advantage in the financial service sector targeting international capital. The few aggregate estimates that exist point to large positions with around 8% or 4.5 trillion

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[1]The 2015 report of the German Investment and Development Society (DEG), an official aid institution, shows nine fund participations in Mauritius; in 2017 that number rose to 36. See: https://www.deginvest.de/International-financing/DEG/Download-Center/Jahresberichte/, last accessed October 13th, 2018.

of private wealth held offshore (Zucman, 2013). Tørsløv et al. (2018) estimate artificial profit shifting by multinational companies to be in the magnitude of 600 billion in 2015 alone. If anything, financial integration with OFCs is increasing (Milesi-Ferretti and Lane, 2017).

However, surprisingly little reliable evidence is available concerning the activities carried out in OFCs. Most empirical research focuses on indirect identification strategies. Johannesen and Zucman (2014) show reactions of bank deposits to information exchange upon request agreements aimed at detecting tax evaders inside the OFC with Hanlon et al. (2015) providing similar results for US portfolio investment inflows. Work on the EU savings directive also confirms such tax evasion effects (Johannesen, 2014). Another strand of the literature targets the evaluation of profit shifting strategies of multi-nationally active firms by showing, for example, firms shifting subsidiaries or banks moving trading activity into OFCs to avoid regulation or taxation (Caruana-Galizia and Caruana-Galizia, 2016; Langenmayr and Reiter, 2017). Again, indirect strategies in reaction to certain policy changes dominate (Dharmapala et al., 2011).

Crucially, while many financial service activities profit from an accommodative regulatory environment, they also rely on financial service providers setting up the tax avoidance scheme, incorporating the shell company, and managing the offshore trust. On paper, such financial services inflate macroeconomic statistics about OFCs. With an estimated GDP per capita of $85,700 Bermudans are the richest population on the planet on paper (PPP adjusted, CIA World Factbook estimate). However, it is an open question how much of this activity actually takes place in OFCs and to what extent these jurisdictions are instead used as shells that feature these large positions in financial statistics but in reality do not contribute the financial services. The theoretical literature has maneuvered around the issue by providing models that allow for both interpretations (Slemrod and Wilson, 2009, footnote 14 makes it explicit). To the best of my knowledge the only available empirical evidence showing that financial service activity on OFCs is artificial is provided in Langenmayr and Reiter (2017). For a sample of German banks, they provide tentative evidence that banks themselves use OFCs for their own profit shifting strategies by shifting trading activity but not employees to OFCs. Whether such behavior extends to services they provide to their customers is an entirely open question.

Studies into the nature of OFCs are plagued by data limitations. In order make progress, I construct and employ several new data-sources that shed light on both real economic activity and financial activity in OFCs. First, I construct a comprehensive monthly nightlight dataset based on satellite images for both entire jurisdictions as well as their sub-national regions. This measure is used as a proxy for economic activity that physically takes place on the island in question. The sub-national data allows an investigation of the capital regions, where potential financial activity is expected to agglomerate. Second, I use bilateral bank claims from the Locational Banking Statistics of the Bank for International Settlements reported by a significant

number of OECD economies against the small islands jurisdictions under study here. These mirror claims measure bank integration and bank investment. Third, equity price data on banks and non-bank financial institutions (NBFIs) domiciled in OFCs are used to capture investor responses to hurricanes. Finally, I construct a dataset on daily company incorporations - including shell companies - from six OFC corporate registries leaked in the Paradise papers. With the exception of these incorporation series, all measures are also constructed for non-OFCs. This allows me to investigate developments and reactions in non-OFCs as a 'real-world' test of the identification strategy.

Having access to these new data sources allows for evaluating economic developments in OFCs and other small island economies for which no conventional data are available. A first set of descriptive results documents that international financial integration and local economic activity are not correlated on OFCs, neither within nor between islands. For non-OFCs, on the other hand, a positive correlation between the two is readily observable. While this is unusual, it does not inherently prove that the financial industry does not operate on the OFC, rather just that it is disconnected from the local economy. Therefore, I check the reactions to exogenous shocks in order to see if such reactions are visible in both types of activity.

I exploit the natural experiment of re-occurring hurricanes in the Caribbean and typhoons in the Pacific (both subsumed under 'hurricanes' here). Based on the commonly used lists of 'treasure islands' provided by Hines (2010) and Gravelle (2015), 18 such offshore finance islands are located in the 'hurricane alley' of the Caribbean and the Atlantic Ocean. Another 10 are situated in the Pacific and regularly hit by typhoons. Both regions also include numerous islands that do not carry out offshore finance activities. As around 50% of offshore capital is booked through islands hit by hurricanes, it is possible to analyze a relevant fraction of the offshore world. Disaster type hurricanes in these regions lead to extended power outages, disabled infrastructure, evacuations, flooding, and direct casualties.

Indeed, local economic activity in OFCs, as measured in the monthly nightlight dataset constructed here, drops by around 30-50% after a hurricane hits. Recovery takes around six months on average, an effect in line with the literature on natural disasters (Mohan and Strobl, 2017; Strobl, 2011, 2012). These results hold both on the national and the sub-national levels. However, effects of these natural disasters on financial activity in OFCs are entirely absent. They are insignificant both statistically and economically with no sign certainty. Financial activity continues unabated while local economic activity drops by a third, on average. This begs the question who carries out these activities and if whoever it may be is actually on the island. To test the identification strategy, the 'real world' baseline in the form of non-OFC islands is also investigated. Here, claims held by international banks against the island are reduced by 10-30%.

In two sets of extended results, I first show that investor responses verify the relationships observed in the bank data. In line with the other results, financial service providers in OFCs do not experience significant abnormal returns while their counterparties incorporated in non-OFCs do. However, there is one measure for which a small reaction on hurricane impacts is visible in offshore financial centers. One of the most cited activities taking place in OFCs is the incorporation of shell companies. While data here is limited to a few OFCs, a significant drop is visible following hurricanes. This suggests that there is a differentiated effect across service provision in OFCs and that some activity does take place there, even if it is just a stamping incorporation documents. However, this is not the sort of high-powered financial service activity that would lead to the international capital positions of OFCs that we observe in the data. Rather, it suggests that OFCs play a role as a front for the activity of international financial service providers. This conjecture is bolstered by descriptive evidence provided here that shows strong decreases of incorporation activity on the island during public holidays in London that are normal work days in the OFCs in question.

This project contributes to the literature in three important ways: First, research on offshore financial centers is plagued by the absence of reliable data. Here, this situation is improved upon by (a) employing monthly satellite data on nightlight intensity as a measure of real economic activity available for any island no matter how small, and (b) establishing what kind of financial activities takes place on the island using several data sources: BIS mirror data, equity prices on banks and NBFIs domiciled there, and leaked incorporation data. Second, these data sources allow for investigating contested claims, such as a disconnect between finance and local economic activity. Little to no previous empirical evidence is available to verify such claims for OFCs. Third, the project employs the natural experiment of re-occurring hurricanes as a source of exogenous variation in local conditions. This setup allows for differentiating two factors in the attractiveness of offshore financial centers: Their accommodative regulatory environment, which should not react to hurricanes, and their contribution to efficient banking by potentially being home to some of the most advanced financial service providers and internationally active banks and their subsidiaries.

The paper proceeds as follows. Section 2 introduces the identification strategy based on hurricane impacts in detail. Section 3 outlines the data sources used: geo-spatial data on nightlight intensity, hurricane data, and data measuring financial activity. Section 4 briefly investigates descriptive statistics showing a disconnect between financial and real economic activity, but only on OFCs. Section 5 provides the main results on hurricane impacts, comparing the responses of local economic activity and international bank positions. In section 6, extended results on investor responses and incorporation data are provided. Section 7 concludes.

2 Identification: The natural experiment of re-occurring hurricanes

Empirical research on offshore finance faces two non-trivial problems: First, even if it is available, macroeconomic data on small island economies are notoriously unreliable and, as the example of GDP per capita in Bermuda shows, potentially inflated. Second, the researcher has to identify reactions of activities that are oftentimes shrouded in secrecy or at least not officially recorded. The data problem is addressed in the data section. This section focuses on the identification of offshore finance activities in the second part of the analysis: differentiated reactions of the real economy and financial positions and service provision to an exogenous shock.

Usually, identification in research on offshore finance is achieved by exploiting regulatory changes that change the incentive structure of agents who exploit certain regulations (see Slemrod, 2015; Zucman, 2014, for overviews). In this project, I propose a different identification strategy based on the natural experiment of re-occurring storms as a source of exogenous variation, alleviating concerns of policy endogeneity.

The Caribbean sample under study here is called 'hurricane alley' due to the re-occurring tropical storms that form over the Gulf Stream . In the Pacific, islands are spread out and regularly hit by typhoons. Only hurricanes categorized as natural disasters are used here. Hurricane Irma in autumn 2017, for example, directly affected 1.2 million people with wind speeds of up to 295 kilometers per hour, causing at least 130 deaths, leading to damages of 50 billion USD in the United States alone, and cut electricity for several million inhabitants on Caribbean islands and in Florida (US Office for Coastal Management[2]). The hurricane affected eight OFC territories[3] and five non-OFC islands[4] as well as parts of the 50 US States . Local impacts were substantial, 90% of all buildings on Barbuda, for example, were destroyed.

Such storms affect local economic activity. Economic impact of hurricanes established in the literature range from 0.45% to 1.5% lower GDP growth in a given year (Bertinelli and Strobl, 2013; Strobl, 2011, 2012). Effects usually last several months before the drop is made up for. Two existing studies on drop of nightlights on single islands show an effect lasting up to 15 months in the Dominican Republic (Ishizawa et al., 2017) and around 7 months for cyclone Pam hitting the pacific island of Vanuatu (Mohan and Strobl, 2017). If significant effects are detected, such hurricanes provide a meaningful exogenous shock to local activity. I use these reactions of real economic activity to test if hurricanes actually affect OFCs to a significant extent. Additionally, I compare the impact in non-OFCs to provide a 'real world' test.

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[2]Last accessed September 20, 2018, at: https://coast.noaa.gov/states/fast-facts/hurricane-costs.html

[3](1) Anguilla; (2) Antigua and Barbuda; (3) Barbados; (4) the British Virgin Islands; (5) St. Lucia; (6) St. Kitts and Nevis, (7) St. Maarten (Dutch Part); and (8) the US Virgin Islands

[4](1) Cuba; (2) Guadeloupe; (3) Haiti; (4) Puerto Rico; and (5) Saint Martin (French Part).

Figure 1: **Schematic reactions to hurricane impacts**
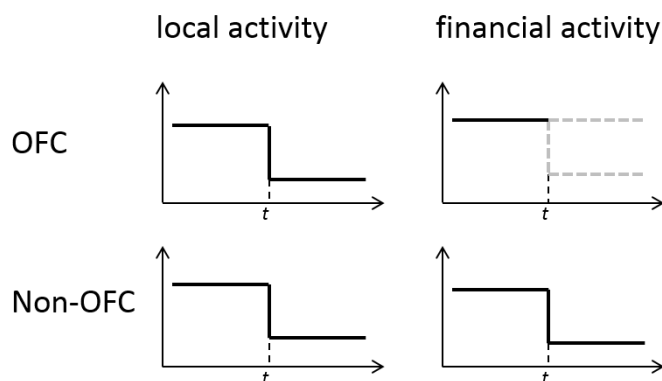
Notes: Hypothetical reactions to hurricane impact at time t on the horizontal axis for offshore financial centers (OFCs) and non-OFCs.

Figure 1 summarizes the resulting hypothesis. Assume a hurricane hits an OFC at time t. The first column of figure 1 indicates the potential drop in real economic activity that I expect. The identifying assumption now is that banks and non-bank financial institutions (NBFIs) cannot completely isolate themselves from this shock. The magnitude of the effect can differ but the presence or absence of financial service provision as an activity physically carried out in OFCs would be mirrored by the reaction in column 2 row 1 of figure 1. Indeed, if it is the skilled banker providing the service that leads to the large capital positions of OFCs, her activity should suffer from power outages, infrastructure breakdowns, and the physical destruction of her office. If hurricanes decrease real economic activity on OFCs and leave financial data unaffected, however, this is evidence that the financial service is carried out elsewhere and merely booked through the OFC. In this case, the only 'service' that the OFC provides is an opportunity for regulatory arbitrage or legal environments and no contribution to the efficiency of financial service provision can be attributed to OFCs. The offshore banker remains elusive.

Non-OFCs are investigated as an additional test of this identification strategy: they provide a 'real world' comparison. Still, if no reaction of hurricanes in financial activity on non-OFC is visible, this would cast serious doubt on the identification strategy. In effect, testing non-OFCs relaxes the identifying assumption to: Banks and NBFIs cannot completely insulate themselves from hurricanes *when their counterparts on non-OFCs also cannot.*

However, it is necessary to establish that hurricanes hit OFCs and cause significant damage. Only then would we expect reactions in financial service provision. Thus, investigating these reactions is completed in two steps in the main results: First, the impact of hurricanes on real economic activity is determined. Second, the reaction of variables capturing financial service activity is tested. The following section outlines the data necessary to carry out these exercises.

3 Filling the data gap in offshore finance

The strength of the identification strategy outlined above is that there are a large number of OFCs and non-OFCs in the Caribbean[5] and in the Pacific[6] that are regularly hit by hurricanes. This differentiation is based on common tax haven lists employed in the literature and, for both regions, quite consistent both over time and over different studies (for commonly used lists see Gravelle, 2015; Hines, 2010; Hines Jr and Rice, 1994). All of these countries are small island economies and most have little to no available macroeconomic data.

To fill this gap, I propose using several data sources with large to complete coverage of small island economies with less than 100,000 inhabitants, even as few as 5,000. First, satellite data on nightlight intensity is introduced and used in combination with geo-spatial data on geographic boundaries of the jurisdictions in question to construct a monthly dataset of nightlight intensity from 2012:4 to 2017:12. Second, BIS data on bank claims reported by all reporting non-OFCs, including large OECD countries, is introduced. These positions are reported for a large number of jurisdictions, including the majority of countries under study here. In the extended results section, two other data sources are analyzed: Daily company incorporations on offshore financial centers and equity prices of financial service providers domiciled in the island economies under study. These data sources are introduced directly in the respective sections. Crucially none of the data sources employed here rely on information deliberately reported by the OFCs themselves. This should alleviate concerns of mis-reporting or data quality.

3.1 A monthly nightlight dataset including small island jurisdictions

Satellite data is frequently used by development economists trying to measure economic conditions in remote areas or countries with unreliable national accounts. Henderson et al. (2012) provide the seminal contribution relating nightlight data to economic growth and a useful summary of applications of satellite data in the empirical economics literature is available in Donaldson and Storeygard (2016). Most sources in the literature relating storms to nightlight as well as most studies in development economics are based on an older yearly data source of DMSP[7] satellites (Bertinelli and Strobl, 2013).

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[5]Caribbean OFCs in the sample: Aruba, Anguilla, Antigua & Barbuda, the Bahamas, Bermuda, Barbados, Curaçao, Cayman Islands, Dominica, St. Kitts & Nevis, St. Lucia, Montserrat, Sint Maarten, Turks & Caicos Islands, Trinidad & Tobago, St. Vincent & Grenadines, British Virgin Islands, U.S. Virgin Islands. Caribbean non-OFCs: Cuba, Dominican Republic, Guadeloupe, Haiti, Jamaica, Martinique, and Puerto Rico

[6]Pacific OFCs in the sample: Cook Islands, Marshall Islands, Nauru, Niue, Samoa, Seychelles, Tonga, and Vanuatu. Pacific non-OFCs: Fiji, French Polynesia, Guam , Kiribati, New Caledonia, Palau, Papua New Guinea, Solomon Islands, Sri Lanka, Tuvalu, and Wallis & Futuna.

[7]The Defense Meteorological Satellite Program (DMSP) of the US military.

Figure 2: **Nightlights and Jurisdictions in the Caribbean**
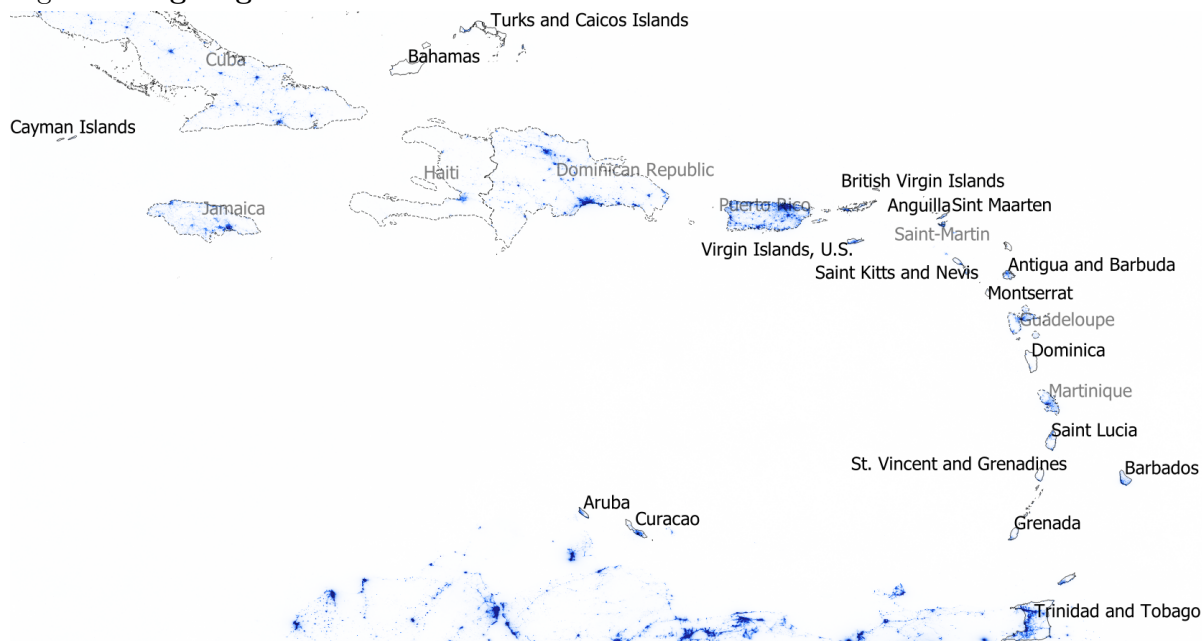
Notes: Shows VIIRS nightlights and administrative boundaries of Caribbean Island economies and some larger jurisdictions. Offshore financial centers are shown with black labels and solid boundaries, non-offshore financial centers with grey labels and dashed lines. The nightlights visible in the lower part of the figure show South America without country borders. Data sources: NASA, GADM, NOAA.

This satellite Program has been followed up by NASA and the NOAA National Geophysics Data Center with the Visible Infrared Imaging Radiometer Suite (VIIRS), which provides several improvements useful for the analysis at hand. First, it is much more precise with a resolution of around 750 meters at the equator, lower light detection limits, and several technical improvements for data comparability as scans move away from the equator (see Elvidge et al., 2017, for further details). The new satellite has a nightly overpass time at 1:30 am and has no light saturation point that limited distinctions of very light areas in the DMSP data(Mohan and Strobl, 2017). The resulting images are aggregated into monthly composites and corrected for stray light, lightning, cloud cover, and other outliers (Elvidge et al., 2017). Figure 2 shows the Caribbean part of the sample with the borders of the island economies plotted over such a nightlight map.

These large monthly nightlight maps are available from the Earth Observation Group, NOAA National Geophysical Data Center.[8] I combine them with geospatial data on national and regional boundaries. These spatial polygons are available for all jurisdiction relevant here via the Global Administrative Areas dataset. [9] Figures 3 and 4 plot a part of the Caribbean using these data sources at different points in time. Visible in shaded areas are the British and the US Virgin Islands. The spatial polygons of the country boundaries, plotted in grey, are only added for the British Virgin Islands. Hurricanes Irma and Maria hit the British Virgin Islands

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[8]Last accessed June 12, 2018, at: https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html

[9]Last accessed June 12, 2018, at http://www.gadm.org/country

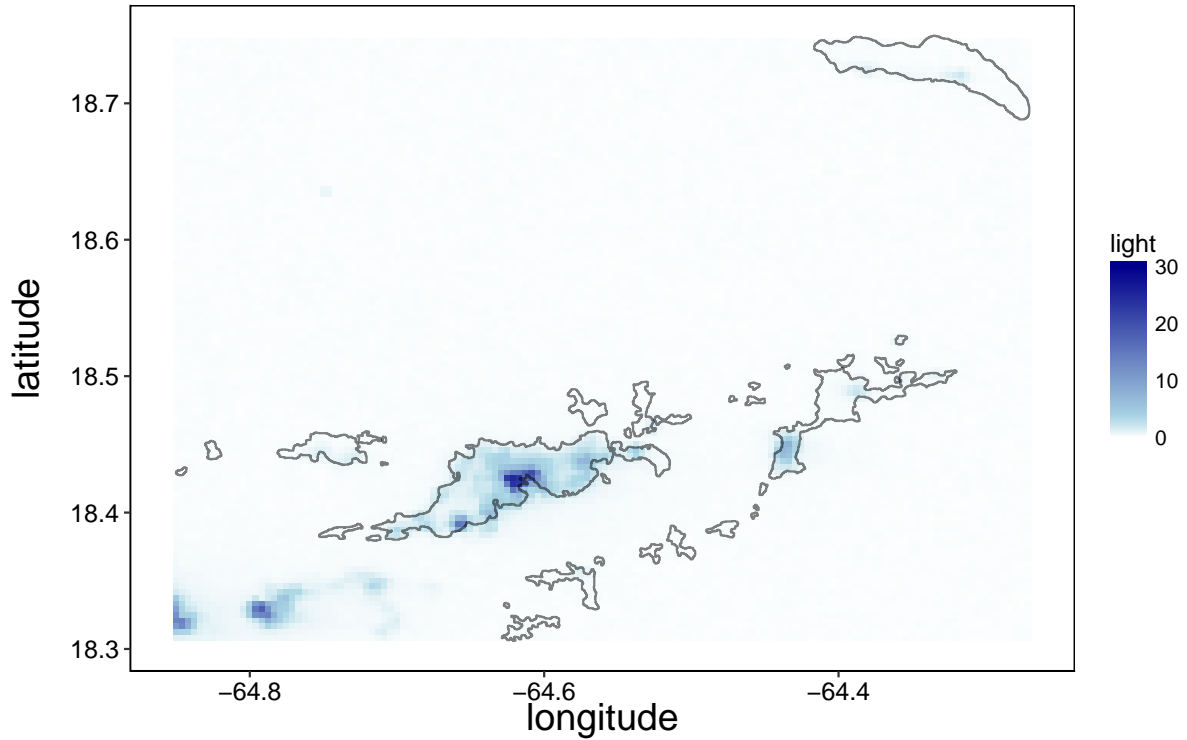Figure 3: **Nightlights in the British Virgin Islands pre Irma & Maria**

Figure 4: **Nightlights in the British Virgin Islands post Irma & Maria**
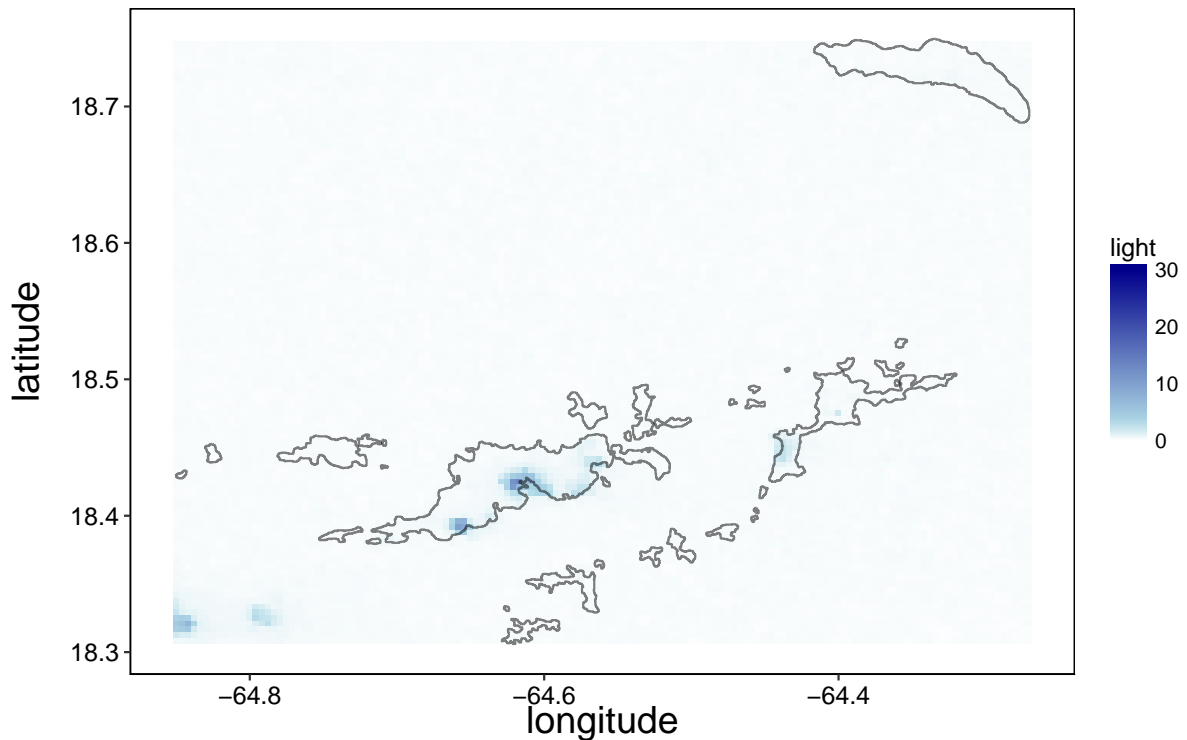
Notes: Shows nightlight intensity for the British Virgin Islands (center) and the US Virgin islands (south-west) and the country polygon (in grey borders) for the British Virgin Islands only. Figure 3 shows nightlight intensity in August 2017, before hurricanes Irma and Maria hit the islands. Figure 4 shows the same area in October 2017 after these hurricanes. The mean of nightlight intensity inside a country polygon forms the basis of the monthly nightlight dataset used as a measure of real economic activity. Radiance of nightlight is measured in units of $Wcm^{-2}sr^{-1}$, or watt per steradian per square centimeter multiplied by $1E9$.

in September 2017 and the drop in nightlight intensity of this one hurricane is already visible by visual inspection.

Within the country polygon, it is then possible to calculate statistics of the nightlight intensity in each jurisdiction and each month available.[10] By performing such calculations for each jurisdiction and going though all available monthly nightlight maps, a monthly panel dataset is created running from April 2012 through December 2017 for every jurisdiction in the sample.[11]

These data are the basis for calculating the real local impact of hurricanes. The advantage of this dataset is that is completely free of data gaps and of a relatively high frequency. Data on Montserrat, a British Overseas Territory with only around five thousand inhabitants and little usable data from other sources, are just as readily available as data on Jamaica with 3 million inhabitants. The subnational dataset is used for robustness checks to confirm the main results for capital regions only.

3.2 Mirror data of bank claims

The data availability problem in offshore finance extends to data on financial positions and service provision. In order to be meaningful for the identification strategy outlined above, financial data has to satisfy three conditions. First, the activity needs to take place in an OFC, ruling out most industry or agricultural activities. Second, the activity needs to take place in a non-OFC ruling out pure profit shifting strategies. Third, the activity needs to react to hurricane impacts meaning that their needs to be a physical manifestation of these activities, at least in theory. A first data source is introduced here with two additional sources outlined directly in the extended results section.

In its Locational Banking Statistics (LBS), the Bank for International Settlements provides bilateral quarterly time series on banks' international claims and liabilities on an immediate counterparty basis. So far, only bank deposits, a subsets of the liabilities reported in these data, are analyzed in the tax evasion literature with claims relegated to robustness checks (Johannesen and Zucman, 2014; Menkhoff and Miethe, 2018). Here, instead, I propose the use of mirror data on bank claims reported by non-OFCs. These positions include loans to banks

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[10]Radiance of nightlight is measured in units of $Wcm^{-2}sr^{-1}$, or watt per steradian per square centimeter. For usability, these radiance values are multiplied by $1E9$ by the NOAA National Geophysical Data Center. They are used in the resulting unit here, which leads to a continuous scale leading to a maximum of around 30 for most jurisdictions in the sample.

[11]The resulting monthly nightlight dataset and the associated R-code is available on request from the author. However, these data do not control for rural versus urban agglomerations within regions. Goldblatt et al. (2017) provide some a proof of concept how this could be achieved in the future using high resolution imagery taken from the Landsat satellite, but this is not necessary here.

and non-bank financial institutions (NBFIs), thus capturing the integration of the local financial system with international intra-bank markets.[12]

While coverage is not complete, the BIS dataset includes most relevant OECD countries including the United States and the United Kingdom. A total of 46 national central banks report the international claims and liabilities of banks under their supervision to BIS on a bilateral basis and at quarterly frequency. While only 5 OFCs from the Caribbean sample report such data, reports against 19 island and coastal OFCs[13] and 18 island or coastal non-OFCs[14] are available, all exposed to hurricanes, whether in the Caribbean or in the Pacific. In addition to the nightlight data introduced above, these mirror claims are a second step in filling the data gap in offshore finance.

Thus, mirror claims of sample countries are calculated as follows:

$$(1) \qquad Mirrorclaims_{it} = \sum_{j=1}^{J} claims_{jit}$$

Where country i can either be an OFC or a non-OFC and claims are summed for the entire population of non-OFCs, $j = 1, ..., J$, that report bank claims data to the BIS. Reports by different countries and against different counterparties start at different points in time. A sample balanced in the second quarter of 2011, when satellite data becomes available as well, shows almost complete coverage and no systematic bias. Figure 5 shows mirror claims against three countries to highlight the main results in three different balancing schemes. The green dotted line show a sample balanced in 2003q1 to checked if reporting increased substantially before 2011. The red dashed line shows the sample for which nightlight data is also available and used here. The solid blue line shows a sample balanced in 2015q1 to show how much is lost by choosing an earlier point to balance the mirror claim reporting sample.

The financially largest OFC in the sample, the Cayman Islands (top panel), exhibits increasing claims over time, as do most OFCs. The largest OECD countries already report claims against this country in 2003, meaning that the three series do not deviate much and that both the level and the dynamics are well captured by the series starting in 2011:II. The Marshall Islands have received much less scrutiny and coverage is still increasing as the level shift between the three series shows. Still, the time dynamics especially of the 2015 series seem well captured in the

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[12]The BIS also provides claims against non-banks as a subcategory of these data but since this category would include non-bank financial institutions, such as offshore financial service providers, this differentiation is not used here. Thus, the data used here is reported against both bank and non-bank counterparties.

[13]These are: Aruba, Bahamas, Belize, Bermuda, Barbados, Costa Rica, Curacao, Cayman Islands, Dominica, St. Lucia, Marshall Islands, Panama, Seychelles, Turks & Caicos Islands, Tonga, Trinidad & Tobago, St. Vincent & Grenadines, Vanuatu, Samoa

[14]These are: Cuba, Dominican Republic, Fiji, Guatemala, Guyana, Honduras, Haiti, Jamaica, Kiribati, Sri Lanka, New Caledonia, Nicaragua, Papua New Guinea, French Polynesia, Solomon Islands, El Salvador, Tuvalu, Wallis & Futuna

2011 series used. Some OFCs, such as Curacao (bottom panel) exhibit decreasing deposits over time. Since Curacao split from Sint Maarten and Bonaire (formerly the Netherlands Antilles) in 2010, the 2003 series can be compared here, but the 2011 and the 2015 series are closely aligned.

Figure 5: **Balanced mirror claims three exemplary countries**
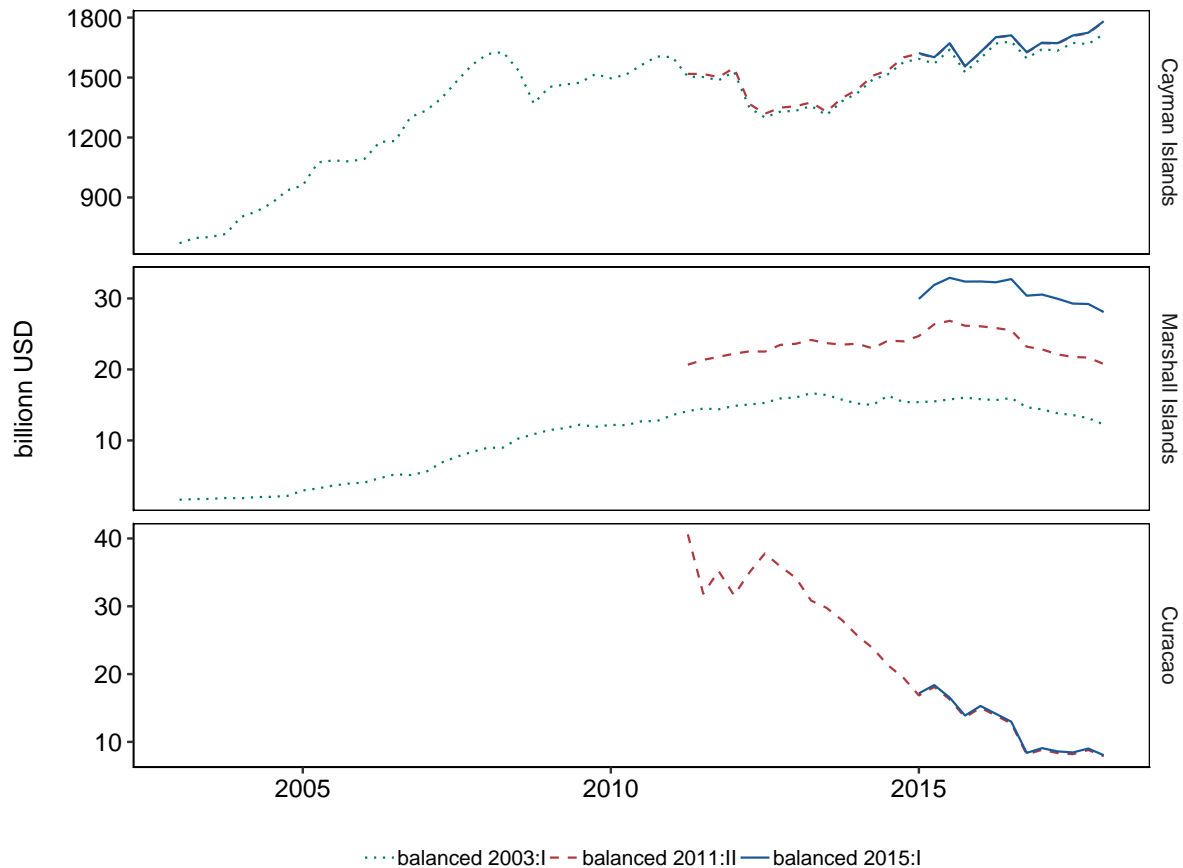
Notes: Shows three versions of balancing the countrypairs from which mirror claims are constructed: one starting with the sample available in 2003:I (green, dotted), one starting in 2011:II (red, dashed), and one starting in 2015:I (blue, solid). The vertical axis reports the total claims reported against the respective country by all reporting countries combined.

Thus, while countrypairs for which data becomes available only after the second quarter of 2011 are lost as a result of this balancing choice, figure 5 suggests that this loss is tolerable. Crucially, these mirror claims can also be constructed for islands as small as the Turks and Caicos Islands with 52,570 inhabitants but a total of 507 million USD of mirror claims reported against it in 2018 Q1, 206 million of which reported by non-OFCs in the sample balanced in 2011. Appendix Appendix A.1, provides more information on the development of coverage over time.

3.3 Data on hurricanes

The literature focusing on establishing precise growth declines due to hurricanes (see for example Strobl, 2011, 2012) goes into great detail when it comes to precise geo-spatial impact estimations

of hurricanes. In the present project, hurricane impacts must be analyzed at the national level because the financial data used here is only available at the national level. Regional data is used as a robustness check and confirms the results. National data on hurricanes is taken from the EM-DAT[15] disaster database that collects the exact timing of hurricanes in the Caribbean, including statistics on the number of inhabitants and locations affected. This dataset includes hurricane Irma, the most devastating hurricane hitting the Caribbean since VIIRS satellite data is available. Since hurricanes can be dated precisely, this data can be used at all frequencies employed here: monthly together with data on nightlight intensity, daily together with incorporation data, and quarterly to analyze BIS bank claim data. Most hurricanes in the sample hit both OFCs and non-OFCs, thus making it possible to compare impacts of the same storm on different islands and different variables.

Table 1 summarizes the data on island economies of the data-sources introduced so far. Several facts are noteworthy. First, the average OFC indeed is quite small. For example, the Cayman Islands and Bermuda have only 60,000 and 70,000 inhabitants, respectively, but large mirror claims. It is also apparent that GDP per capita and poverty rates, retrieved from the CIA World Factbook, where available, vary substantially across the sample. As previously noted, the nightlight mean and standard deviations are available for all OFCs and, thus, can be used to evaluate hurricane impacts, the frequency of which also varies across countries.

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[15]The Emergency Events Database - Universit catholique de Louvain (UCL) - CRED, D. Guha-Sapir - www.emdat.be, Brussels, Belgium

Table 1: **Descriptive statistics on Caribbean & Pacific island economies**

country	population	GDP p.C.	poverty in %	mirror claims 2018q1	mean(light)	sd(light)	hurricanes since 2011q2	OFC
Aruba	115,120	25,300	−	0.049	5.440	1.138	0	1
Anguilla	17,087	12,200	23	−	3.131	0.509	1	1
Antigua & Barbuda	94,731	26,300	−	−	2.497	0.158	1	1
Bahamas	329,988	25,100	9	105.200	0.548	0.085	6	1
Bermuda	70,864	85,700	11	63.570	6.704	0.644	0	1
Curacao	149,648	15,000	25	22.060	6.193	0.930	0	1
Cayman Islands	58,441	43,800	−	1,547.000	4.862	0.473	0	1
Dominica	73,897	12,000	29	0.034	0.325	0.085	3	1
Dominican Republic	10,734,247	17,000	31	2.511	0.799	0.134	7	0
Fiji	920,938	9,900	31	0.368	0.104	0.093	3	0
Guadeloupe	397,990	−	−	−	2.576	0.161	1	0
Haiti	10,646,714	1,800	59	0.176	0.158	0.083	7	0
Jamaica	2,990,561	9,200	17	0.914	1.230	0.107	2	0
St. Kitts & Nevis	52,715	26,800	−	−	2.185	0.192	1	1
St. Lucia	164,994	26,800	−	0.035	1.854	0.116	2	1
Montserrat	5,292	8,500	−	−	0.248	0.091	0	1
Martinique	380,877	27,305	17	−	3.757	0.197	2	0
Nauru	11,359	12,200	−	0.001	3.338	1.057	0	1
Papua New Guinea	6,909,701	3,700	37	0.661	0.046	0.074	2	0
Puerto Rico	3,351,827	37,900	−	−	4.602	0.622	4	0
Solomon Islands	647,581	2,200	−	0.050	0.016	0.078	2	0
Turks & Caicos Islands	52,570	29,100	−	0.199	0.685	0.093	1	1
Trinidad & Tobago	1,218,208	31,200	20	1.546	6.200	0.290	0	1
Tuvalu	11,052	3,700	26	−	0.102	0.093	1	0
St. Vincent & Grenadines	102,089	11,600	−	0.530	0.733	0.105	2	1
British Virgin Islands	35,015	42,300	−	−	1.551	0.254	1	1
U.S. Virgin Islands	107,268	36,100	29	−	5.797	0.971	1	1

Notes: Shows data on island economies in the Caribbean and in the Pacific. Population, GDP per capita, and poverty rates (where available) are taken from the CIA World Factbook estimates (Jul. 2017, where available). Column 4 shows the sum of international claims (in billion USD) reported on the OFC by all non-OFCs that provide data to the BIS locational banking statistics in 2011q2 or earlier. Columns 5 and 6 show means and standard deviations of nightlight intensity over the sample period (2012:4 - 2017:12). Column 7 shows the number of hurricanes after 2011q2 and column 8 finally indicates if the jurisdiction is classified as an OFC or not.

4 Descriptive Evidence: Local real- and financial activity

The large financial positions documented in the data section could lead to high income in the form of fees or taxes. Such income can be substantial, even with very low tax rates due to the inflated foreign tax base relative to small island economies (see Zucman (2013) and Tørsløv et al. (2018) for a similar point regarding European tax havens). However, it is an open question how these funds are used and to what extent it ends up in the local economy. In this section, I make use of the nightlight and BIS mirror data to investigate the direct relationship of these variables.

With access to data on real economic and financial activity in small coastal and island economies, it is possible to provide an initial indication. Satellite data on nightlights is used in the development literature to approximate local economic activity (Henderson et al., 2012) and mirror claims are used to measure the international financial integration of banks and non-bank financial institutions providing financial services. Using these two data sources at quarterly frequency, figure 6 plots average nightlights over international bank mirror claims. Both variables are transformed using the log-equivalent inverse hyperbolic sine transformation to retain negative and zero observations.[16]

The top panel of figure 6 shows that there is no such relationship in the OFC part of the sample, neither between nor within jurisdictions. This is an interesting finding in its own right: it suggests that foreign financing in the form of loans and assets held by foreign banks is not directly associated with higher economic activity in OFCs. The bottom panel shows the 'real-world' relationship and a positive relationship for non-OFCs both between countries as well as within countries. This relationship is not linear but increases over mirror claims. Maintaining that nightlights proxy real economic activity, this image is intuitive: higher foreign capital positions are associated with higher local economic activity.

This missing link in OFCs needs explaining. If local economic activity does not benefit from large foreign capital positions, and indeed shows no correlation to them, what actually constitutes these positions? They measure the integration with the international banking sector but, contrary to non-OFCs, these banks do not seem connected to local conditions. Still this does not in itself prove that the financial industry does not operate on the OFC. Thus, in the following section, I turn to the natural experiment of hurricanes and show (non-) reactions that indicate just that.
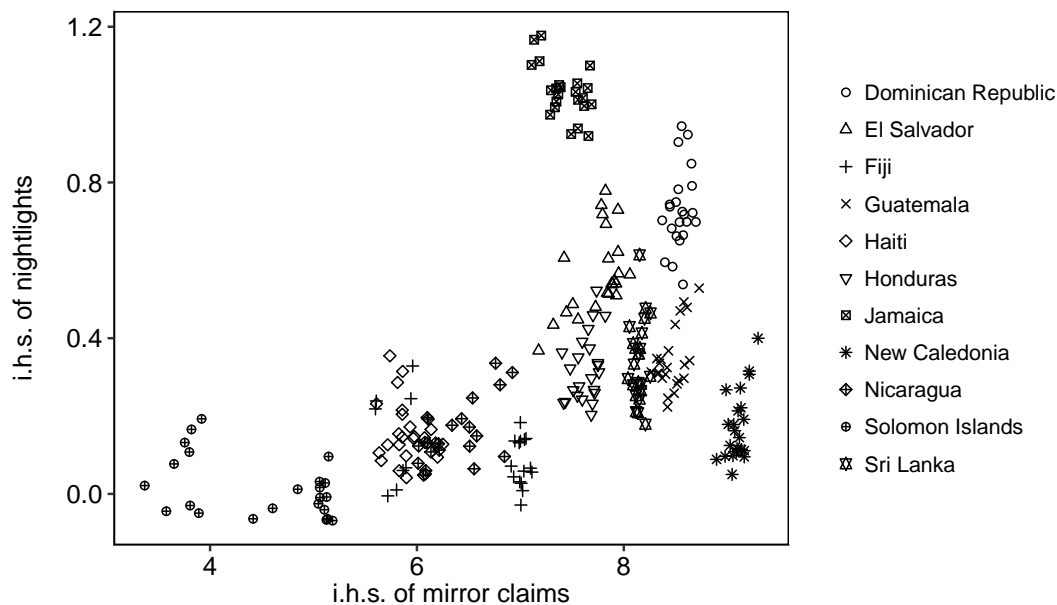
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[16]The inverse hyperbolic sine transformation is calculated as $ihs(x) = log(x + (x^2 + 1)^{1/2})$.

Figure 6: **The disconnect between nightlights and foreign capital**

(a) OFC sample: no correlation
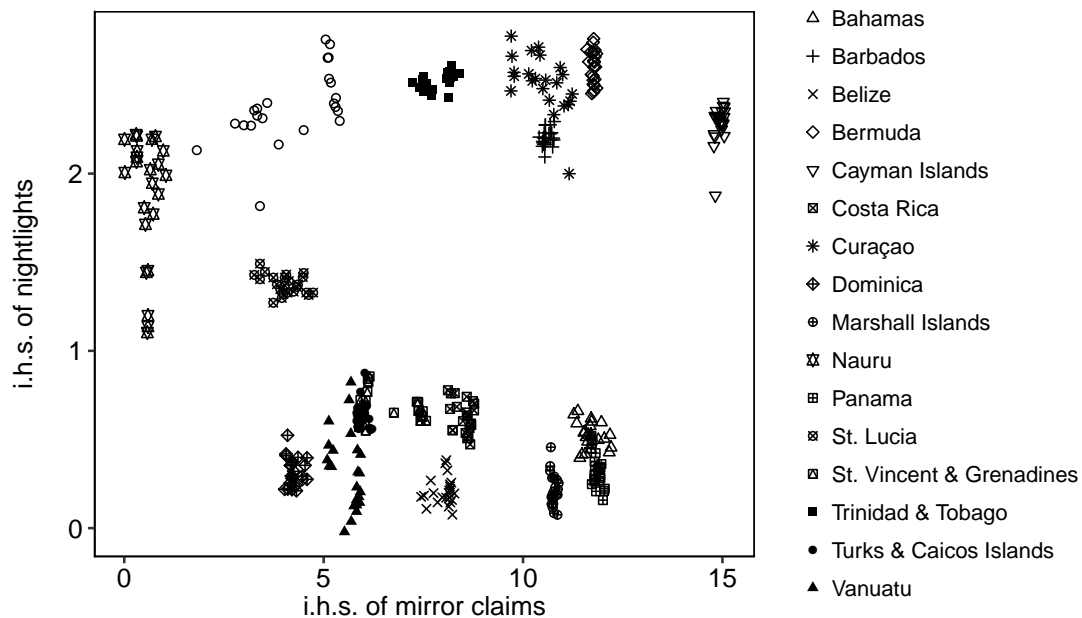
(b) Non-OFC sample: positive correlation

Notes: Both figures plot the inverse hyperbolic sine of nightlights over the inverse hyperbolic sine of the sum of international bank claims by all reporting non-OFC economies. The sample is limited by the availability of offshore mirror claims. Panel (a) shows the OFC part of the sample where no correlation is visible. Panel (a) shows the non-offshore part of the sample with a positive relationship of both variables.

5 Main Results: Hurricane impacts

To provide more robust evidence on the disconnect between local economic activity and international financial service activity, the main results presented in this section show reactions to hurricane impacts. This section proceeds in two steps. First, results of the impact of hurricanes on real economic activity measured by nightlight intensity are analyzed. These results are then compared to reactions of foreign bank claims that include loans to, and, to a lesser extent, assets of, local banks and non-bank financial institutions (NBFIs) on OFCs. In both steps, I also provide tests in the non-OFC sample to test the identification strategy in the 'real world.' In the entire section, the samples are reduced to island economies only.

5.1 Nightlights and hurricanes in OFCs and non-OFCs

Adding to the anecdotal evidence on hurricane impacts, such as 95% of houses on Sint Maarten uninhabitable after hurricane Irma, my results on hurricane impacts on nightlight intensity are a modest contribution in their own right. No panel results on the Caribbean using VIIRS data exists to date. Available studies focus on the effects on GDP of hurricanes hitting South America and the Caribbean (Strobl, 2011) as well as US county per capita income (Strobl, 2011). Hurricane impacts on nightlights is analyzed in the Caribbean using the aforementioned older yearly DSMP data (Bertinelli and Strobl, 2013) with only one study employing VIIRS data to analyze the impact of cyclone Pam in the Pacific Ocean (Mohan and Strobl, 2017). Still, the main target of the results shown here is to test if hurricanes significantly affect local economic activity on OFCs. Additionally, results on non-OFCs are presented. This provides the baseline against which to compare reactions in financial data.

Using the monthly nightlight dataset outlined in the data section, figure 7 shows the development of average nightlight intensity of Caribbean islands around the dates of hurricanes Irma and Maria in September 2017 (vertical line). Hurricane Irma appeared on the 30th of August 2017 and hurricane Maria dissolved on the 30th of September 2017. Data for islands affected by the storms are averaged in the green line, which exhibits a significant drop following the hurricanes. The red line averages nightlights in non-affected islands and shows no decline. Pre-trends are quite comparable and never significantly different from one another. All series are standardized by country and then averaged within the two groups. In levels, the associated drop registers at around one-third of nightlight observed (see Appendix figure A.2 for drops in the raw data).

Going beyond descriptives, nine distinct hurricanes classified as disasters in the Emergency Events Database hit the Caribbean and another nine Cyclones or Typhoons hit the Pacific Islands. Since nightlight data is available for every jurisdiction under consideration and since

Figure 7: **Impacts of hurricanes Irma & Maria on nightlight intensity**

Notes: The figure plots average nightlight intensity in the sample starting in 2016 till the end of the sample. The vertical line indicates September 2017 when hurricanes Irma and Maria hit the Caribbean. Countries are categorized into affected (green) and non-affected (red). All series are standardized by country to eliminate level effects before being averaged within the two groups.

these hurricanes hit different jurisdictions at different time points, a panel analysis can exploit within variation of a single island with a control group that varies over time. In what follows, I provide panel evidence on average effects. Reactions to hurricanes are investigated in a standard panel regression of the form:

$$(2) \qquad log(lightmean)_{it} = \alpha_i + \gamma_t + \sum_{k=-4}^{K} \beta_k d_{it+k} + \epsilon_{it}$$

Where the log of the mean of the nightlight intensity in country i at time t is regressed on a country intercept α_i, year-month dummies γ_t and treatment dummies d_{it} that take value 1 during and after the time of the hurricane for a number differing across lag specifications k. Figure 8 shows the results of such an estimation in the OFC part of the sample. The average effect is immediate and strong at around 27%, further decreasing to 54% by the second month after the hurricane when recovery is starting to pick up. Full recovery takes an average of six months.

Figure 8: **Hurricane impacts on OFC nightlights**
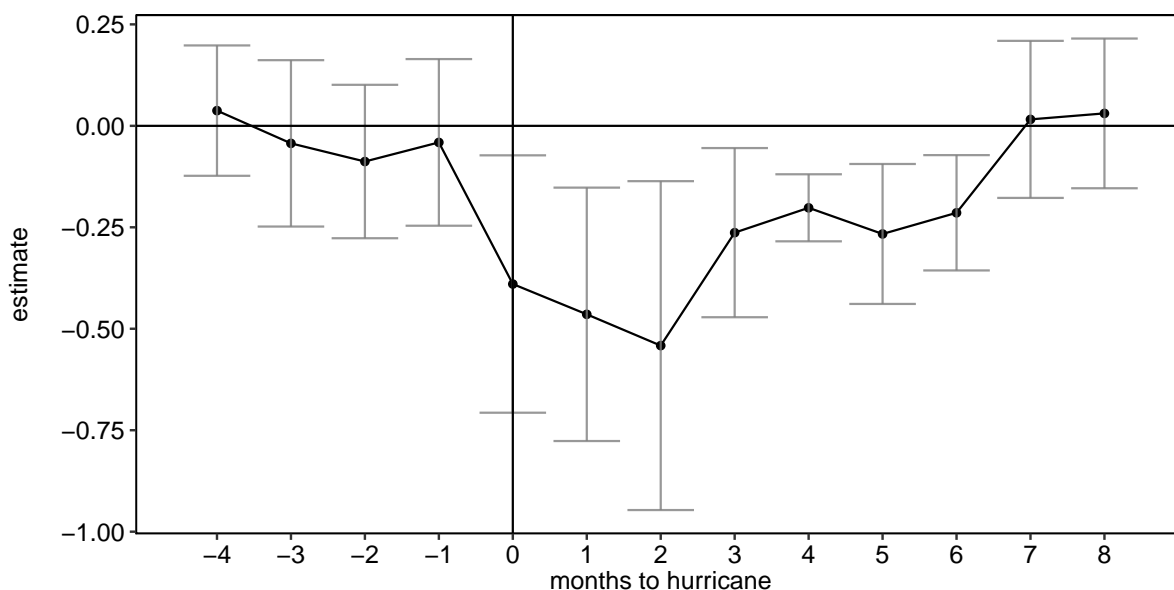
Notes: Plots leads and lags of a hurricane dummy in a difference in difference estimation within the OFC sample. The estimation takes the following form: $log(lightmean)_{it} = \alpha_i + \gamma_t + \sum_{k=-4}^{K} \beta_k d_{it+k} + \epsilon_{it}$, notation being identical to the main text. All coefficients are based on the same regression with k, the distance to the hurricane, plotted on the horizontal axis and the respective coefficient on the vertical axis. 95% confidence intervals are plotted in grey based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level.

Table 2: **Hurricanes impacts on nightlights across samples**

	Dependent variable: log(lightmean)		
	all	OFCs	non-OFCs
	(1)	(2)	(3)
hurricane$_{k=0}$	−0.208**	−0.328**	−0.069
	(0.084)	(0.149)	(0.089)
hurricane$_{k=0:k+2}$	−0.343***	−0.428***	−0.240**
	(0.093)	(0.156)	(0.108)
hurricane$_{k=0:k+5}$	−0.287***	−0.364***	−0.231**
	(0.083)	(0.125)	(0.109)
country f.e.	Yes	Yes	Yes
year-month f.e.	Yes	Yes	Yes
Observations	2,212	1,374	838

Notes: Each coefficient is the result of a separate regression. Column 1 shows results in a panel including all countries, column 2 reduces the sample to only offshore financial centers (OFCs), and column 3 to non-OFCs. The first row shows reactions to a treatment dummy taking value 1 in the month of the hurricane. The second row includes the first two months after a hurricane in the dummy and the third row the first five months after the hurricane hit the island. Heteroskedasticity and autocorrelation robust standard errors clustered at the country level in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Summarizing the results, table 2 shows coefficients of treatment dummies in nine separate regression. The first column shows results in the entire sample, column 2 shows results for OFCs only, and column 3 reduces the sample to non-OFCs as a 'real-world' comparison. Reactions are negative across the board. The first row shows the contemporaneous effect. The second row shows results of a hurricane dummy that includes the first two months after hurricane impact on top of the hurricane month. Effects are large and significant across the board ranging from a 24% reduction in non-OFCs to a 40% reduction on OFCs. This indicates that the impact of hurricane does not die out quickly, in line with existing research that shows recovery periods of at least half a year (Ishizawa et al., 2017; Mohan and Strobl, 2017). Extending the treatment duration to six months still shows significant results, but effect are somewhat weaker indicating that recovery is taking place. Here, effects converge at around -29% of nightlight intensity. Table A.1 in the appendix repeats this analysis in the regional nightlight dataset for nightlight intensity in the capital regions and confirms the results.

Thus, the impact of Irma and Maria as well as average hurricane impacts over the sample lead to the same conclusions: Hurricanes hitting island economies in the Caribbean and the Pacific and are associated with a significant drop in nightlight intensity of $30 - 50\%$. These impacts, visible to a similar extent in both OFCs and non-OFCs, only start to die out half a year after the hurricane hit. In the next section, the reaction of variables capturing financial service activity is compared to these baseline impacts.

5.2 BIS mirror claims and hurricanes in OFCs and non-OFCs

A drop in a GDP proxy 30-50% for at least 6 months is a catastrophic event. Maintaining the identifying assumption that banks and NBFIs on OFCs cannot completely insulate themselves against such shocks, some reaction in variables capturing financial activity is likely. Banks and NBFIs could reduce their activities as the result of evacuations, power outages, and infrastructure breakdowns. Foreign banks and investors should react to such changes, at least marginally. Before turning to investor reactions in the extended results, results on BIS mirror claims are provided here. These claims include loans to banks and NBFIs as well as assets held by banks against OFCs. Loans could be reduced, either because local actors demand less loans or because foreign actors are less likely to provide them. A shedding of assets would also indicate a loss of confidence of foreign banks. In both cases, a drop in mirror claims would indicate less active participation in the international bank market both by banks and NBFIs in OFCs.

As reactions of nightlight intensity data shows, hurricane impacts are visible for at least half a year, thus validating the use of a quarterly dataset, the lowest time frequency available from the BIS. Both aggregate mirror claims as introduced in the data section and the original bilateral data are used here. Both are reported by 19 large non-OFC economies including mostly OECD countries and excluding island economies.[17] In line with the setup for nightlight intensity, an estimation of the following form is made:

$$(3) \qquad log(mirrorclaims)_{iq} = \alpha_i + \gamma_q + \sum_{k=-8}^{K} \beta_k d_{iq+k} + \epsilon_{iq}$$

Where q denotes the quarter in question, i the island against which claims are reported or the bilateral countrypair and k the time period of the (lag of the) hurricane. Figure 9 shows the striking non-result in BIS mirror claims. No significant reaction is visible here for the OFC part of the sample. Despite plotting 2 years before and after hurricane impacts, not a single coefficient is significantly different from zero and most are even positive, albeit small. The non-OFC comparison, where reactions are visible, is provided in Appendix A.3.

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[17]These reporting non-OFCs countries are: Australia, Brazil, Canada, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Italy, Japan, South Korea, Mexico, Philippines, Sweden, Taiwan, United States, and South Africa . Luxembourg and the Netherlands are excluded due to their presence on several lists of tax havens.

Figure 9: **Non-impact of hurricanes on OFC mirror claims**
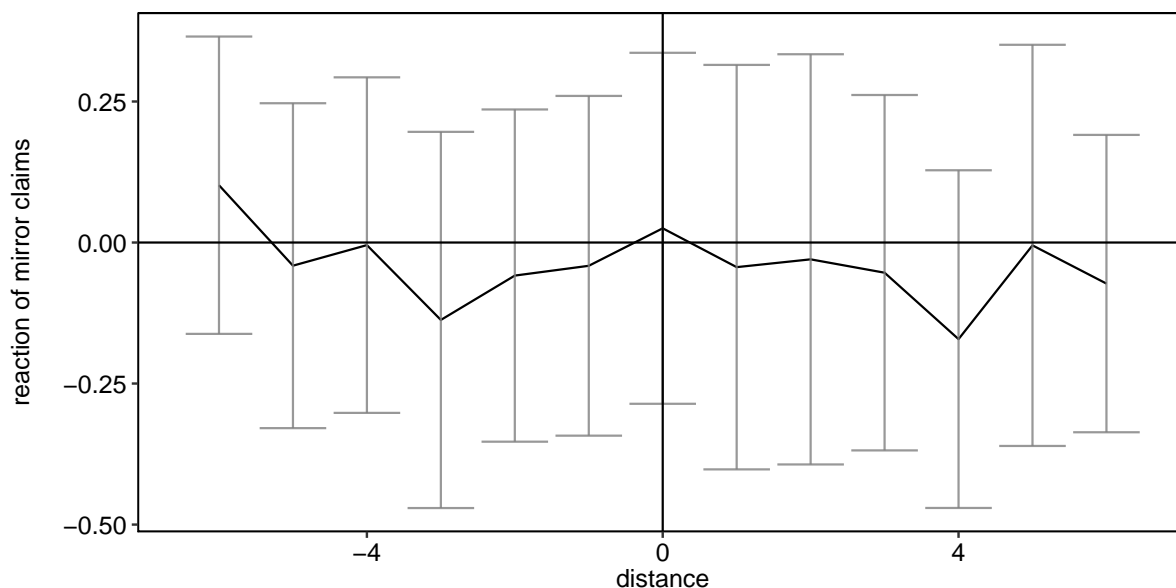
Notes: Plots leads and lags of a hurricane dummy in a difference in difference estimation within the OFC sample. The estimation takes the following form: $log(mirrorclaims)_{iq} = \alpha_i + \gamma_q + \sum_{k=0}^{K} \beta_k d_{iq+k} + \epsilon_{iq}$, notation being identical to the main text. All coefficients are based on the same regression with k, the distance to the hurricane, plotted on the horizontal axis and the respective coefficient on the vertical axis. 95% confidence intervals are plotted in grey based on heteroskedasticity and autocorrelation robust standard errors clustered at the countrypair level.

Table 3: **The impact of hurricanes on BIS mirror claims**

	Dependent variable:							
	log(mirrorclaims)							
	OFC		**OFC**		**non-OFC**		**non-OFC**	
	Caribbean Sample		Caribbean + Pacific		Caribbean Sample		Caribbean + Pacific	
	aggregated	bilateral	aggregated	bilateral	aggregated	bilateral	aggregated	bilateral
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
hurricane$_{k-1}$	−0.047	0.048	−0.085	0.053	−0.028	−0.068	0.003	−0.077
	(0.104)	(0.101)	(0.073)	(0.082)	(0.025)	(0.087)	(0.044)	(0.069)
hurricane$_{k-2}$	0.003	−0.034	−0.035	0.008	−0.123***	−0.043	−0.059	0.024
	(0.134)	(0.104)	(0.085)	(0.086)	(0.033)	(0.130)	(0.065)	(0.084)
hurricane$_{k-3}$	−0.077	0.096	−0.097	0.110	−0.173***	−0.100	−0.162**	−0.019
	(0.185)	(0.093)	(0.124)	(0.083)	(0.034)	(0.090)	(0.081)	(0.070)
hurricane$_{k-4}$	−0.172	−0.007	−0.118	0.040	−0.156***	−0.195**	−0.196***	−0.110*
	(0.162)	(0.100)	(0.118)	(0.084)	(0.036)	(0.089)	(0.050)	(0.065)
hurricane$_{k-5}$	−0.166	0.016	−0.102	0.057	−0.123**	−0.263**	−0.219***	−0.173***
	(0.152)	(0.095)	(0.097)	(0.082)	(0.053)	(0.109)	(0.062)	(0.062)
hurricane$_{k-6}$	−0.070	0.049	−0.124	0.063	−0.141***	−0.216***	−0.213***	−0.096*
	(0.163)	(0.092)	(0.103)	(0.080)	(0.042)	(0.069)	(0.054)	(0.056)
country f.e.	Yes	-	Yes	-	Yes	-	Yes	-
countrypair f.e.	-	Yes	-	Yes	-	Yes	-	Yes
year-qtr f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	302	2,674	382	3,005	112	950	302	2,194
R^2	0.102	0.017	0.102	0.021	0.329	0.070	0.162	0.029

Notes: Shows reactions of mirror claims to hurricane treatment dummies taking value one in the quarter specified in parentheses. Columns 1 and 2 show reactions of claims against all counterparties in offshore financial centers (OFCs) in the Caribbean. The first column shows aggregate mirror claims, the second is based on bilateral data. Columns 3 and 4 add the Pacific part of the sample in the same specifications. Columns 5-8 repeat the same specifications for the sample of non-OFCs with columns 5 and 6 again showing the reaction of Caribbean islands both aggregated (column 5) and bilateral (column 6) and column 7 and 8 add Pacific islands to the sample. Heteroskedasticity and autocorrelation robust standard errors are provided in parentheses.

*p<0.1; **p<0.05; ***p<0.01

This result is consistent across both aggregated and bilateral mirror claims as well as Caribbean and Pacific islands. All specifications for OFCs show non-results, all specifications for non-OFCs significant drops. Table 3 collects these results for six lags of the hurricane impact over the different samples. The first two columns provide results on the Caribbean OFCs in the sample. Column 1 uses mirror claims aggregated by OFCs in a sample balanced on the second quarter of 2011 as introduced in figure 5 above. Column 2 uses the same data, but unbalanced and disaggregated for each reporting country. The second column employs country-pair fixed effects instead of country fixed effects. Both columns show entirely insignificant results with coefficients close to zero, especially in the bilateral panel. The picture does not change when the sample is extended to include Pacific OFCs in the same setup (columns 3 and 4). There is no reaction of financial activity targeted at offshore financial centers. Comparing these non-results to the statistically significant drop of 30-50% in nightlight intensity on OFCs is striking.

To verify the identification strategy, column 5 changes the sample entirely. Here, the 'real-world' alternative of claims against non-OFCs is investigated. In line with expectations and with the identifying assumption that banks and NBFIs cannot insulate themselves completely, positions react here. Effects are statistically significant and economically meaningful. Effect sizes are smaller than those observed on nightlights, so some insulation seems plausible. Nevertheless, declines of 12-17% are visible for the quarters after hurricanes. Columns 6 again provides results of a bilateral sample without aggregating banks claims. Here, hurricanes lead to a significant reduction in bank claims against affected non-OFCs of 12-26%. Columns 7 and 8 add the Pacific islands to the sample and confirm these results.

Thus, the disconnect between local economic activity and international financial activity on OFCs is not only visible in direct correlations but also in reactions to shocks. Non-OFCs, on the other hand, exhibit a positive correlation of both variables and a drop after a hurricane. This is true despite the very similar impact of hurricanes on nightlights over these two country groups. If, indeed, local legal, administrative, or banking skills are useful for international customers, it is an open question why the positions and lending activities of international banks to OFCs are not affected by hurricanes that reduce economic activity by a third. Instead, these results suggest that financial activity in OFCs is detached from local economic activity. The following section provides extended results confirming the findings presented here and showing some indicative evidence of where the high-powered financial activity is potentially taking place.

6 Extended Results

The main results show a strong impact of hurricanes on local economic activity with no reaction in the banking sector of OFCs. Non-OFCs, however, show such reactions. In the first part of this extended results section, I confirm these effects with a different approach and data-source: I provide an event study showing the response of international investors who hold equity of financial service providers domiciled in the sample islands. The second extended results section focuses on company incorporations where finally a hurricane effect is visible on OFCs. Thus, having found a measure reacting to local shocks, I go further and provide some descriptive evidence that shows decreases of this incorporation activity during public holidays in Tokyo, New York, and, in particular, London. This final piece of evidence is not representative but indicates a promising avenue for future research.

6.1 Responses of international investors

Since OFCs are integrated internationally and some of the banks and non-bank financial institutions (NBFIs) domiciled there are listed on international stock exchanges, it is possible to test market reactions to hurricanes. I construct a daily dataset of 395 equity price series taken from Bloomberg. While these equities are traded on large international stock exchanges, the issuing financial service providers under study are domiciled in the island economies. The series are limited to the sample period used above: starting on the first of April 2012 and ending on the last day of 2017. Data is available on banks as well as non-bank financial institutions, such as holding companies, insurance firms, credit companies, and other financial service firms.

In the spirit of Kothari and Warner (2007), I carry out an event study using hurricanes as a potential shock to the net present value of equities of banks and NBFIs on OFCs. While hurricanes can be anticipated in the short term, the extent of the impact comes as a surprise, especially for the disaster-type hurricanes used here. Using the 395 equity price series introduced in the data section, I first discard returns below the 1st percentile and above the 99th percentile. I then compute daily abnormal returns (AR_{it}) as the deviation of realized returns (RR_{it}) from expected returns (ER_t). For expected returns, I follow convention and use the S&P Global 1200 stock market index (see Johannesen and Larsen, 2016, for a similar setup). Thus, expected returns are not equity specific. Only realized and therefore abnormal returns are equity specific since they include the price data of the specific equity.

$$(4) \qquad\qquad AR_{it} = RR_{it} - ER_t$$

In equation 4, i denotes the 395 equity price series and t the respective day. Following Johannesen and Larsen (2016), I choose a treatment window of four trading days, including the hurricane date, and use abnormal returns of the last four trading days before the event as a point of comparison. Average abnormal returns are computed as the simple average of daily abnormal returns. These are then cumulated over the post-treatment window to generate cumulative average abnormal returns that I interpret as the response of investors to unexpected hurricane impacts. For statistical inference, I both compare the two four day windows using a simple t-test and use the ratio of post-event cumulative abnormal return over the pre-event standard deviation of abnormal returns (Kothari and Warner, 2007).

Table 4: **Cumulative average abnormal returns after hurricanes**

naïve	domiciled in OFCs	domiciled in non-OFC
CAARs (k=0 : k+3)	-0.556	-1.076***
t-statistic	(1.195)	(3.014)
Kothari Warner (2007) statistic	(-0.674)	(-3.311)

refined string search	domiciled in OFCs	domiciled in non-OFC
CAARs (k=0 : k+3)	-0.930	-1.521***
t-statistic	(1.549)	(3.194)
Kothari Warner (2007) statistic	(-1.127)	(-3.527)

drop 5% and 95% outliers	domiciled in OFCs	domiciled in non-OFC
CAARs (k=0 : k+3)	-0.973	-1.615***
t-statistic	(1.339)	(3.708)
Kothari Warner (2007) statistic	(-1.107)	(-9.475)

Notes: *p<0.1; **p<0.05; ***p<0.01

Table 4 shows the results. The top panel shows the naïve specification outlined above. While cumulative abnormal returns are negative for OFCs, statistical significance is not visible for either of the two tests; indeed, conventional critical values are quite far off. As before, I provide the reaction of non-OFCs, not as a direct comparison but as a benchmark showing that in a real-world sample, reactions are highly significant and quite pronounced. The middle panel reduces the panel to equity issuers with names that indicate banks, holding companies or NBFIs[18] and

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[18]The precise terms used for the three groups are the following: Banks ("bank", "banco", "bancorp", "scotia", and "sagicor group"), Holdings ("holding"), and NBFIs ("insurance", "capital investor", "investment", "financial", "finance", "financiero", "fund", "trading", "financial services", "trust", "inversiones", and "credit".)

the bottom panel reduces the sample by dropping the top and bottom 5% of returns. Results are consistent across specifications.

On average, foreign investors do not seem to perceive an exogenous shock that reduces local economic activity by 30% for half a year as detrimental to their portfolio of OFC bank and NBFI stock. This result is especially striking when compared against the strong real-world drop in stock returns in non-OFCs. It does, however, confirm the main results on international bank claims.
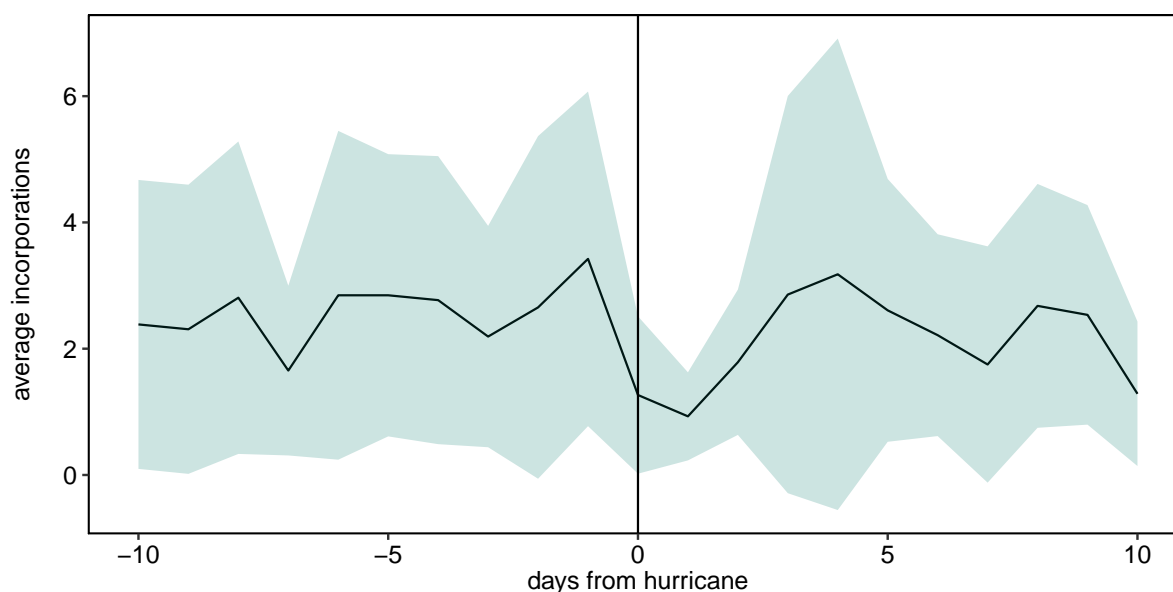
6.2 Reactions of daily incorporations

Corporate registries of OFCs are generally not publicly available. However, in February 2018, the international consortium of investigative journalists (ICIJ) published the leaked corporate registries of Aruba, the Cook Islands, Bahamas, Barbados, Malta, Nevis, and Samoa. While such incorporations are most likely prepared elsewhere, as the case of Appleby in the same leak shows, at least a formal signature signing the document and a local authority accepting the incorporation is necessary. Still, there are historic scandals where the names of deceased directors appeared on such applications, which is why it is still plausible that this common route is circumvented in practice. Without Appleby, the leaked registries have data on 265,150 unique company registrations including their incorporation dates. For the six OFCs for which the complete company register was leaked, these data are aggregated into time series counting the number of incorporations per day. These time series can then directly be compared around hurricane dates. This incorporation data is much smaller in scope than the datasets employed so far and results are not generalizable to the same extent.

As figure 10 shows, during hurricane days, the number of incorporations decreases. The figure plots the mean of the raw data as well as 95% confidence intervals for a +/- 10 day window around hurricanes with hurricanes taking place at time 0. Compared to the reactions visible in nightlights, recovery is fast, taking only a few days. This is consistent with an interpretation that the local activity needed to incorporate is not dependent on fully functioning infrastructures; for example because most of the work in preparing company incorporation is carried out elsewhere. Still, a short but pronounced effect of the hurricane is visible.

To go a bit further, figure 11 shows incorporation activity over the entire sample by weekday. In line with the hurricane results, the fact that almost no incorporations take place on weekends suggests some connection to local human activity. It is likely that there are also no incorporations during local public holidays and indeed this is visible in the data, using all public holidays on these OFCs since 1990 (see Appendix A.4). However, the incorporation data now provides

Figure 10: **Impact of Hurricanes and Typhoons on all Incorporations**

Notes: Shows mean daily incorporations and 95% confidence intervals 10 days before and after hurricane strikes (vertical line) in the sample.

a unique opportunity to investigate if the financial activity on OFCs is connected to the large financial centers where banks and financial service providers employ most of their personnel. If the local administrations are mainly concerned with stamping documents but the actual incorporation is prepared and filed abroad, then incorporation activity on OFCs should decrease during public holidays in London, Tokyo, and New York.

Without claiming representativeness across OFCs, Figure 12 shows the difference in daily incorporations on public holidays in these three hubs. The baseline against which these incorporations are compared exclude weekends and public holidays on the OFCs. Thus, the effects are a lower bound, as holidays such as New Years Eve and Christmas are also local holidays and, therefore, excluded. Nevertheless, almost all differences are negative. During a public holiday in London that is a normal workday on St. Kitts and Nevis, incorporation activity on St. Kitts and Nevis still drop by 4.5 incorporations (panel 1) or 50% (panel b). Barbados, the Cook Islands, and Malta also show drops of around 20%. This evidence is very selective since only a few corporate registers were leaked, but it hints at an interesting avenue for future research. It suggests that the one measure for which a connection to local activity on OFCs can be shown is also contingent on activity in financial hubs such as London. As such, one venue for future research is to establish in a more robust and representative manner the locations to which the financial service activity on OFCs is connected. This would be a first step in establishing for each OFC where the high-powered financial service activity that is booked through it is actually taking place.

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Figure 11: **Incorporations over the week**
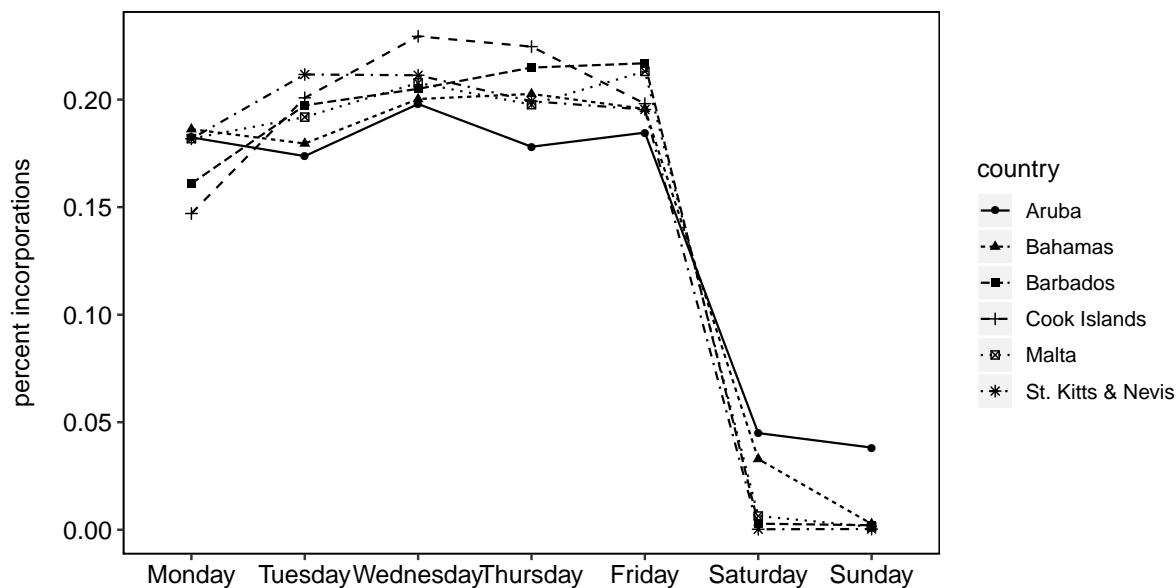
Notes: Shows percentage of daily incorporations by weekday for the six OFCs for which corporate registries were leaked

Figure 12: **Changes in incorporations on foreign public holidays**

(a) absolute changes

(b) standardized changes
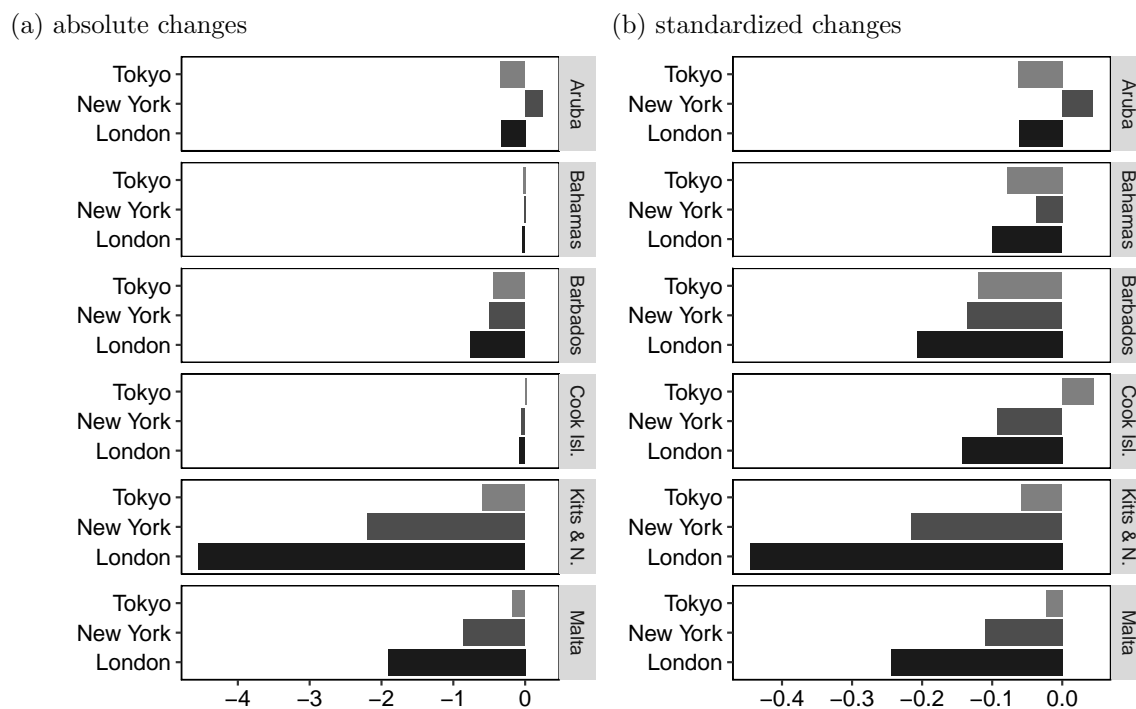
Notes: Shows absolute (panel a) and standardized (panel b) changes in incorporation activity relative to the average incorporation activity excluding weekends and local holidays. Data on public holidays is publicly available and used starting with 1990. Foreign holidays are public holidays in London, New York, and Tokyo.

7 Conclusions

Although offshore finance remains a hotly debated topic in academic and policy circles, there is little reliable empirical evidence available to illuminate or quantify what really happens in such jurisdictions. Despite numerous attempts at regulation, introducing international information exchange and increasing pressure on offshore financial centers (OFCs) to comply with such regulation, capital positions in OFCs still rise contrary to what economic theory would predict when a threat of detection increases. Statements by financial service providers in OFCs suggest, as an explanation, that they form an integral part in the international financial system by providing a unique combination of specialized human capital and financial service products that attract international capital. My results roundly reject such claims. It does not seem likely that the financial service activity that leads to high international capital positions takes place on the OFCs under study here. Rather, my results suggest that they are used as a front to cover for activity taking place elsewhere.

To provide such answers, this study introduces and constructs several novel datasets measuring local economic activity and three variables capturing the performance of the financial service sector on small islands jurisdictions including OFCs. In a short descriptive analysis, I observe a clear disconnect between local activity measured in nightlight intensity on these islands and international bank mirror claims that measure international banking activity. While a correlation is visible for islands not engaged in offshore finance, these measures are entirely detached on OFCs. This suggests that fees or taxes accruing in OFCs do not immediately translate into economic activity on the island raising the question who benefits from them.

In order to provide more robust evidence, this contribution exploits the natural experiment of re-occurring hurricanes and typhoons in the Caribbean and the Pacific to determine if financial activity registered to OFCs is physically taking place there. A first set of results shows significant impacts of around -30% to -50% of hurricanes on nightlight intensity is visible. These effects last an average of six months and this negative reaction is visible in both OFCs and non-OFCs. It is robust to different timeframes, samples, and a limitation of the data to capital regions only. It is also quantitatively in line with the literature on natural disasters. Thus, hurricanes have a strong and lasting impact on the economy of OFCs.

However, when investigating data measuring claims reported by banks in non-OFCs on banks and non-bank financial institutions (NBFIs) in OFCs, no reactions are visible whatsoever. International financial activity seems to continue unabated, with no significant effects in either direction and positive but small coefficients. As a 'real-world' baseline, I investigate reactions of non-OFCs, which show significant drops in bank claims reported against them, thus validating the identification strategy. These results are robust across a number of specifications and hold

both for bilateral mirror claims and for bank data aggregated on the level of the island economy. Compared to the several month-long impacts of hurricanes on nightlights, these results are striking.

In two sets of extended results, I first confirm the results of financial service activity by showing that international investors react similarly. Banks and NBFIs domiciled in OFCs and traded on international stock exchanges do not experience significant drops in returns after hurricanes hit. Again, institutions domiciled on non-OFCs do. They experience strong and highly significant negative abnormal returns in the days following a hurricane. The only variable where some reaction to hurricanes on OFCs is visible are daily company incorporations, taken from the leaked corporate registries of six OFCs. Here, albeit it short, a reaction is visible. This indicates that some activity does take place on OFCs but it seems to have much less to do with banking and much more with putting a stamp on an incorporation document. This leaked data also allows some preliminary investigation of where financial service activity might actually be taking place. I show suggestive evidence on declines in daily incorporation activity on weekends and public holidays. During a public holiday in London that is a normal workday on the islands of St. Kitts and Nevis, average daily incorporations there decline by around 50%. Effects are smaller but still visible on Barbados, the Cook Islands, and Malta, with declines of around 20%.

Taken together, these results suggest that the positions booked through offshore financial centers are not connected to financial service activity that is physically present in OFCs. Despite strong effects on local economic activity, hurricanes do not seem to impact any variable measuring the performance of the high-powered financial service sector. If anything, OFCs are principally involved in the incorporation of shell companies, a task that does not need specialized human capital. This is especially true if these incorporations are contingent on Londoners going to work. Therefore, my results cast doubt on the interpretation of OFCs as contributors of a certain set of skills and human capital that improve the efficiency of the international financial system. Instead, they are consistent with the interpretation that OFCs mostly provide opportunities for regulatory arbitrage and a front for financial service providers elsewhere.

8 References

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Appendix

Appendix A.1 Coverage of bilateral BIS data over time

The locational banking statistics used in the main text are derived from reports of a reporting country against a large number of counterparties. The coverage of this dataset changes along both dimensions. A continuous increase is visible over time as shown in figure A.1. The top panel shows the total number of countrypairs available starting in 1977 with the earliest reports. The middle and bottom panels show the underlying developments on the country and counterparty dimension. The number of countrypairs almost doubles between the earliest balanced series (starting in 2003:I, vertical dotted line) and the data used in the main text (starting in 2011:II, vertical dashed line).

However, as was shown in figure 5, this increase is neither changes the level nor the time dynamic of total reported mirror claims against one counterparty drastically. The large OECD countries that report the highest positions start reporting early in the sample and the large number of countrypairs where data becomes available late in the sample (the vertical dashed line in figure A.1 shows the panel available for balancing in 2015:I) report relatively small positions that follow similar trends.

Figure A.1: LBS time series availability
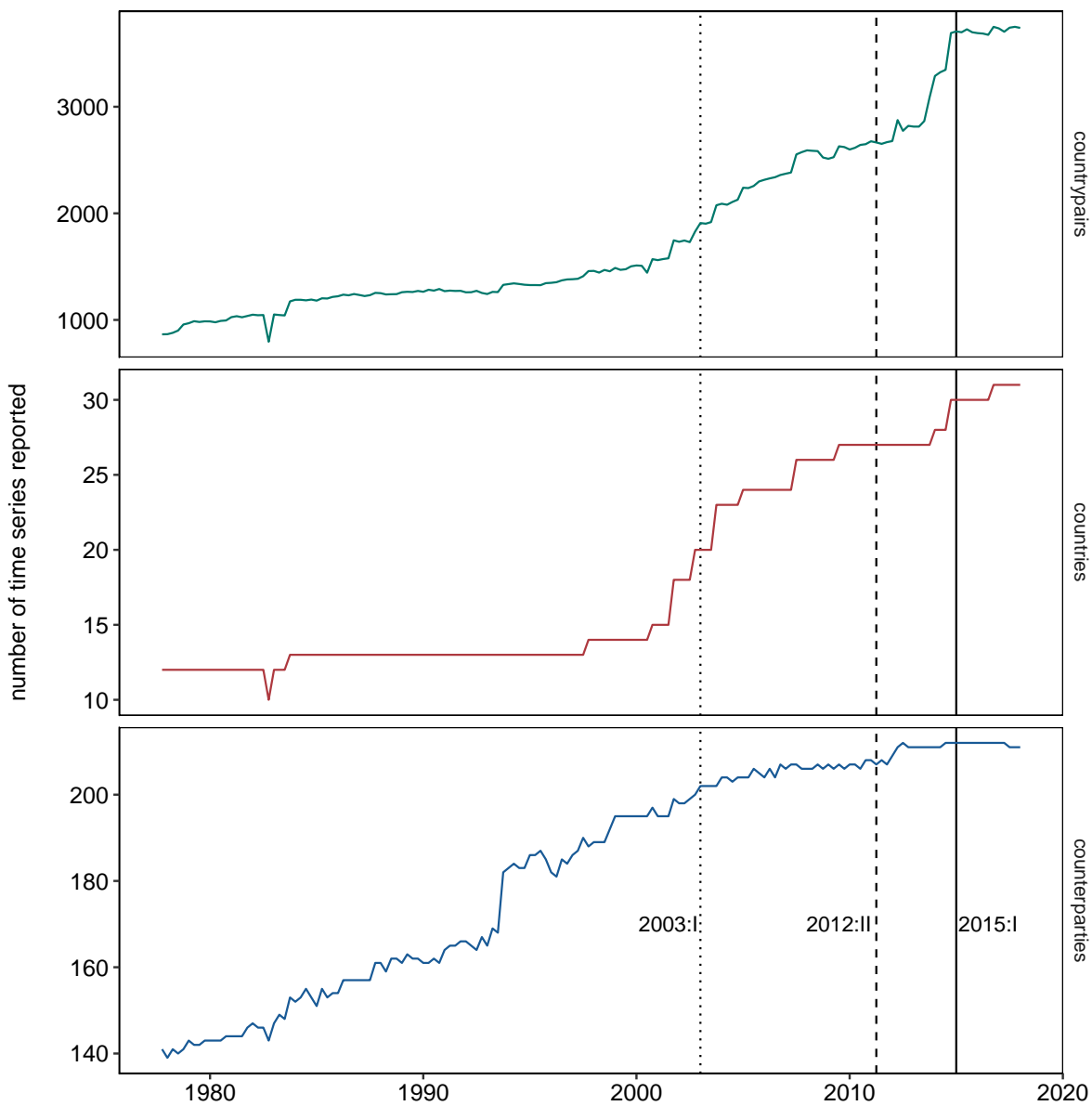
Notes: The three panels show the availability of bilateral time series on international claims against all counter-parties in the BIS' locational banking statistics. Observations are counted on the vertical axis when reports are available. The top panel shows total available countrypairs. The middle panel shows the number of reporting countries that report bilaterally (excluding those countries that only report against all countries aggregated). The bottom panel shows the total number of counterparties bilaterally reported against. The three vertical lines indicate the times at which balanced series are created for the main analysis: 2003:I, 2012:II and 2015:I as mentioned in the main text

Appendix A.2 Extended results on nightlight impacts

This appendix shows further results for nightlight impacts alluded to in the text but relegated to the appendix for brevity. Figure A.2 shows the impact of hurricanes Irma and Maria on the raw data demeaned by country and averaged over affected and non-affected group. These two hurricanes are associated with a drop of nightlight intensity by around a third.

Table A.1 shows impacts of nightlights for capital regions only. As pointed out in the data section, monthly nightlight datasets were constructed both at the national and the regional levels. Here, one region for each country is used: The de facto capital region if available. If no regional polygons data are available in the GADM dataset (this is the case for Aruba, Anguilla, Curacao, and the Marshall Islands), the national data is used here as well. These are jurisdictions that are so small that their entire area is comparable to a capital region of a larger island. For those countries where de facto capitals are also de jure capitals, the regions containing those were used. These regions are (with the country or jurisdiction in question in parantheses): Saint John (Antigua and Barbuda), New Providence (The Bahamas), Pembroke (Bermuda), Saint Michael (Barbados), George Town (Cayman Islands), Saint George (Dominica), Distrito Nacional (Dominican Republic), Basse-Terre (Guadeloupe), Ouest (Haiti), Kingston (Jamaica), Saint Gerorge Basseterre (St. Kitts and Nevis), Castries (St. Lucia), Saint Peter (Montserrat), Fort-de-France (Martinique), San Juan (Puerto Rico), Grand Turk (Turks & Caicos Islands), Port of Spain (Trinidad & Tobago), Saint George (St. Vincent and the Grenadines), Tortola (British Virgin Islands), Saint Thomas (Virgin Islands, US), Central (Fiji), Hagatna (Guam), Colombo (Sri Lanka), Sud (New Caledonia), Yaren (Nairu), Melekeok (Palau), Honaira (Solomon Islands), Funafuti (Tuvalu), Shefa (Vanuatu), San Jose (Costa Rica), Guatemala (Guatemala), Francisco Morazan (Honduras), Managua (Nicaragua), Panama (Panama), Central and Western (Hong Kong), Macau (Macau), Dili (Timor-Leste), Central (Singapore), Saipan (Northern Mariana Islands), Brunei and Muara (Brunei), Pohnpei (Federated States of Micronesia), Saint George (Granada), Belize (Belize), Taipei (Taiwan), San Salvado (El Salvador).

Nightlight data on identically named capital regions (for example Granada, Saint Vincent and the Grenadines, as well as Dominica all name their capital regions Saint George) are of course still used as distinct time series. The dataset is constructed for all capital regions mentioned above, however only small Caribbean and Pacific Island economies are used in the estimations in line with the main text. Coastal economies, such as Panama, Costa Rica, or El Salvador are excluded in the estimations of table A.1. The reactions in table A.1 compare in magnitude to the results for national data but the negative effect for capital regions on offshore financial centers stays significant for a shorter amount of time and only dominates the first three months. The main results showed that recovery does pick up after the first three months, consistent with

these findings.

Figure A.2: Impacts of hurricanes Irma & Maria on raw nightlight data

Notes: Shows the average nightlight intensity of the sample starting in 2016 till the end of the sample. The vertical line indicates September 2017 when hurricanes Irma and Maria hit the Caribbean. Countries are categorized into being hit and not being hit by these hurricanes.

Figure A.3: Hurricane impact and recovery
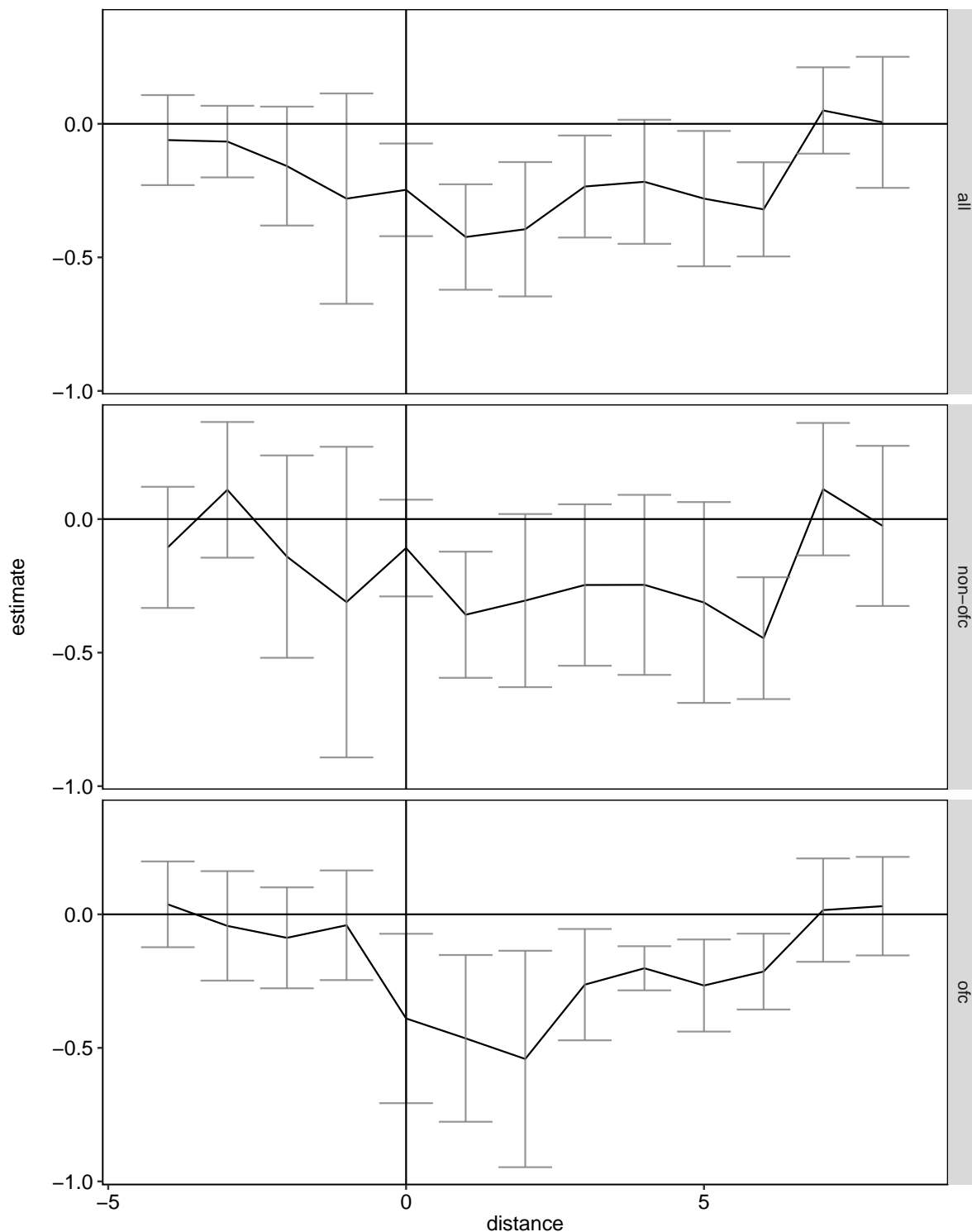
Notes: The figure plots single leads and lags of a hurricane dummy in a difference in difference estimation within the entire sample (top panel), the non-OFC sample (middle panel) and the OFC sample (bottom panel) . The estimation takes the following form: $log(lightmean)_{it} = \alpha_i + \gamma_t + \sum_{k=-4}^{k=8}(d_{it+k}) + \epsilon_{it}$, notation being identical to the main text. All coefficients are based on the same regression with k, the distance to the hurricane, plotted on the horizontal axis and the respective coefficient on the vertical axis. 95% confidence intervals are plotted in grey based on heteroskedasticity and autocorrelation robust standard errors clustered at the country level.

Table A.1: **The impact of hurricanes on nightlight intensity in capital regions**

	Dependent variable: log(lightmean)		
	all	OFCs	non-OFCs
	(1)	(2)	(3)
hurricane (k)	−0.214**	−0.351**	−0.057
	(0.091)	(0.178)	(0.083)
hurricane (k : k + 2)	−0.265***	−0.410***	−0.116*
	(0.081)	(0.148)	(0.063)
hurricane (k : k + 5)	−0.186***	−0.237	−0.125**
	(0.070)	(0.145)	(0.053)
country f.e.	Yes	Yes	Yes
year-month f.e.	Yes	Yes	Yes
Observations	2,228	1,361	867

Notes: Nightlight data here is only based on the capital region. Each coefficient is the result of a separate regression. Column 1 shows results in a panel including all countries, column 2 reduces the sample to only offshore financial centers (OFCs) and column three to non-OFCs. The first row shows reactions to a treatment dummy taking value 1 in the month of the hurricane. The second row includes the first two months after a hurricane in the dummy and the third row the first five months after the hurricane hit the island. Heteroskedasticity and autocorrelation robust standard errors are provided in parentheses.

*p<0.1; **p<0.05; ***p<0.01

Appendix A.3 Extended results on mirror claim impacts

Figure A.4: **Impact of hurricanes on non-OFC mirror claims**
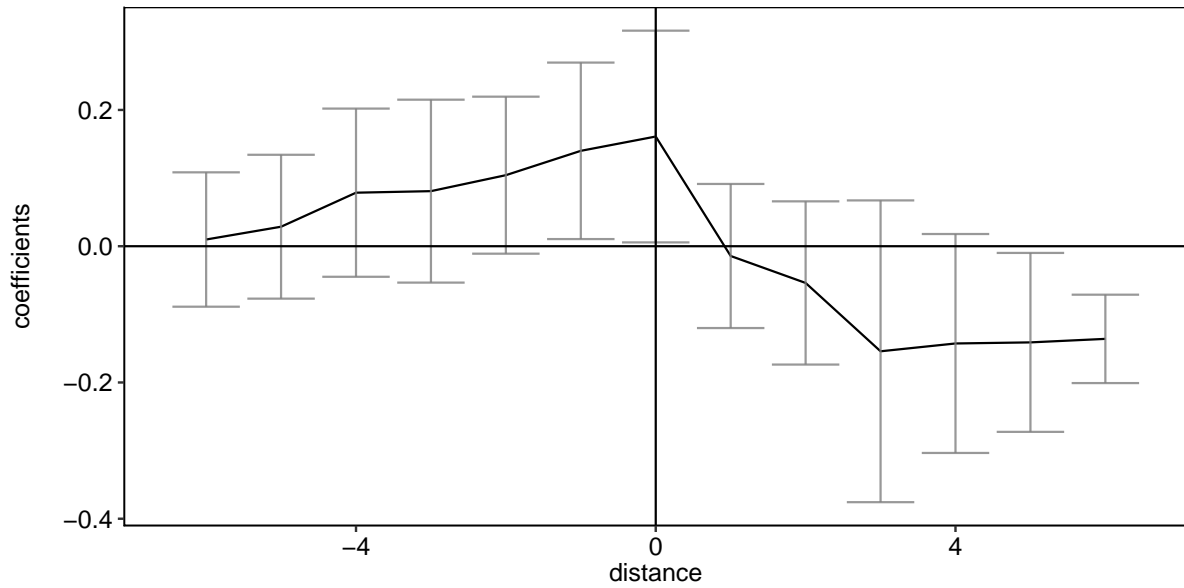
Notes: Plots leads and lags of a hurricane dummy in a difference in difference estimation within the non-OFC sample. The estimation takes the following form: $log(claims)_{iq} = \alpha_i + \gamma_q + \sum_{k=0}^{K}(d_{iq+k}) + \epsilon_{iq}$, notation being identical to the main text. All coefficients are based on the same regression with k, the distance to the hurricane, plotted on the horizontal axis and the respective coefficient on the vertical axis. 95% confidence intervals are plotted in grey based on heteroskedasticity and autocorrelation robust standard errors clustered at the countrypair level.

Appendix A.4 Extended results on incorporation data

Figure A.5: **Absolute changes in Incorporation activity**

Notes: Shows the mean drop of incorporations on weekends, local holidays and holidays in Tokyo, New York, and London. All changes are compared to average incorporations on non-weekend workdays.