Natural Assets: Surfing a wave of economic growth

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DRAFT

Abstract

Many natural assets can not be valued at market prices. Non-market valuations typically focus on the value of an individual asset to an individual user, ignoring macroeconomic spillovers. We estimate the contribution of a natural asset to aggregate economic activity by exploiting exogenous variation in the quality of surfing waves around the world, using a global dataset covering over 5,000 locations. Treating night-time light emissions as a proxy for economic activity we find that high quality surfing waves boost activity in the local area (<5km), relative to comparable locations with low quality waves, by 0.15-0.28 log points from 1992-2013. This amounts to between US$ 18-22 million (2011 PPP) per wave per year, or $50 billion globally. The effect is most pronounced in emerging economies. Surfing helps reduce extreme rural poverty, by encouraging people to nearby towns. When a wave is discovered by the international community, economic growth in the area rises by around 3%.

JEL codes: H41, O13, Q26, Q51, Q56

Key words: Non-market valuation, natural capital, surfing, night-time lights.

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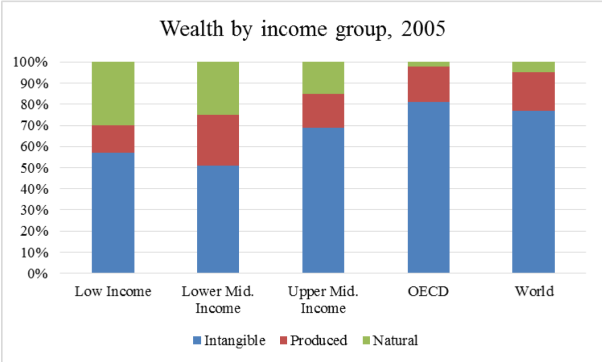


Figure 1.1: Wealth breakdown by income group (Jarvis et al., 2011)

1 Introduction

Natural assets are an important part of the world's capital stock. According to the World Bank (Jarvis et al., 2011) they account for approximately 5% of global capital, and 30% of that in developing countries (Figure 1.1). Existing estimates of natural capital focus on assets that can be valued at market prices, including non-renewable assets like energy and mineral resources, and renewable assets like cropland, pasture and forests. Many other forms of natural capital are excluded from estimates because they can not be valued at market prices. These non-market assets include spectacular mountain ranges, tree-covered forest paths and, to some eyes, clean six-foot waves peeling seductively down a point break.

This paper estimates the contribution to aggregate economic activity of a particular non-market natural asset: surfing waves. We choose surfing waves to exploit a natural experiment: the exogenous distribution of high quality waves around the world; and a unique dataset: a crowd-sourced online database of wave location, characteristics and quality. In doing so we estimate the value to individual users as well as macroeconomic spillovers in the surrounding area.

The quality of surfing waves provides a clean natural experiment. It is entirely predetermined by a specific combination of environmental characteristics that include the shape of the coastline, the sea-floor, and the direction of prevailing winds and swells. For much of history this specific combination was of no interest to humans, until surfing became a popular pastime in the 1960s. Unlike most non-market assets we are able use the exogenous variation in the measured quality of waves to determine the marginal contribution of these assets to economic activity.[1]

There are two mechanisms by which non-market assets like waves may contribute to local economic activity: by stimulating activity within the region, and attracting new activity to it. Stimulating local activity happens by creating a demand for complementary goods and services. For surfing this includes manufacturing and retail of surfboards, wetsuits and other specialised accessories, and services such as board repairs, surfing lessons and lifeguarding. Attracting new activity happens by drawing new demand to the

[1] The quality of surfing waves has also been used as a natural experiment to study the emergence of informal property rights in California (Kaffine, 2009).

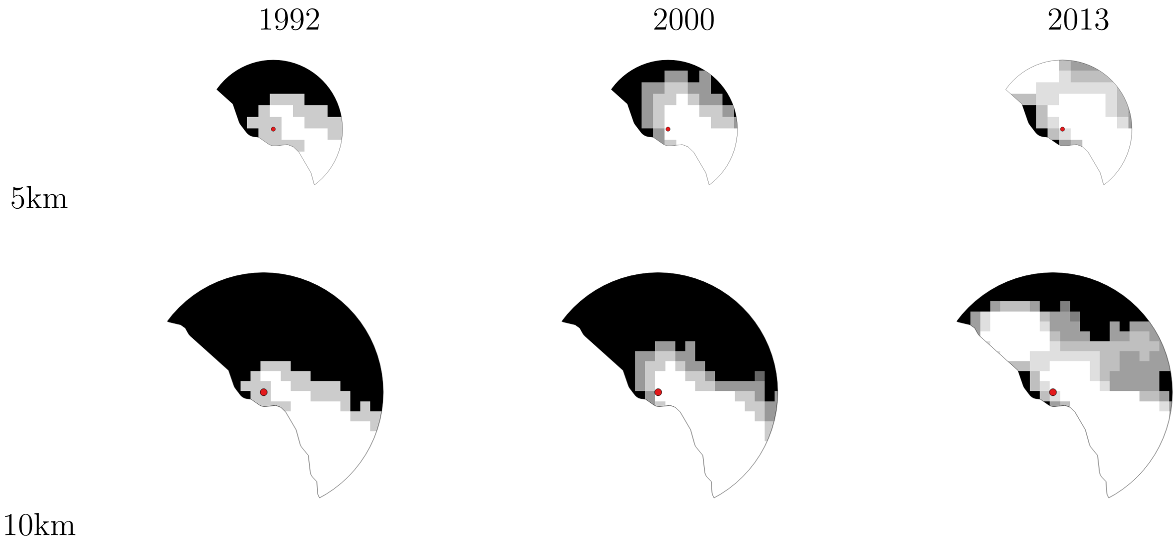


Figure 1.2: Example of illumination growth in the 5km and 10km surrounding Anchor Point, a "World Class" (quality 3) wave in southern Morocco.

area to exploit the scarce resource. For surfing this may include transient and seasonal demand, like tourism; or more permanent demand like retirees and people relocating for lifestyle reasons. Surfing is particularly well suited to studying these mechanisms because waves are a common pool resource and, as such, are liable to over-use (Rider, 1998).[2] The historical solution has been for surfers to travel and discover new waves, making exploration a core part of surfing lore.

We are able to determine how good quality waves contribute to economic activity by combining a unique dataset on the characteristics of 5,151 waves around the world, with two detailed and geographically disaggregated datasets on night-time lights and population. The wave data is compiled using Python from the website www.wannasurf.com. WannaSurf is an online database of surf spots recording their location, quality, difficulty, coastal geography, best wind, swell and tide conditions and accessibility, amongst other things. The data on the website is crowd-sourced (like Wikipedia) from a community of 78,000 "WannaSurfers", on whom data is also available. The second dataset records the amount of light emitted at night-time around the globe, at a 1km^2 resolution, which is a useful proxy for economic activity (Henderson et al., 2011; 2012). The third is from LandScan and uses a variety of spatial inputs to measure population, also at a 1km^2 resolution.

We employ a polynomial distributed lag model to determine how waves affect illumination, and in turn economic activity. Our control group is areas surrounding the lowest quality waves. This is a relatively high hurdle, as these areas are coastal and of sufficient interest to surfers to appear in our crowd-sourced database. The model measures the marginal contribution of higher quality waves to economic activity over the course of our sample, controlling for both wave and time fixed effects.

We find that high quality waves increase economic activity (proxied by lights) in the surrounding 5km area by 0.15-0.28 log points, or 16%-32%, over 21 years (1992-2013), relative to places with low quality waves. This amounts to US$18-22 million (2011 PPP)

[2] Attempts to allocate property rights and charge entry, as at Cloudbreak in Fiji, have been short-lived due to public outcry.

per wave per year in the surrounding 50km, or US$48 billion globally, which is consistent with existing survey-based estimates.[3] The effect is highest for 4-star waves (out of 5) because the highest quality waves tend to be too difficult for the average surfer. Emerging economies benefit the most, so long as they have a sufficient level of political stability and ease of doing business.

Economic activity increases in aggregate, rather than simply being reallocated from other areas. It is shared amongst nearby towns, and is particularly pronounced in the closest town and the largest town within 50km. Activity in unlit-rural areas, which are typically extremely poor, does not increase. However, surfing does reduce extreme poverty by encouraging the rural poor to move to more urban areas. Overall the permanent population around 4-star waves falls, consistent with tourists driving up rents. When new waves are discovered, surrounding economic growth can rise by up to 3 percent. These results are robust to other, non-surf related, characteristics of the coastline. Our estimates are a lower bound for the utility value of indirect natural assets, because many of the rents from the asset will not accrue to the local area (such as profits to surfwear companies, and the travel costs of tourists spent to get to the waves).

This work contributes to the extensive literature on valuing natural assets. Market-based techniques are the most straightforward, but are only suited to traded assets and ecosystem services. This can be extended to non-traded assets through securitisation (Chichilnisky and Heal, 1998). Non-market techniques are based on either stated or revealed preferences (Freeman, 1993; Kopp and Smith, 1993). While stated preference methods like contingent valuation are widely used, bias remains an issue. It can be improved with appropriate incentives (Carson et al., 2014). Our method relies on revealed preferences, building on a small literature valuing individual surf breaks using travel costs (Mavericks, California: Coffman and Burnett, 2009), and hedonic pricing (housing in Santa Cruz, California: Scorse et al., 2015). We extend these works by studying a panel of more than 3000 waves in over 130 countries; and by capturing the macroeconomic spillovers of the asset to surrounding economic activity beyond those captured by the user or home-owner.

Academic work on valuing non-market natural assets has not yet been adopted consistently by policymakers. Since the Agenda 21 agreement at the 1992 UN Earth Summit in Brazil there has been an international movement towards integrating environmental and economic accounts. The most recent iteration is the System of Environmental Economic Accounting 2012 (SEEA: UN, 2014). This measures natural assets in both physical and monetary terms, though the scope of the latter is limited to market or near market assets. The SEEA can encompass the value of non-market assets in land values, though isolating them is difficult. It has prioritised developing "consistent valuation techniques beyond the System of National Accounts in the absence of market prices". The World Bank also estimates natural capital but excludes most non-market assets due to a lack of data (Jarvis et al., 2011). However, it acknowledges that "missing ecosystem services" like recreation and aesthetic views may be important, especially in high-income countries.

This work also contributes to the literature on the geographic determinants of economic activity. Many papers have used night-time lights to this end (Ghosh et al., 2010; Chen

[3] Lazarow (2009) uses surveys to find that surfing contributes approximately $113-216 million (US$ 2011) in direct expenditure to the economy of the Gold Coast, Australia. This covers 8 high quality waves but excludes macroeconomic spillovers.

and Nordhaus, 2011; Henderson et al. 2012; Michalopoulos and Papaioannou, 2013; Smith and Wills, 2016). Other work uses satellites to study non-marketed ecosystem services using data on landcover (Sutton and Costanza, 2002; Costanza et al., 2014). Faber and Gaubert (2015) study the local effects of tourism in Mexican beach towns, using an instrument for beach quality based on sand colour and offshore islands. In contrast our quality instrument comes from direct ratings by users, and covers the entire world.

We hope that valuing surf breaks is useful in two ways. The first is development: by understanding the benefits of surf breaks to local economies, policymakers might be more willing to invest in infrastructure needed to access them. This is particularly true in developing countries, where waves remain under-utilised. The second is conservation: by assessing the value of surf breaks, better cases can be made to conserve them from coastal erosion, pollution and rising sea levels.

The paper proceeds as follows. Section 2 provides a background to surfing and the geographical characteristics that give rise to good waves, which underpins our identification strategy. Section 3 describes our data. Section 4 presents the methodology. Section 5 presents and discusses our findings, and a range of robustness checks. Section 6 concludes.

2 A primer on surfing

Surfing was originally a central part of Polynesian culture. Europeans first observed this "very dangerous diversion" (King, 1779) in the 1760s, but it was not until the turn of the 20th century that the sport appeared in North America and Australia. It was in these areas that, after World War II, the global phenomenon of surfing began. Recent reports estimate continuing growth in the popularity of surfing, with the global population of surfers rising from 26 million in 2001 to 35 million in 2011 (The Economist, 2012). This is expected to continue as highly-populated, wave-rich emerging economies like Brazil and Indonesia increasingly consume leisure.

The waves where surfers practice their craft are created through wind acting on the surface of the ocean. These waves propagate along the ocean's surface for up to thousands of kilometres until they approach shallow water. Resistance from the sea floor slows movement at the base of the wave, causing the top to spill over, or "break" (Figure 2.1). For surfers each wave has three key characteristics: size, shape and length, which are determined by a broad range of factors. The specific combination of factors that creates good waves underpins our identification strategy.

The size, or amplitude, of a wave is mainly determined by winds that generate swell, hundreds or thousands of kilometres away from where it is eventually ridden. Important are the wind's strength and direction at its source, the area over which it acts, the length it blows, and how far away the source is. For example, many of the best surfing waves in Europe occur in the Basque country of northern Spain and southern France. These waves typically originate in the North Atlantic and are funnelled into the region by the deep ocean trench of the Bay of Biscay (Figure 2.2).

The shape of a wave describes whether it spills down the face, pitches over, or surges when it breaks. This is determined locally by the gradient of the sea floor and local wind

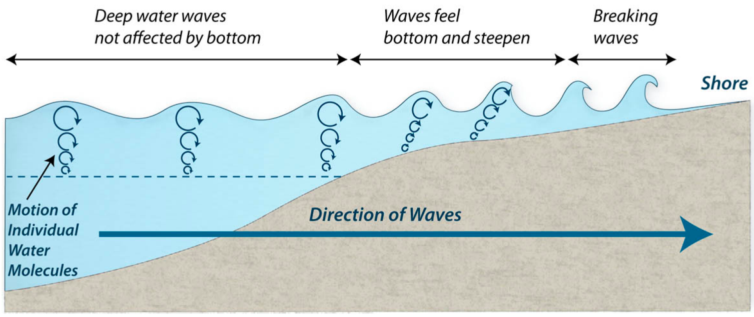


Figure 2.1: Waves form through wind acting on the surface of the ocean, and break when they reach shallow water.

i. ii.

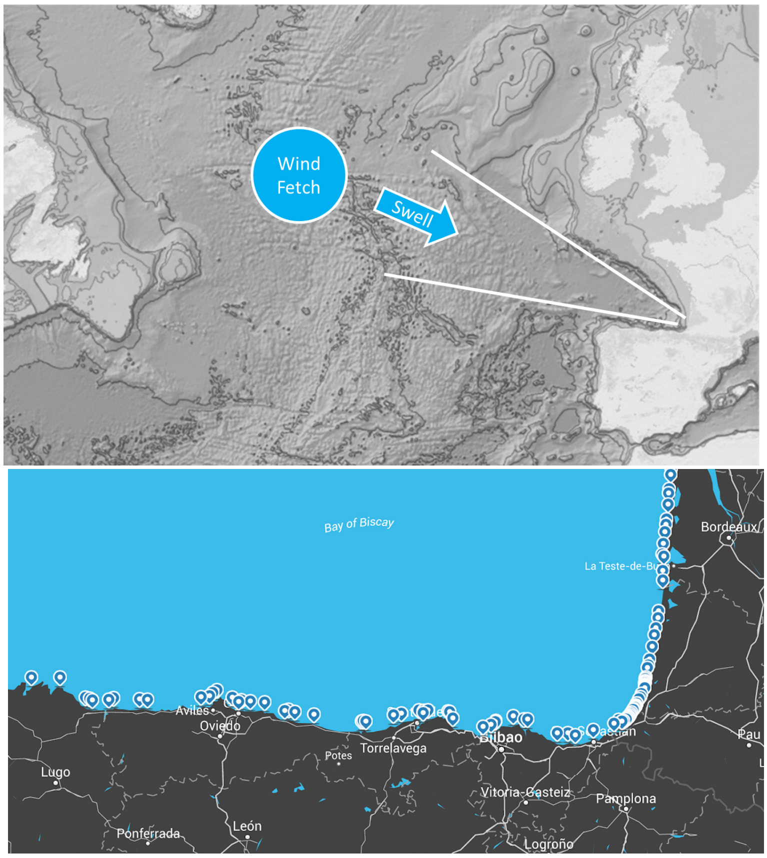
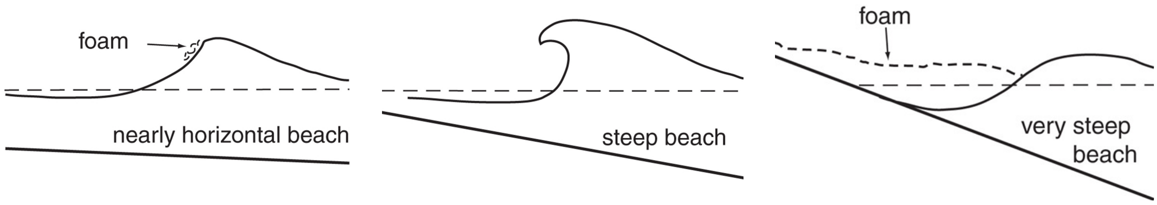


Figure 2.2: Waves formed in the North Atlantic are funnelled by a deep trench into the Bay of Biscay, creating good surf breaks.



i. Spilling wave ii. Pitching wave iii. Surging wave

Figure 2.3: Surfers tend to prefer pitching waves

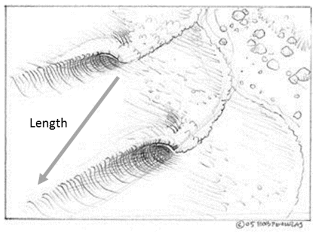


Figure 2.4: Length describes how long a wave can potenially be ridden.

conditions. A gradual rise in the sea floor causes white-water to spill down the face of the wave when it breaks. A steep rise in the sea floor - such as moving from deep ocean to a reef - causes the breaking wave to pitch, creating a “barrel”. A very steeply rising sea-floor will create a surging wave, as seen at the base of sea cliffs. Local winds also affect this: “offshore” winds blowing from beach to ocean hold the wave up longer, causing it to pitch more when it eventually breaks. Onshore winds do the opposite.

The length of a wave describes how long it breaks before reaching the shore. This is determined locally by the shape of the coastline. Waves break for longer when they reach the coastline at an angle, causing the whitewater to spill continuously to the left or right. Long waves therefore typically occur along headlands (“point-breaks”), rivermouths or coral reefs.

Surfers ride these waves as close to the point of breaking as possible, so the nature of the breaking process matters. High quality waves will be larger, pitching and longer, all else being equal. Surfers naturally prefer higher quality waves, but only up to a point dictated by ability. The direction of the breaking wave is also a consideration as surfers prefer to face the wave as they ride it (which for most is a wave that breaks to the right). The shape of a surfboard can be tailored to suit particular types of waves, resulting in local shaping industries.

High quality waves therefore require a very specific combination of global weather, local weather and bathymetric conditions, small deviations from which will result in lesser quality waves. Such a specific combination of characteristics are unlikely to affect economic activity through any mechanism other than surfing. The range of characteristics also allows for a lot of natural heterogeneity. Two locations on the same coast may receive exactly the same swell, but have vastly different quality waves because of the shape of the sea-floor and coastline. We exploit this heterogeneity in our identification strategy.

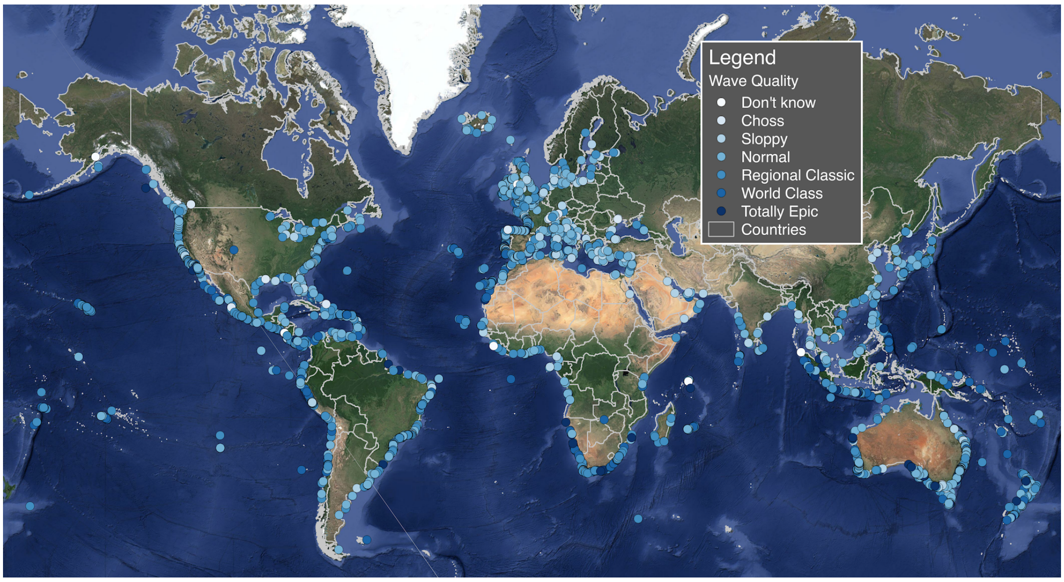


Figure 3.1: Overview of WannaSurf wave locations

3 Data

3.1 Waves

Wannasurf (www.wannasurf.com) is an online "world surf spot atlas, made by surfers for surfers". It records the location, quality, type, accessibility, coastal and oceanic characteristics of 5,288 surf spots (waves) around the world (Figure 3.1). Of these we drop 137 for which the data on quality is either missing or rated 0 stars ("choss"), leaving 5,151 surf spots in our dataset. The data is crowd-sourced from a community of 78,000 website users who create and edit the information on each surf spot, in a similar way to Wikipedia.[4]

The geographic coordinates of each wave are given precisely. The waves are distributed amongst 146 countries, though they are particularly concentrated in Australia (888 waves) and the US (878), as shown in Figure 3.2. This is to be expected because of the long coastline and large surfing population in these countries, from whom the data is crowd-sourced.[5]

Each wave is assigned one of five quality ratings, ranging from "sloppy" (1-star) to "totally epic" (5-star).[6] Most waves fall into the 2 and 3-star ratings, as shown in Figure 3.1. Wave quality is not evenly distributed across countries, with Namibia, Western Sahara and the Maldives having the highest average quality, and Ukraine, Qatar and Kuwait the lowest. There is a large exogenous element to this, because coastal structure and exposure to wind and swell are important components of quality. There is also some degree of selection. Wannasurf contributors are more likely to record unremarkable waves in countries with

[4] Each user has a publicly available profile including information on their age, location and surfing preferences, which we do not use.

[5] The website was created in 2004, and mainly codified existing knowledge that was previously available offline. As such we do not have the "discovery date" of each wave.

[6] This rating is crowd-sourced. There is also a user poll for wave quality rating, though we don't use this as it typically has less than 100 respondants for most locations.

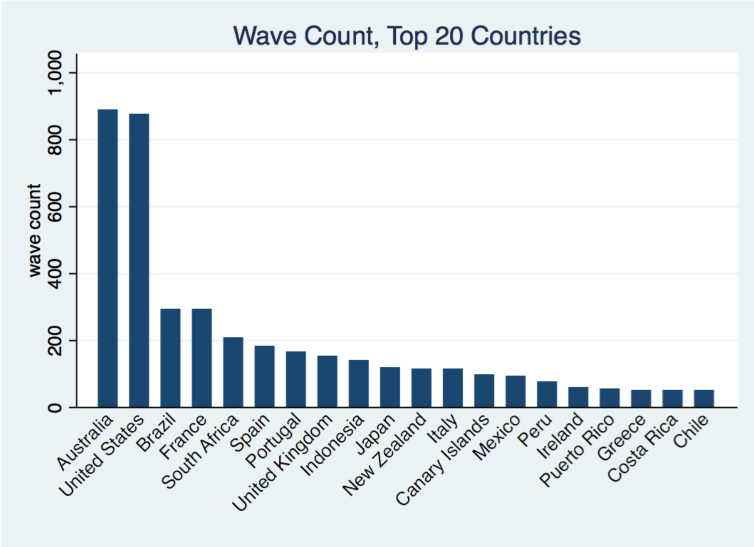


Figure 3.2: Our data on waves is distributed around the world, though is particularly concentrated in Australia and the US.

Star Rating	Description	Frequency	Share
1	Sloppy	384	7.5%
2	Normal	2,027	39.4%
3	Regional Classic	2,129	41.3%
4	World Class	450	8.7%
5	Totally Epic	161	3.1%
Total		5,151	100%

Table 3.1: Breakdown of waves by quality.

large surfing populations, either local or tourist. On the other hand, only good waves tend to be recorded away from the beaten path. Western Sahara is an example. Of the four waves recorded, three are 4-star, and one is 5-star.

The characteristics of each wave are also recorded. These include variables on accessibility ("Distance", "Easy to find?", "Public access?", "Crowd"), difficulty ("Experience"), the type of wave ("Frequency", "Type", "Direction", "Length", "Bottom", "Power") and oceanic conditions ("Good swell direction", "Good wind direction", "Swell size", "Best tide"). Of these we make particular use of the "Type" variable, which indicates whether the shoreline is a beach, a reef, a rivermouth, a headland (point-break) or a breakwater. Wave quality also varies by Type, as shown in Figure 3.3.

Finally, we also conduct a small event study around the date that waves were discovered. The date of discovery is taken from two sources. The first is the date of the "Rip Curl Pro Search" competition, which was an event on the surfing world tour organised by the Association of Surfing Professionals annually from 2005-2010. It took place in a different location each year, which was previously relatively unknown to the global surfing community. The second is the "Google Earth Challenge", which was a competition run by Surfing Magazine in 2007 to discover a previously unknown wave using Google Earth. Surfing Magazine is a leading industry publication read by millions worldwide. Table 3.2 shows the seven wave discoveries in our sample.

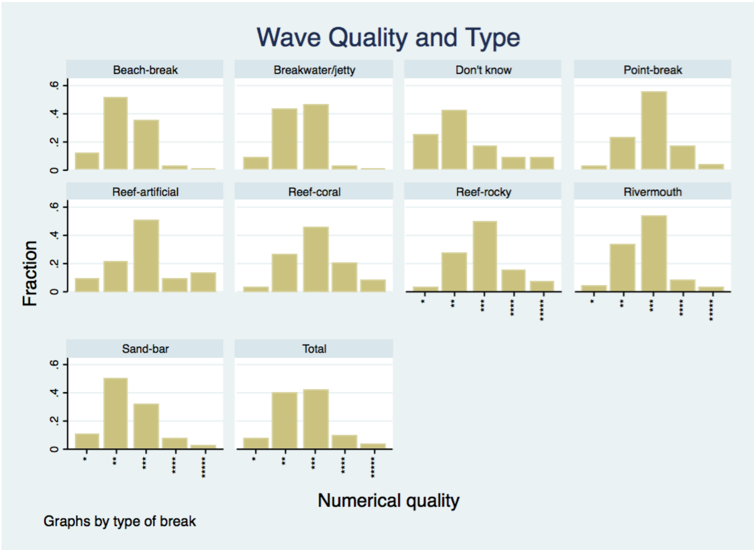


Figure 3.3: Breakdown of wave quality by type.

Wave	Country	Date of Discovery	Quality	Source
St Leu	Reunion	2005	World Class	Rip Curl
La Jolla	Mexico	2006	World Class	Rip Curl
El Gringo	Chile	2007	World Class	Rip Curl
Skeleton Bay	Namibia	2007	Totally Epic	Surfer Mag
Uluwatu	Indonesia	2008	Totally Epic	Rip Curl
Supertubos	Portugal	2009	Totally Epic	Rip Curl
Middles	Puerto Rico	2010	Regional Classic	Rip Curl

Table 3.2: Wave Discoveries

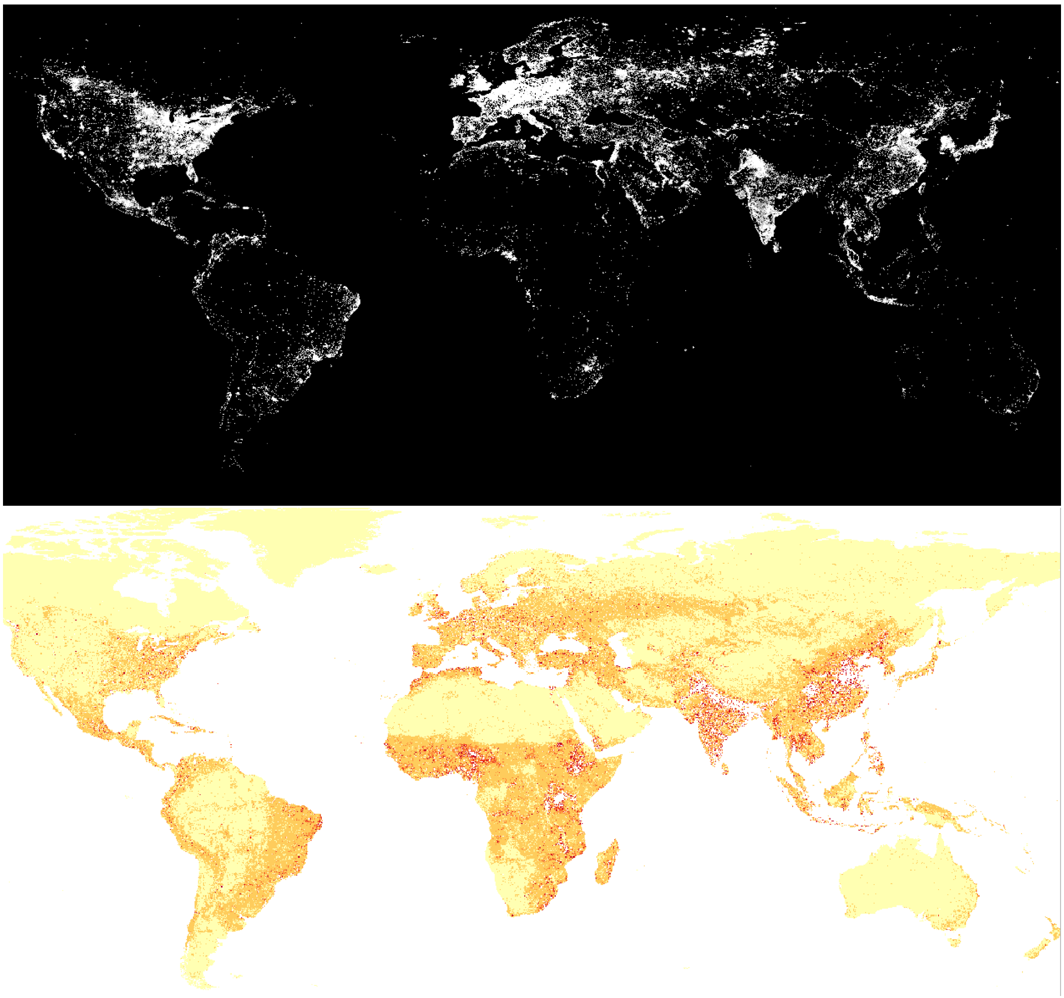


Figure 3.4: Night-time light and population data

3.2 Night-time lights

The Defence Meterological Satellite Program's Operational Linescan System (DMSP-OLS) uses satellites to record the average annual night-time light intensity around the world, from 1992-2013 (Figure 3.4). The data is provided at a resolution of 30x30 arc-seconds (approximately 1 square kilometre near the equator), and ranges from 0 to 63. The data is constructed by overlaying all daily images over the course of a year, discarding those that are obfuscated by cloud cover, lightning, aurora, etc. for a given pixel.

There is a strong link at the national level between the growth of GDP and mean light intensity (Doll et al., 2006; Henderson et al., 2012; Michalopoulos and Papaioannou, 2014). This is illustrated in Figure 3.5, which plots the log of the sum of light readings by country against two measures of log PPP-adjusted GDP: based on expenditure and production (Penn World Tables 8.1). The associated regressions yield an adjusted r-squared of .82 and .80 respectively. We make use of the high spatial resolution of the data to study economic activity at a sub-national level, as has been done in a number of other studies (Chen and Nordhaus, 2011; Michalopoulos and Papaioannou, 2013; Hodler and Raschky, 2014; Jedwab and Moradi, 2015; Jedwab et al., 2015).[7]

[7] This data is subject to "top-coding", where economic activity beyond the maximum luminosity rating

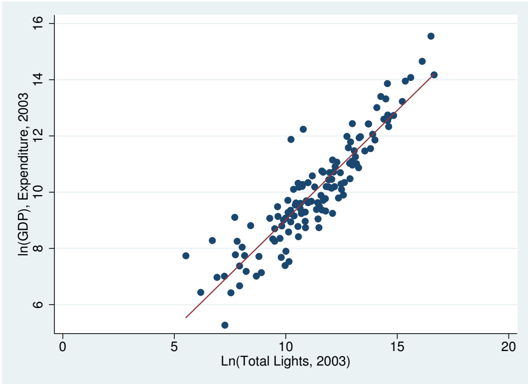


Figure 3.5: PPP-adjusted GDP vs Night-time lights (in logs), 2003 (see Smith and Wills, 2016).

3.3 Population

The LandScan data set is produced by the Oak Ridge National Laboratory and provides annual mid-year spatial population counts at a 30x30 arcsecond resolution from 2000-2013 (Figure 3.4).[8] It reports "ambient" population, which is the average over a 24 hour period, rather than simply where people sleep. However, it excludes intermittent populations such as tourists or temporary relief workers, and may not reflect things like seasonal migrations or refugee movements. The dataset is constructed by distributing known national and sub-national population counts across the grid according to a likelihood model that uses inputs including land cover data, roads data, and high resolution satellite imagery, among other sources.[9] This data is similar to that from NASA's Socioeconomic Data and Applications Center (SEDAC) which also measures population at a 30x30 arcsecond resolution, but is only available for the years 1990, 1995 and 2000 (see Dell, 2010 and Alesina et al., 2015 amongst others).

The LandScan data pays special attention to coastal features. To account for the dynamics of coastal change the LandScan model extends all coastal boundaries several kilometres seaward. This ensures that all shore and small island features are included within an administrative unit boundary.[10]

3.4 Urban and rural classification

SEDAC also provides an "Urban Extents Grid", which uses 1995 population count estimates to classify each square of a 30x30 arcsecond global grid as either urban or non-urban.

of 63 cannot be distinguished. This is mostly an issue in the centre of dense, economically active areas in developed countries (Michalopoulos and Papaioannou, 2014), and is not a particular concern in our study of coastal areas. The data is also subject to "overglow", where lights appear larger over water and snow. We address this by clipping our dataset to the shoreline.

[8]This is the same resolution as the lights data, although the pixels are not aligned. We use grid cells aligned with the lights rasters but not the population rasters. To address this the Zonal Statistics tool in ArcGIS internally resamples the raster files so that they are aligned.

[9]For further detail http://web.ornl.gov/sci/landscan/landscan_documentation.shtml)

[10]For more information see the LandScan documentation http://web.ornl.gov/sci/landscan/landscan_documentation.sh

The classification is based on contiguous lighted squares (as of 1995) and squares known to hold at least 5000 people.

3.5 Political stability and ease of doing business

The World Bank provides data on political stability in its Worldwide Governance Index, and on the ease of doing business in its Doing Business Survey. We collect countries into four groups with similar numbers of waves based on their 2014 scores on each. Table B.2 groups countries by political stability, and table B.1 groups them by the quality of their business environment.

4 Methodology

4.1 Measuring economic activity

In our analysis we use two measures of economic activity as the dependent variable: illumination in the immediate vicinity and illumination in nearby towns.

Illumination in the immediate vicinity is measured using luminosity in surrounding circles of various radii. We draw these circles at 1km, 5km, 10km and 50km around each wave and take the sum of illumination within each circle for each year. Because waves are located on the coastline, and there is no economic activity generated out to sea, we clip these circles so as only to include area covered by land.

We also separate each circle into urban, lit-rural and unlit-rural areas. The distinction is based on the 1990 SEDAC Urban Extents Grid dataset, which demarcates urban and rural areas using a combination of population counts (persons), settlement points, and the presence of night-time lights. Urban areas are those with significant lit cells, a buffered settlement point, or a total population greater than 5,000 persons. Lit-rural areas are non-urban cells that were lit in 1992. Unlit-rural areas are non-urban cells that were not lit in 1992 but have a positive population. Studying unlit-rural areas allows us to determine the impact of natural assets on rural poverty (see Smith and Wills, 2016).

Illumination in nearby towns is measured by endogenously locating towns by their population density. A town is defined by a perimeter enclosing cells with a population density of 300 persons per square kilometre or more.[11] Each wave is linked to two towns: the closest town and the largest town within 50km radius (based on total population).

4.2 Identification

Estimating the economic return to a non-market natural asset presents challenges of endogeneity and attributability. We address this using a natural experiment that exploits the exogenous variation in the quality of surfing waves.

[11] We also use a cut-off of 600 persons per square kilometer as a robustness check.

Endogeneity can arise for a variety of reasons. The first, and most obvious is due to omitted variables: observable and unobservable characteristics that are correlated with both the location of waves and local economic activity. If these omitted variables are time-varying then controlling for time fixed-effects will not help. Examples of omitted variables for areas near waves could include geographic characteristics, political stability and institutional quality.

Endogeneity can also arise due to reverse causality. The exploitation of surfing waves may depend largely on the level of economic activity, and associated infrastructure, already established in the area. We believe this to be less of an issue for surfing, given the strong history of intrepid exploration by surfers, the rarity of top quality waves and the sheer isolation of some locations in our data. For example, to access Red Bluff in Western Australia (a "totally epic" quality 4 wave) one must drive for 4.5 hours along a dirt road from Carnarvon, an isolated town with population less than 5000. Reverse causality remains a concern.

Attributing changes in economic activity to a specific natural asset requires strong identification of the asset itself. There may be many other factors, natural or otherwise, that attract economic activity to the area surrounding a wave specific area. For surfing waves this may include trade, boating, fishing and the benefits of nearby beaches.

We address the identification challenges of endogeneity and attributability by exploiting the exogenous variation in wave quality, rather than the existence of waves per se. Whilst the location of a wave may well be endogenous to local economic activity for the aforementioned reasons, the variation in the quality of a wave's surfing potential is exogenous. In other words, the quality of a surfing wave can be treated as a natural experiment.

We also conduct robustness tests to verify the success of our identification strategy. This includes varying the baseline quality to control for selection of low quality waves into our database, and testing whether particular coastal features (reefs, rivermouths, etc) drive our results.

4.3 Estimating Equations

The effect of surfing wave quality on spatial outcomes are estimated using the following polynomial distributed lag model:

$$\begin{aligned} Y_{i,t} &= \alpha + \beta(t)Q_i + \gamma(t) + W_i + Z_t + \epsilon_{i,t} \\ &\quad \text{where} \\ \beta(t) &= \beta_1 t + \beta_2 t^2 + \beta_3 t^3 + \beta_4 t^4 \\ \gamma(t) &= \gamma_1 t + \gamma_2 t^2 + \gamma_3 t^3 + \gamma_4 t^4 \end{aligned} \tag{4.1}$$

where $Y_{i,t}$ is the outcome of interest for wave i at time $t = [0, \ldots, 21]$, Q_i is an indicator equal to zero if the wave is of poor quality (1-star) and one if the wave is of some higher quality (2-5 stars), Z_t is time fixed effects and W_i is wave fixed effects. The polynomial structure is imposed on $\beta(t)$ and $\gamma(t)$ to reduce the effects of collinearity in the data. The standard errors are clustered at the wave level to address the spatial correlation between observations (surf breaks).

An alternative linear specification is used test the relative significance of wave qualities,[12]

$$Y_{i,t} = \alpha' + \sum_{s=0}^{t} \beta'(Z_s \times Q_i) + Z_s + W_i + \epsilon_{i,t}. \tag{4.2}$$

The dependent variable in our estimating equation, $Y_{i,t}$, varies between the log of lights and the log of population, either in the immediate vicinity of waves or in nearby towns, depending on the outcome of interest.

We drop observations for which there is no GPS data for the location of the wave which leaves us with 5,288 waves globally. We then drop those observations for which the wave quality is either missing or rated 0 stars. In total these make up 2.6% of all waves, leaving 5,151 observations in total.

5 Results

This section shows that good quality waves boost economic activity in the surrounding areas, relative to areas with low quality waves. The effect is most pronounced in emerging economies. Activity (proxied by night-time illumination) increases overall, rather than simply being reallocated from nearby areas. However we do find that the permanent population falls around good waves, which we attribute to tourism. The increase in activity is broad-based: it occurs in the immediate vicinity and in nearby towns. It also reduces rural poverty by encouraging the poor to move to areas of higher activity. These results are robust to a variety of controls, including non-surfing related coastal characteristics and alternative specifications.

5.1 Good surfing waves boost nearby economic activity

Areas with high quality surfing waves have higher economic activity than those with low quality waves, peaking with 4-star waves. This is a relatively high hurdle. Our control group is the area surrounding the lowest quality waves, and so is already on the coast and sufficiently known by surfers to appear in WannaSurf. We also control for time and wave fixed effects, to isolate the marginal effect of good surfing conditions.

Figure 5.1 uses the model in equation 4.1 to show how waves affect economic activity within a 5km radius. Higher quality waves increased economic activity, with 4-star waves increasing activity by 0.28 log points relative to 1-star waves over our sample. 5-star increased relative activity by 0.19 log points, 3-star waves by 0.15 log points, and 2-star waves by 0.03 log points (which was not significant). The relative effect on activity at

[12]Results available online.

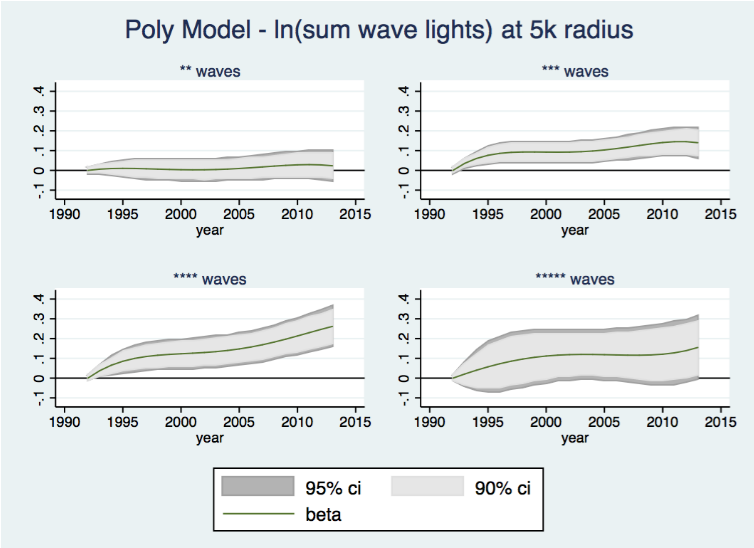


Figure 5.1: Effect of waves of various qualities on economic activity within 5km.

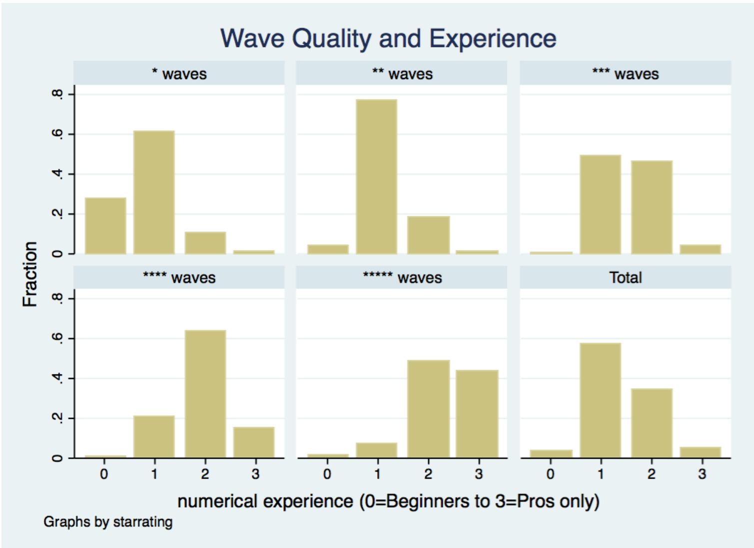


Figure 5.2: Distribution of experience required by wave quality.

1km, 10km and 50km radii display a similar pattern, where 4-star waves have the largest effect on local economic activity (though slightly less pronounced, see Appendix A).

The economic impact of good quality waves is significantly higher than bad quality waves after 21 years. We test the significance of wave quality against 1-star waves in the main specification, and against other quality waves in the linear specification (equation 4.2). Both 3-star and 4-star waves increase illumination significantly more than 2-star waves at the 1% or 5% level for most distances (1km - 50km). 4-star waves only significantly increase illumination more than 3-star waves at the 50km radius.

Wave quality has an inverse U-shaped effect on economic activity. This is because the highest quality waves require a lot of experience to ride, being disproportionately rated for “Pros or Kamikazes only” (experience level 3) as illustrated in Figure 5.2. This limits their appeal.

5.2 Emerging economies benefit from surfing the most

High quality waves increase economic activity on average, though the effect is concentrated in emerging economies. Waves largely generate economic activity through tourism. The strength of this channel will depend on both supply and demand. The demand for tourism will depend on the institutional and political characteristics of the country. The supply of tourism services will depend on the ease with which new businesses can respond to an inflow of prospective surfers. Using World Bank data on political stability and ease of doing business we find that waves have the most pronounced effect in countries that score "low" on both, as they have significant scope to grow.

Figure 5.3 shows how 4-star waves affect economic activity in the surrounding 5km, based on their country's political stability and ease of doing business. We omit the USA and Australia from the analysis as they are large, developed and stable countries who overwhelmingly dominate our sample. Waves have the largest effect on countries with intermediate political and business environments. Countries with "low" "or moderate" political stability are sufficiently stable to attract surfers, unlike those countries scoring "very low". However, they are unstable enough that their tourism industry still has scope to grow. Similarly, countries with a "moderate" business environment are able to facilitate economic activity,allowing tourism to expand to meet demand from surfers, unlike those scoring "low" or "very low". However, they will not have such well established tourism infrastructure that surfers will not add to economic activity.[13]

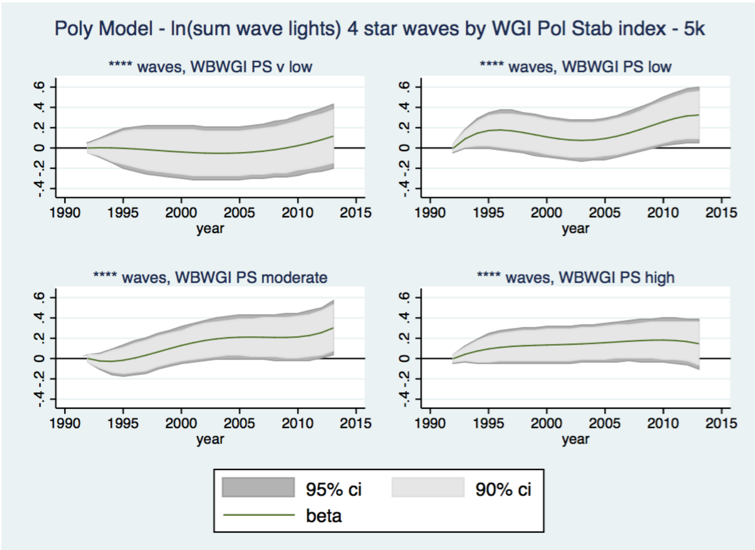
5.3 Surfing increases activity overall, rather that redistributing it from surrounding regions

Economic activity near good waves increases in aggregate, rather than just being drawn away from other areas. Figure 5.4 shows how waves of different quality affect economic activity in surrounding concentric rings out to a 50km radius, relative to 1-star waves. If the increase in activity described in Section 5.1 simply reallocated activity from surrounding areas, then we would expect higher activity in the closest rings, and lower activity further out. Instead we find that activity is higher in all rings, and falls the further from the wave one travels. If anything this suggests that surfing generates positive spillovers for the surrounding areas.

We find that 4-star waves drive the largest increase in surrounding activity at all distances over 21 years. Within 5km the effect was 0.28 log points, falling to 0.26 log points in the 5-10km, and 10-50km rings. The effect of 2-star waves remained insignificant at all distances, 3-star waves fell from 0.15 to 0.10 log points, and 5-star waves rose from 0.12 to 0.20 log points. This is again consistent with an inverse-U relationship between wave quality and economic activity.

While surfing does not redistribute economic activity it does redistribute the permanent population. The permanent population falls in the 5km surrounding 2-5 star waves, relative to 1-star waves (see Figure 5.5, panel i.). This is most pronounced for 4-star waves,

[13]To confirm that our results are not being driven by large, developed, wave-rich countries we re-run the analysis specifically for Australia and the USA, as shown in Figure B.1.



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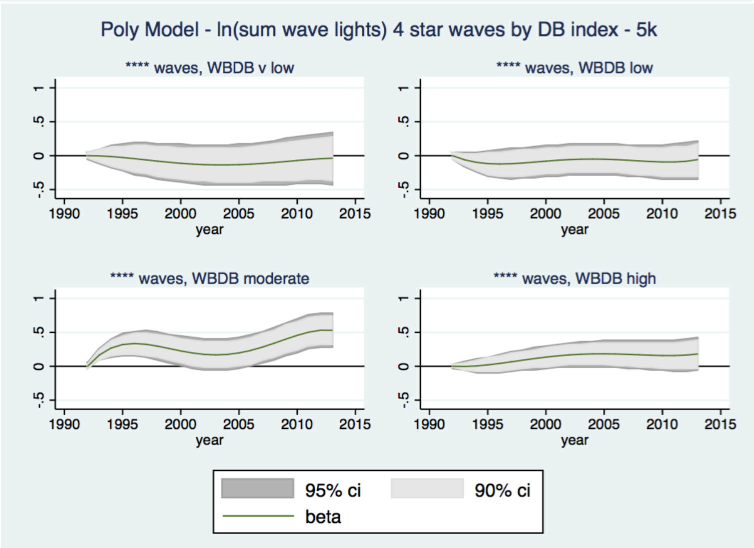

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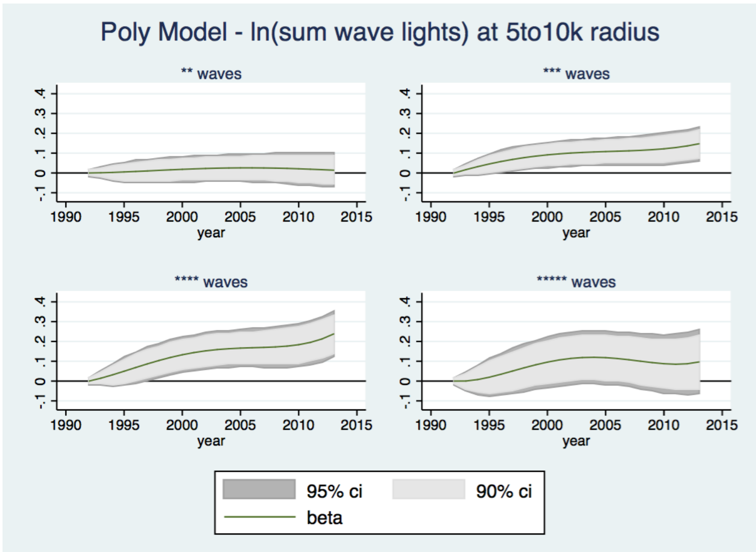
Figure 5.3: Effect of wave quality on local illumination by i. business environment and ii. political stability



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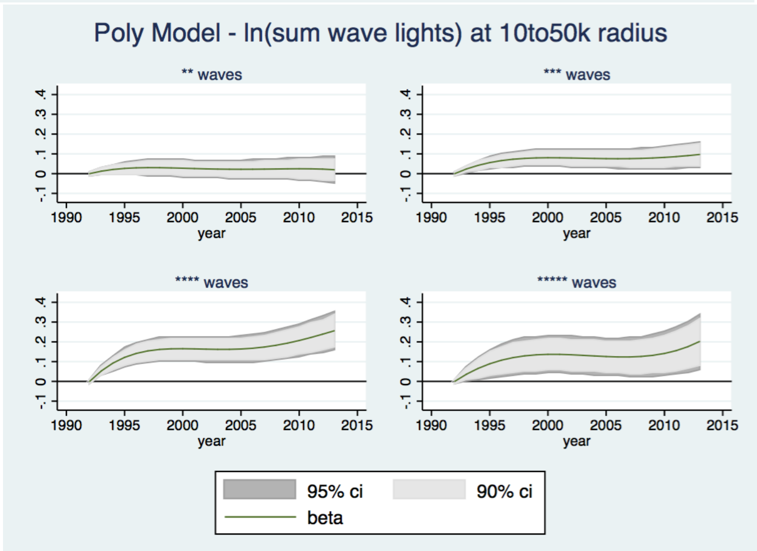


ii.

Figure 5.4: The effect of waves of various quality on economic activity in expanding concentric rings of i. 5-10km and ii. 10-50km.

which increase economic activity the most and reduce the local permanent population by -0.35 log points over our sample. Panel iii. of Figure 5.5, shows that the population increases at further distances, particularly at 10km-50km. This is consistent with the permanent population moving away from the waves because tourists, which are not included in the LandScan data, drive up property values.

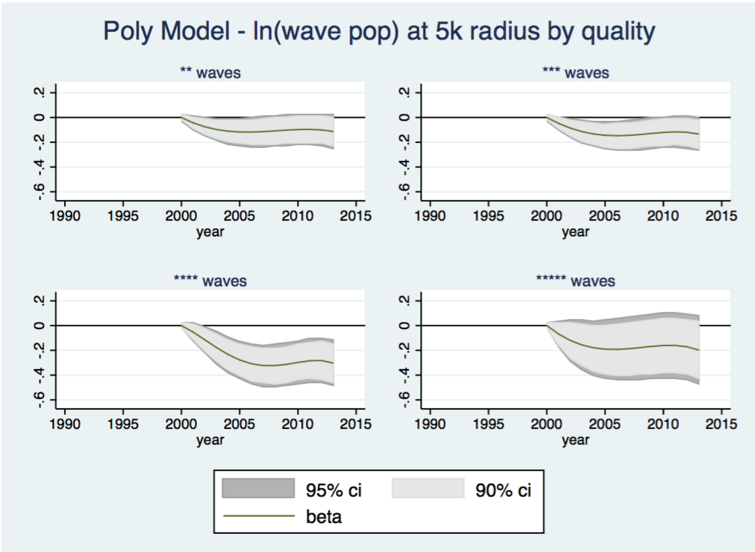
5.4 Surfing benefits areas of existing economic activity, including nearby towns

We have seen that surfing waves increase nearby economic activity. Now we investigate how this happens. First, we break the 5km circle surrounding each wave into urban and lit-rural areas. Second, we construct our own measure of the closest town, and the largest town within 50km. We find that good waves increase activity in each. In the next section we turn our attention to unlit-rural areas, and the role of natural assets in economic development.

Figure 5.6 shows how the 5km surrounding each type of wave is divided between urban, lit-rural and unlit-rural areas. Overall the largest proportion of waves are in urban areas (48%), followed by lit-rural (43%) and unlit-rural areas (9%). As wave quality increases, so too does the share of waves in rural areas. This is consistent with selection in the WannaSurf database. While a 1-star wave in an urban area might be surfed sufficiently often to warrant entry in the WannaSurf database, the same wave in a rural area might not. In contrast, surfers might be willing to travel to rural areas to surf a totally epic (5-star) wave. Selection may affect our results, because our interpretation of faster light growth near high quality waves might actually be a story of faster light growth in rural areas. As we will show next, the second interpretation can be discarded because our results also hold when considering urban, and rural areas individually.

Figure 5.7 investigates how aggregate light growth in the 5km surrounding each wave is allocated between urban and lit-rural areas. The main results in Section 5.1 is confirmed: better quality waves increase illumination in the surrounding areas, peaking with 4-star waves. The effect is larger in lit-rural than urban areas because their initial level of illumination is lower, allowing for a larger percentage change. As well as understanding the nature of growth near natural assets, this also provides some robustness for the selection effects mentioned above.

As well as increasing economic activity in their immediate surroundings, waves also increase economic activity in nearby towns. Figure 5.8 shows how waves affect illumination in the closest town (defined as having a population density over 300 people per km^2), and in the largest town within 50km. Illumination in the closest town increases by 0.14 log points for 3 and 4-star waves, while there is a small an insignificant effect for 2 and 5-star waves. In contrast illumination in the largest nearby town increases for all wave qualities, with the largest effect of 0.15 log points for 4 and 5-star waves. The effect on the largest nearby town is larger than on the closest town for each wave quality. This suggests that the economic benefits of natural assets like surfing waves tend to accrue to areas of existing economic activity, where there is the infrastructure needed to support tourism and other non-recreation activities. The effect is most pronounced for the highest



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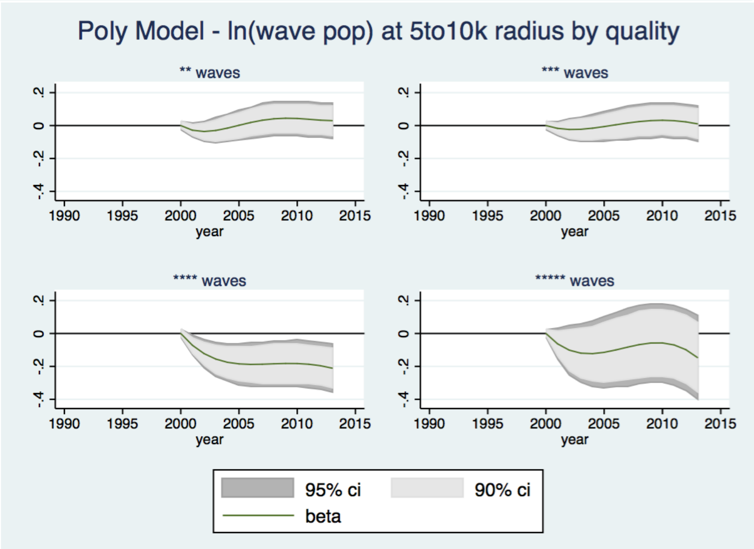

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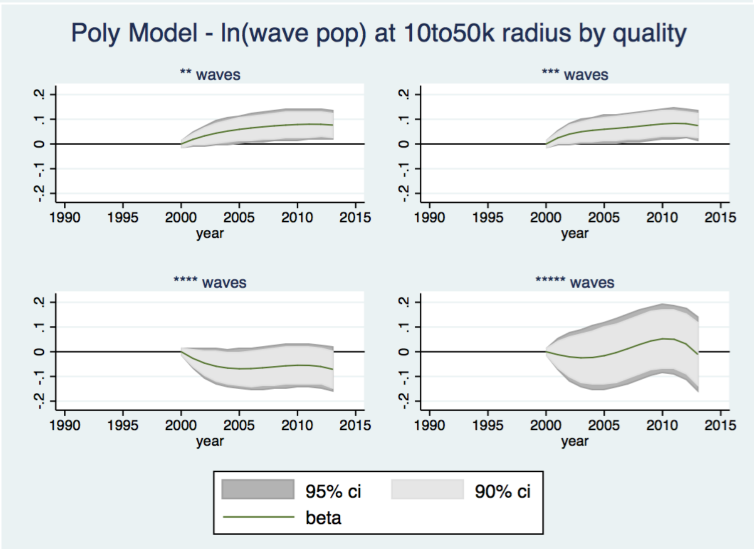


iii.

Figure 5.5: Effect of waves on population within surrounding i. 5km, ii. 5-10km and iii. 10-50km concentric rings.

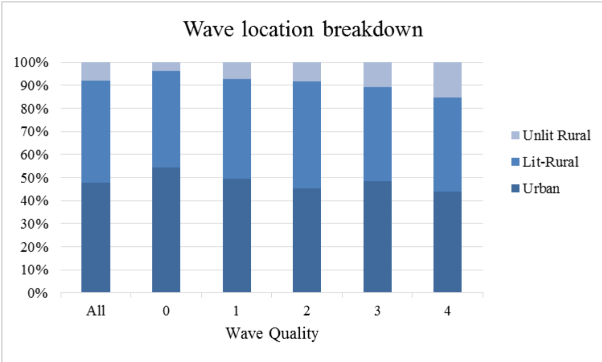
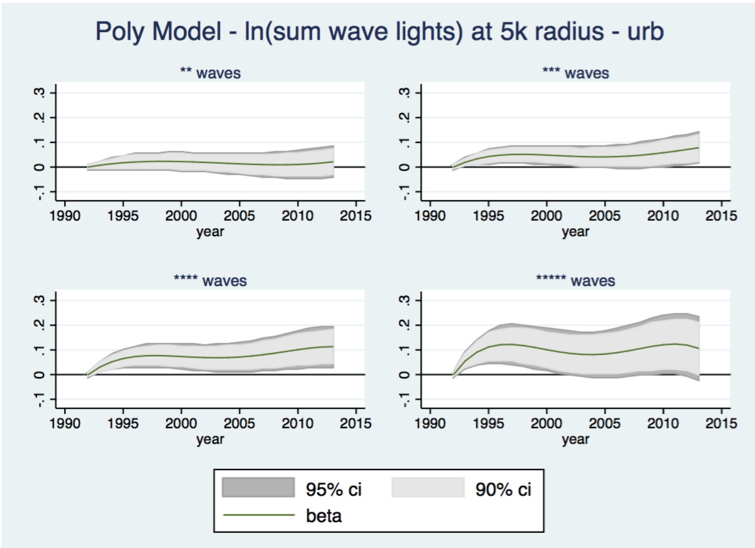


Figure 5.6: Breakdown of the 5km surrounding waves of each quality



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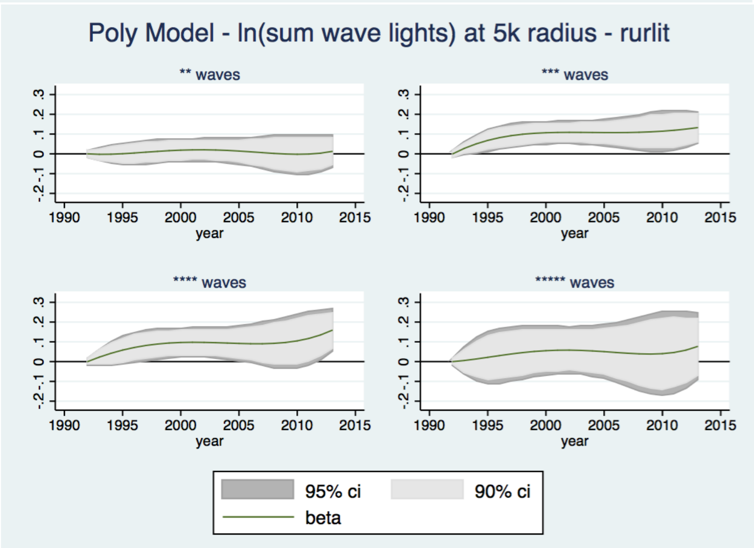
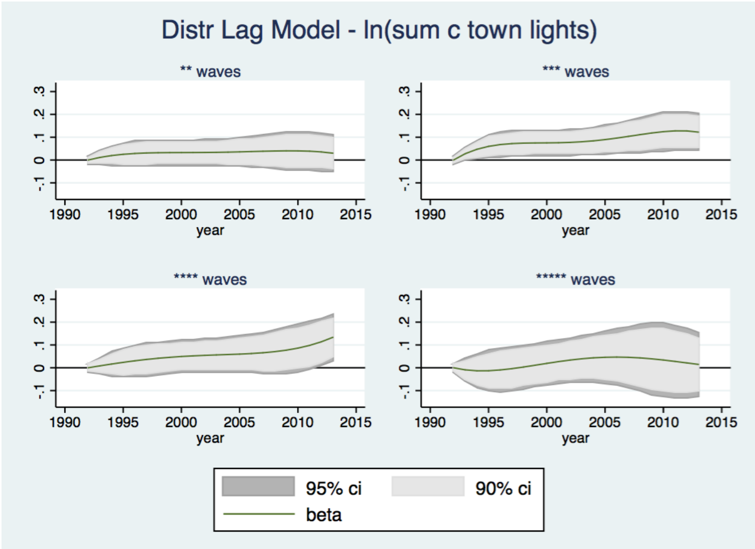


ii.

Figure 5.7: Effect of waves on lights in i. urban and ii. lit-rural areas within a 5km radius.



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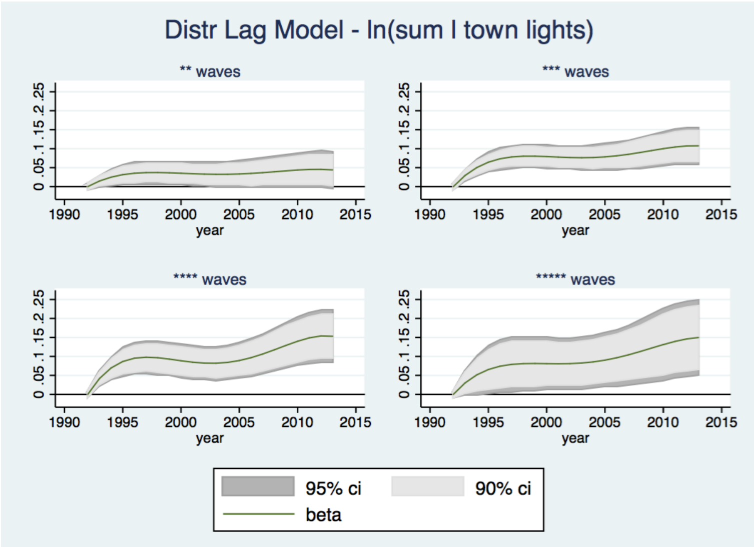


ii.

Figure 5.8: Effect of wave quality on the i. closest town (>300 people per km2) and ii. largest town within 50km, relative to lowest quality waves

quality waves, which can be attributed to their proportionally greater incidence in rural areas, and the greater requirements needed to service surfers riding those waves (such as board repairs, healthcare, etc).

5.5 Surfing also reduces rural poverty

Natural assets account for a large share of the capital stock in developing countries. There is 365,000km of coastline in the world - nine times the circumference of the earth. A significant proportion of this lies in developing countries, with Africa's coastline stretching for 26,000km, and Asia's 62,800km. The potential for surfing assets to exist along these coastlines is huge. This section shows that waves have significant potential for reducing poverty in their local areas.

To understand the potential for waves to reduce poverty we turn our attention to unlit rural areas. These are areas within 5km of a wave that were unlit but had a positive

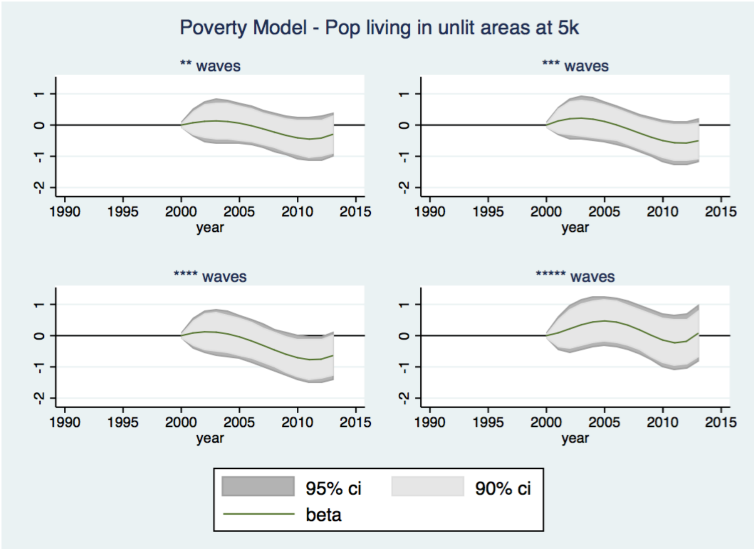


Figure 5.9: Population living in unlit rural areas within 5km of surfing waves.

population in 2000 (when our data begins). Smith and Wills (2016) show that the share of population living in unlit rural areas - the rural poor - is a good proxy for extreme poverty. When households cross the extreme poverty line they quickly illuminate, due to the high returns from longer working hours. Figure 5.9 shows that the population living in unlit rural areas falls in areas near good waves by up to 0.7 log points, relative to 1-star waves. This suggests that there is significant potential for natural assets like surfing waves to be harnessed for reducing extreme poverty.

There are two ways that the population living in unlit rural areas can fall: by unlit areas becoming lit, or by people moving away from unlit areas. Figure 5.10 shows the proportion of areas that were unlit in 2000 that became lit in subsequent years. Areas near good waves illuminate slower than areas near bad waves. It suggests that waves do not cause unlit rural areas to become illuminated. This implies that people move away from unlit areas. Testing this implication directly produces a statistically insignificant result. However, we do find evidence that the population in nearby towns increases (Figure 5.11). In large towns this amounts to a population rise of up to 0.35 log points for 5-star waves over our sample. Figure 5.11, panel ii.). This is consistent with surfing waves reducing extreme rural poverty by attracting people from rural areas to nearby towns.

5.6 Surfing waves contribute around US$50 billion to global economic activity each year

We find that surfing waves contribute US$51.2 billion (2011 PPP) globally each year to economic activity in their surrounding 50km. To arrive at this figure we allocate all pixels of luminosity within 50km of a wave to a particular wave quality (proportionately if within 50km of more than one wave). This accounts for 9.4% of global illumination. We then aggregate total illumination and total GDP (US$ 94.1 trillion in 2011 PPP , World Bank WDI) to find an average value for each pixel of luminosity. Using the parameter estimates from equation 4.1 we deduce the marginal contribution of surfing waves to activity for

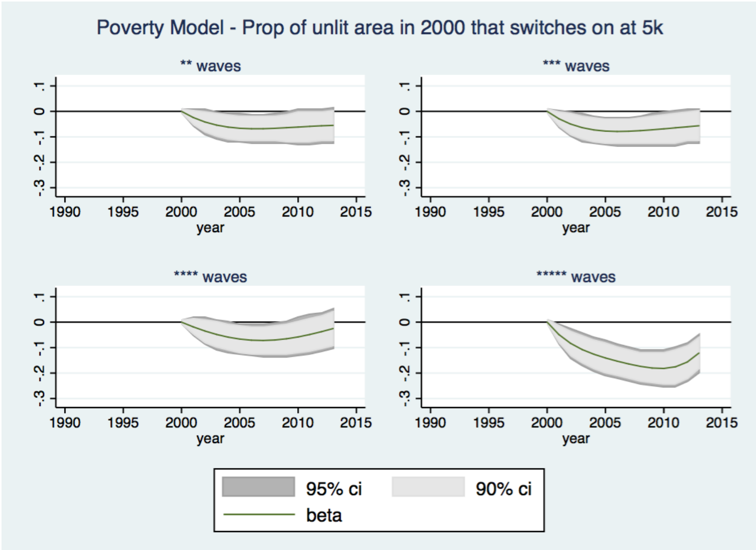
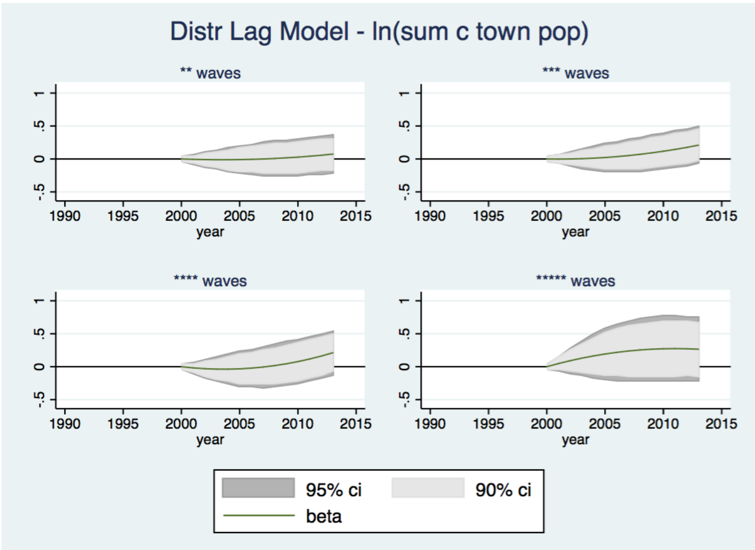


Figure 5.10: Share of unlit areas in 2000 that became lit in subsequent years, within 5k of a wave.



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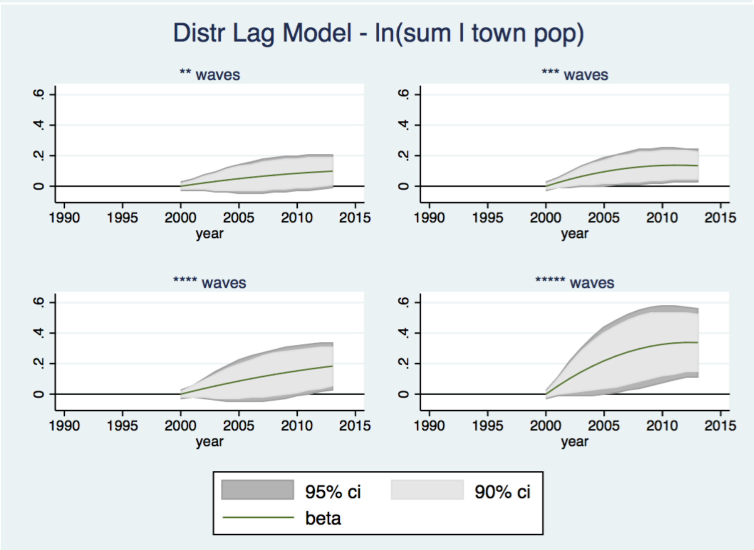


ii.

Figure 5.11: Effect of waves on population in nearby towns (quadratic polynomial model)

Star rating	Annual Contribution per Wave	Frequency	Annual Contribution Total
3	17.9	2,129	38,109
4	22.3	450	10,035
5	19.0	161	3,059
Total		2,740	51,203

Table 5.1: Annual global contribution of waves to economic activity in surrounding 50km (US$ million 2011 PPP)

each wave quality, averaged over 22 years. We exclude 2-star waves because their effect is not statistically significant from zero. The results are reported in Table 5.1.

Each 4-star wave contributes US$22.3 million on average to surrounding economic activity each year. 5-star waves contribute US$19.0 million on average, and 3-star waves US$17.9 million on average. The largest aggregate contribution comes from 3-star waves which, due to their prevalence, account for 75% of surfing's contribution to global GDP.

5.7 Discovering a new wave significantly raises activity in the local area

To provide further evidence that good quality waves improve local economic activity we conduct a small event study, using the date that waves were discovered. This is different to the previous analysis because we are exploiting exogenous variation over time, rather than over space. Using discovery dates from two sources, the "Rip Curl Pro Search" competition and the "Google Earth Challenge" (see Section 3.1), we find that illumination near waves grows 4% faster after they are discovered by the international surfing community.

There are two challenges in conducting this type of event study. First, we require a meaningful definition of a wave being "discovered". If a wave is only known to a handful of locals, it is unlikely to generate much local economic activity. What we really mean by "discovery" is that the global surfing community becomes aware, for the first time, about a new high-quality wave. Second, we need to define when a discovery takes place. There is no official surfing body or archive that stores and maintains this kind of information. Discoveries must also take place within our night-time lights sample, from 1992-2013.

To estimate the impact of the discovery of a surfing wave on local economic activity we fit the following linear model on our sample of seven wave discoveries:

$$Y_{i,t} = \alpha + \beta_{i,t} W_i * T_t + \delta_{i,t} D_i * T_t + Z_i + W_i + \epsilon_{i,t} \tag{5.1}$$

where $Y_{i,t}$ is the log of lights within 50km of each wave $i = [0, \ldots, 5]$ at time $t = [0, \ldots, 21]$, T_t is a continuous time variable cantered on zero at the year of discovery, W_i is a wave fixed effect, Z_t is time fixed effects, D_i is our discovery indicator equal to 0 before the year of discovery and 1 after. The coefficient $\beta_{i,t}$ measures the linear growth rate of lights before the wave was discovered, and $\delta_{i,t}$ measures the change in the rate of growth of lights after the wave was discovered. Eq. 5.1 compares light growth over time pre and post discovery, controlling for changes in light intensity over time that are common to all waves and differences in light intensity between each wave.

Our main coefficient of interest, $\delta_{i,t}$, estimates the change in trend light growth after the wave was discovered: our treatment effect. We find $\tilde{\delta}_{i,t} = 0.04$ which is significant at better that the 1% level ($p_\gamma > |t| = 0.005$).

This result implies that discovering a wave leads to an increase in annual light growth of around 4% per year, on average across our seven discoveries. Translating our headline results to annualised growth rates yields increases in annual growth rates of 0.7% for 3-star waves, 1.2% for 4-star waves and 0.8% for 5-star waves, all relative to 1-star (normal) waves. This is substantially larger than our headline results for 3-star, 4-star and 5-star waves.

The following figures plot the results from Eq. 5.1 for each of our seven wave discoveries. They compare the predicted light growth pre and post discovery with the actual light growth over time, controlling for changes in light intensity over time that are common to all waves. The red line in each of the figures denotes the date of discovery for each wave, centred at zero, whilst the solid and dashed black lines denote the fitted linear model pre and post discovery respectively for each wave. The results are clear. Discovering a wave increases trend growth rates in the local area.

5.8 Robustness

To check the robustness of our main results we investigate two alternative explanations. The first adds to the wave event study of the previous section by investigating whether our results may be driven by other coastal characteristics unrelated to surfing. The second tests whether the selection into our database of low quality waves near towns is driving our results; complementing the town-based analysis in Section 5.4. Our results are robust to both tests.

Non-surfing coastal characteristics To test whether our identification strategy is valid we investigate whether other, non-surfing related, coastal characteristics might be driving our results. If the particular meteorological and bathymetric conditions that create good surfing waves also give rise to other economic activity, like swimming on sandy beaches, diving on coral reefs, fishing from rivermouths, or trading from harbours, then our results may be biased. To test this we exploit data on the type of each wave, outlined in Table 5.2.

Figure 3.3 shows that the distribution of wave quality varies by type, with rivermouths, reefs and point-breaks all being better than average. Rivermouths make up only 2.6% of our observations (2.7% of 4-star and 1.2% of 5-star waves) and so there are not enough to systematically bias our results. Reefs and point-breaks comprise a greater share, so we re-run our analysis excluding these observations to see if our results still hold (see Figure 5.13). Excluding reefs, point-breaks and both produces a similar outcome to the main results in Section 5.1. 4-star waves increase illumination in the surrounding 5km by 0.20-0.25 log points over our sample.We also get broadly similar results when we exclude

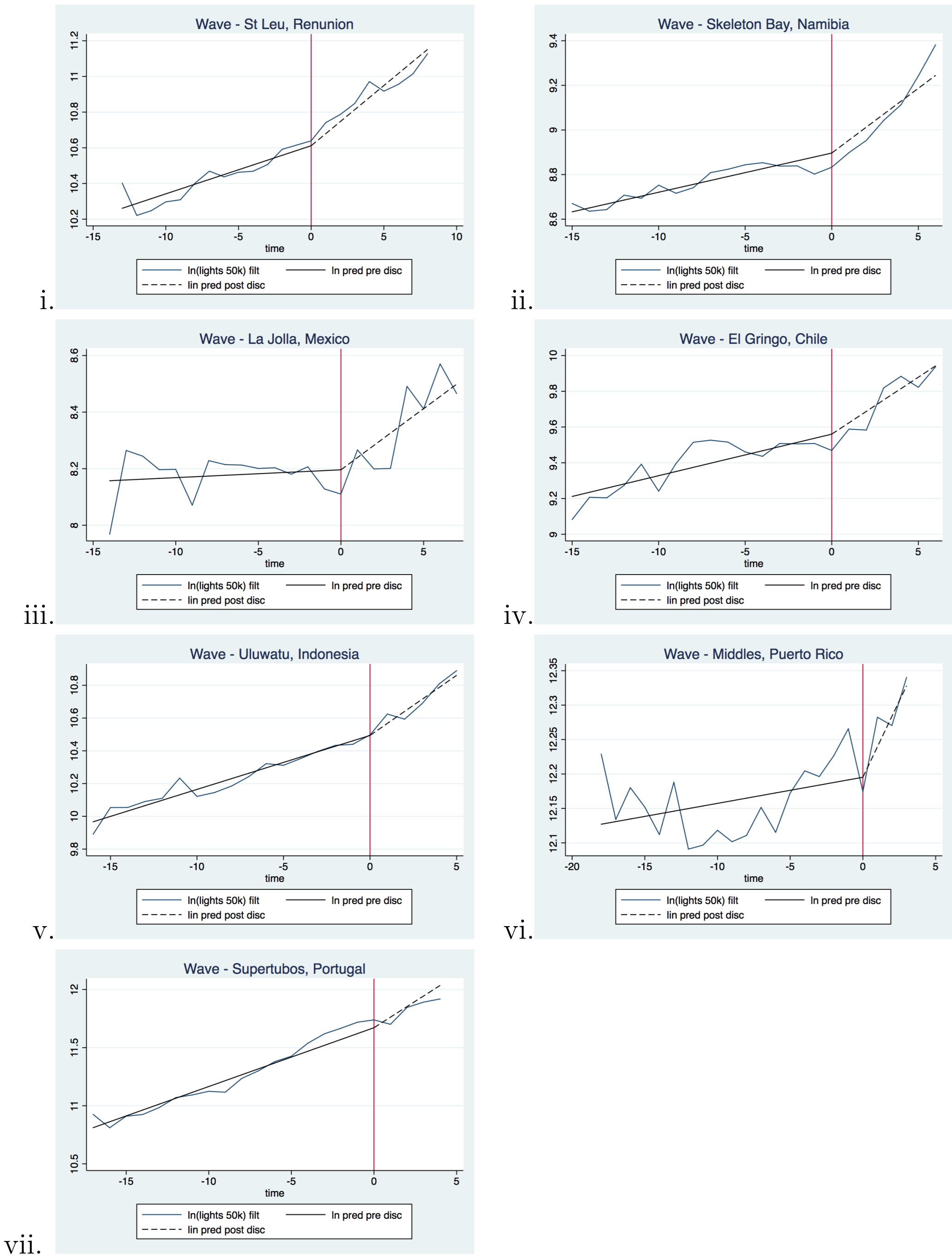


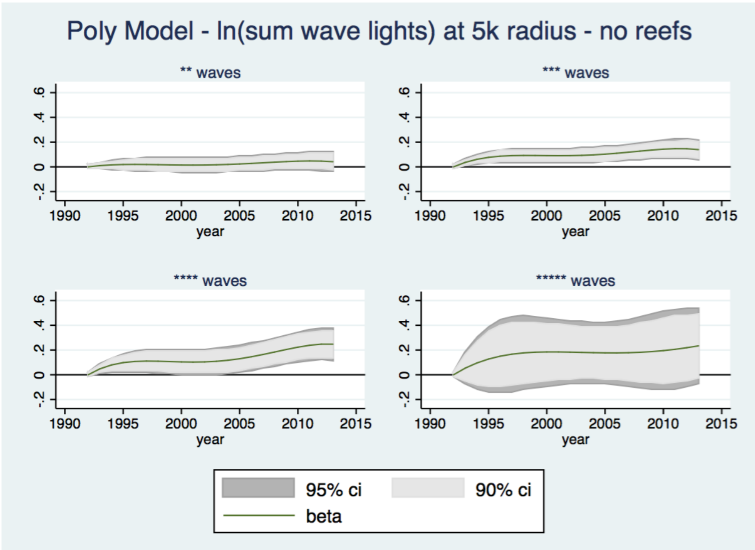
Figure 5.12: Event study results: five wave discoveries

Wave Type	Description	Frequency	Percent
0	Beach-break	2,013	41.6
1	Breakwater/jetty	124	2.6
2	Don't know	12	0.3
3	Point-break	643	13.3
4	Reef-artificial	23	0.5
5	Reef-coral	261	7.5
6	Reef-rocky	998	20.6
7	Rivermouth	118	2.4
8	Sand-bar	549	11.3
N/A	Missing	85	N/A
Total		4,926	

Table 5.2: Breakdown of waves by type

reefs and point-breaks from our analysis of closest and largest nearby towns in Section 5.4, as described in Appendix C. For both the closest and the largest nearby towns the effect is of a similar magnitude to our main results, peaking with 4-star waves for the closest town and 5-star waves for the largest town.

Selection of low-quality urban waves The WannaSurf database exhibits some selection bias, where the lowest quality waves are more likely to appear in the data when they are close to towns and cities (54%). This might bias our results if lights in towns grow slower than in rural areas. To test this we re-run the analysis using 2-star waves as the baseline, rather than 1-star. A similar share of 2-star waves are located in towns or cities (49%), as are the 4-star waves that are our focus (48%). Figure 5.14 shows that our results are broadly the same as with the 1-star baseline, with slightly smaller coefficients (also see Appendix D).



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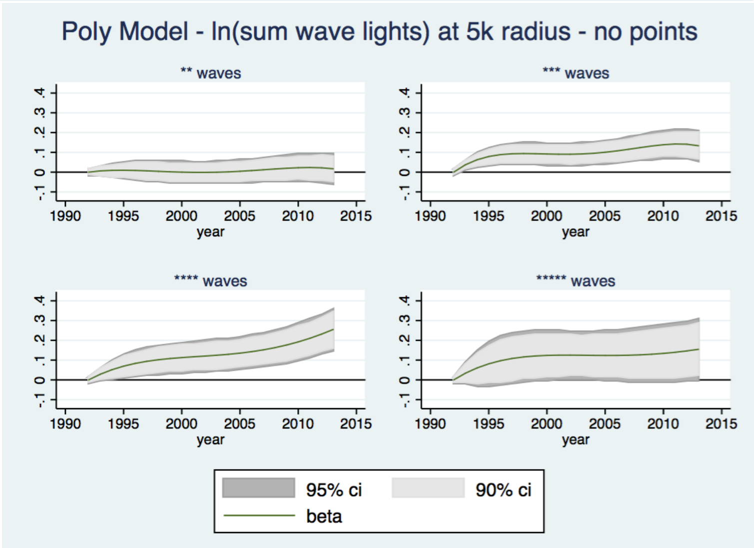

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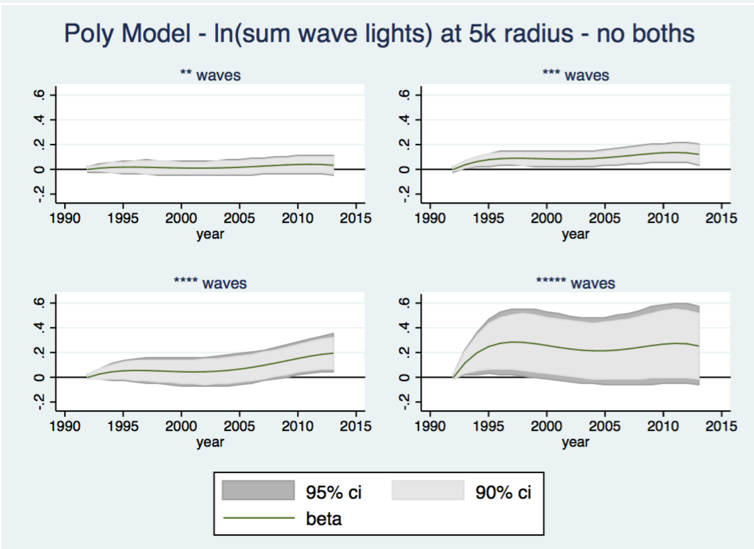

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Figure 5.13: Robustness test excluding i. reefs, ii. points and iii. both.

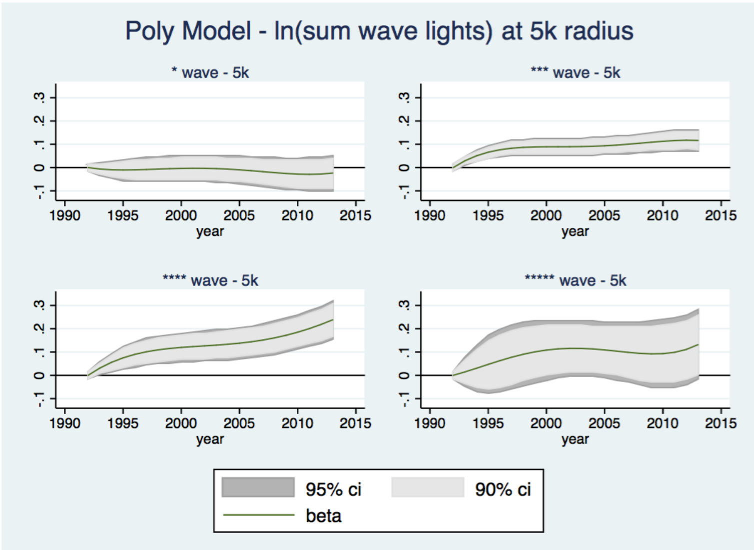

Figure 5.14: Effect of waves on illumination in the surrounding 5km, with quality 1 as baseline.

6 Conclusion

This paper offers a global panel study on the effect of a non-market natural asset on economic activity. We combine three high-resolution spatial datasets, on the location of surfing waves, night-time light emissions and population, to answer the question: how much do surfing waves contribute to the surrounding economy?

We find that surfing waves contribute approximately US$50 billion to global economic activity each year. This amounts to an average contribution of US$18-25 million per wave per year.The effect on activity increases with wave quality, except for the highest quality waves which require a lot of skill to ride. Emerging economies benefit the most from surfing, as long as they have a sufficient level of political stability and ease of doing business. Furthermore, the increase in activity does not just represent a reallocation away from surrounding areas. Waves do, however, cause the permanent population to move further away - which is consistent with tourists driving up property prices. Surfing also appears to play a role in reducing extreme poverty, again by encouraging people to move away from unlit rural areas into nearby towns. These results capture the value of macroeconomic spillovers from the natural asset, in contrast to most existing methods of non-market valuation. The results are also robust to a range of tests for endogeneity and attributability.

While this began as a personal interest project for a couple of sandy-footed economists, it also has several policy implications. The first is to provide policymakers with an understanding of the potential benefits of waves for economic development, especially in developing countries. This is true for both naturally occurring waves and artificially constructed waves - be they offshore artificial reefs or onshore wave pools. The second is to highlight the importance of conserving the quality of waves. This involves limiting both coastal pollution and changes to the characteristics of waves through dredging, coastal manipulation or rising sea levels.[14]

[14]It may also involve protection from sharks, which has been at the forefront of the surfing community's

The paper also suggests a range of extensions. By providing a methodology for valuing the economic spillovers from non-market natural assets we capture externalities that may not be included in other methods of non-market valuation. This methodology is relevant for any natural asset that exogenously varies in quality around the world, including rock-climbing cliffs and natural reserves (including UNESCO natural heritage sites).

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mind since former World Champion Mick Fanning was attacked by a shark in the 2015 final of a World Tour event in Jeffrey's Bay, South Africa

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Appendix

A Aggregate economic activity

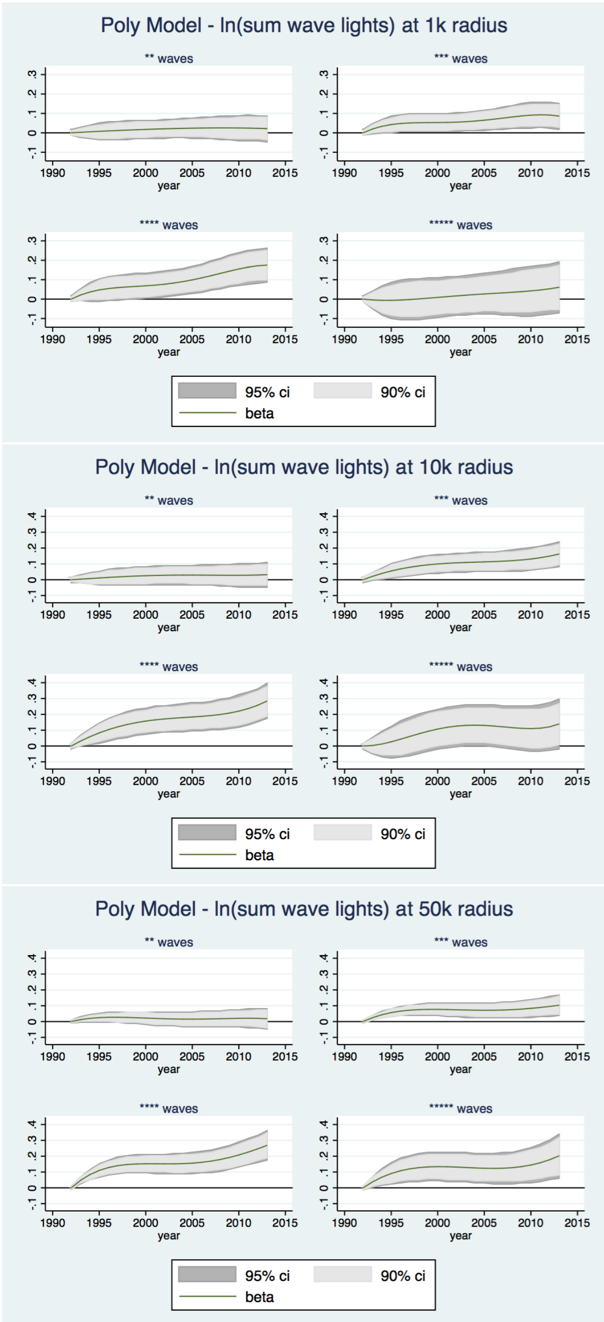


Figure A.1: Effect of waves of various qualities on economic activity within 1km, 10km and 50km.

B Ease of doing business and political stability categories

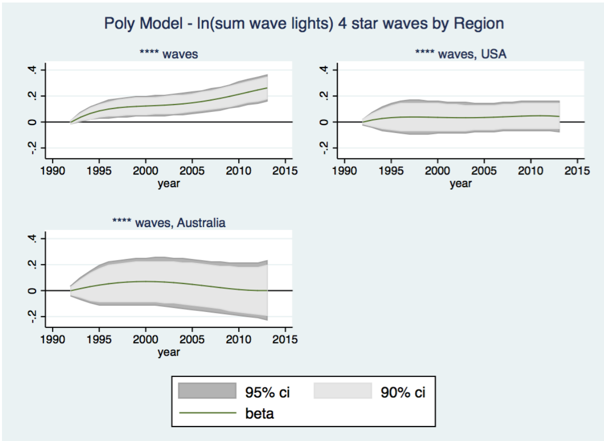


Figure B.1: Headline results are not being driven by the USA or Australia

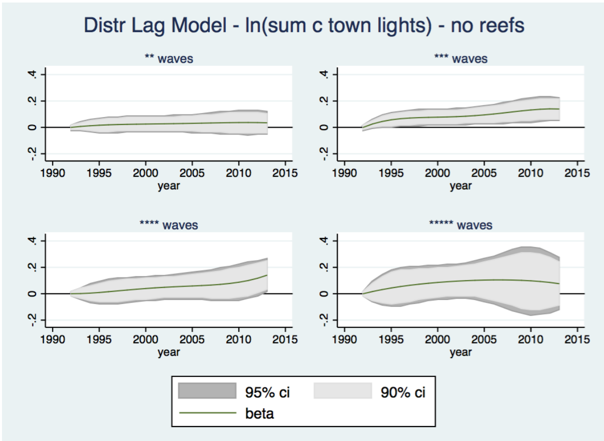
WB DB - very low		WB DB - low		WB DB - moderate		WB DB - high	
Country	**Waves**	**Country**	**Waves**	**Country**	**Waves**	**Country**	**Waves**
Brazil	291	South Africa	207	Spain	182	France	290
Indonesia	136	Puerto Rico	53	Japan	118	Portugal	162
Ecuador	47	Chile	50	Italy	113	United Kingdom	149
Argentina	34	Costa Rica	50	Mexico	92	New Zealand	114
Venezuela	24	Greece	50	Peru	76	Ireland	58
Nicaragua	20	Morocco	43	Mauritius	14	Canada	38
Senegal	20	Philippines	29	Belgium	12	Netherlands	32
Barbados	19	Panama	27	United Arab Emirates	9	Germany	22
Sri Lanka	18	Israel	25	Bulgaria	8	Taiwan	18
India	13	Uruguay	24	Poland	4	Denmark	15
Micronesia	11	Turkey	18	Croatia	3	Iceland	14
Bahamas	10	Namibia	17			Malaysia	14
Papua New Guinea	10	Dominican Republic	16			Sweden	11
Angola	9	Seychelles	15			South Korea	7
Maldives	9	Russia	14			Hong Kong	5
Verde	9	Thailand	14			Switzerland	5
Ghana	8	El Salvador	12			Lithuania	3
Madagascar	8	China	11			Estonia	2
Egypt	7	Colombia	11			Finland	2
Mozambique	7	Tunisia	11			Latvia	2
Lebanon	6	Samoa	10			Austria	1
Guinea	5	Vietnam	10				
Algeria	4	Cyprus	8				
Liberia	4	Guatemala	7				
Sao Tome And Principe	4	Dominica	6				
Togo	4	Fiji	6				
Cameroon	3	Malta	5				
Cote d'Ivoire	3	Oman	4				
Gambia	3	Brunei Darussalam	3				
Kenya	3	Saint Lucia	3				
Myanmar	3	Albania	2				
Nigeria	3	Tonga	2				
Sierra Leone	3	Vanuatu	2				
Tanzania	3	Jamaica	1				
Benin	2	Kuwait	1				
Gabon	2	Qatar	1				
Grenada	2	Trinidad And Tobago	1				
Haiti	2	Ukraine	1				
Kiribati	2						
Palau	2						
Rep Congo	2						
Bangladesh	1						
Belize	1						
Cambodia	1						
Honduras	1						
Iran	1						
Saint Kitts And Nevis	1						
Saint Vincent And T..	1						
Solomon Islands	1						
Timor-Leste	1						
Zimbabwe	1						
Total	**785**		**770**		**631**		**964**

Table B.1: Countries and wave count by World Bank Doing Business categories.

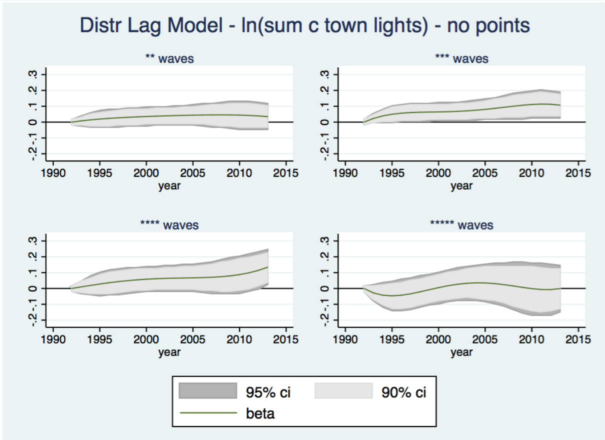
WB WGI Pol Stab - very low		WB WGI Pol Stab - low		WB WGI Pol Stab - moderate		WB WGI Pol Stab - high	
Country	**Waves**	**Country**	**Waves**	**Country**	**Waves**	**Country**	**Waves**
South Africa	207	Brazil	291	France	290	Portugal	162
Indonesia	136	Spain	182	United Kingdom	149	Japan	118
Mexico	92	Greece	50	Italy	113	New Zealand	114
Peru	76	Ecuador	47	Puerto Rico	53	Ireland	58
Morocco	43	Argentina	34	Chile	50	Canada	38
Philippines	29	Panama	27	Costa Rica	50	Netherlands	32
Israel	25	Reunion	21	Namibia	17	Uruguay	24
Venezuela	24	Nicaragua	20	Seychelles	15	Germany	22
Senegal	20	Dominican Republic	16	Malaysia	14	Barbados	19
Sri Lanka	18	Vietnam	10	Belgium	12	Taiwan	18
Turkey	18	Bulgaria	8	Verde	9	Denmark	15
Russia	14	South Korea	7	Cyprus	8	Saint Martin	15
Thailand	14	Sao Tome And Principe	4	Fiji	6	Iceland	14
India	13	Gabon	2	Oman	4	Mauritius	14
El Salvador	12	Benin	2	Croatia	3	Micronesia	11
China	11	Belize	1	Albania	2	Sweden	11
Colombia	11	Trinidad And Tobago	1	French Guiana	2	Bahamas	10
Tunisia	11	Kuwait	1	Kiribati	2	Samoa	10
Papua New Guinea	10	Jamaica	1	Latvia	2	Maldives	9
Angola	9	Cambodia	1	Vanuatu	2	United Arab Emirates	9
Ghana	8			Saint Kitts And Nevis	1	Aruba	7
Madagascar	8			Solomon Islands	1	Dominica	6
Egypt	7					Hong Kong	5
Guatemala	7					Malta	5
Mozambique	7					Switzerland	5
Lebanon	6					Poland	4
Guinea	5					Virgin Islands, U.S.	4
Algeria	4					Brunei Darussalam	3
Liberia	4					Lithuania	3
Togo	4					Saint Lucia	3
Cameroon	3					Anguilla	2
Cote d'Ivoire	3					Bermuda	2
Gambia	3					Estonia	2
Kenya	3					Finland	2
Myanmar	3					Grenada	2
Nigeria	3					Tonga	2
Sierra Leone	3					Austria	1
Tanzania	3					Qatar	1
Haiti	2					Saint Vincent And T..	1
Rep Congo	2						
Bangladesh	1						
Honduras	1						
Iran	1						
Somalia	1						
Timor-Leste	1						
Ukraine	1						
Zimbabwe	1						
Total Waves	**888**		**726**		**805**		**783**

Table B.2: Countries and wave count by WB Worldwide Governance Indicators, Political Stability categories

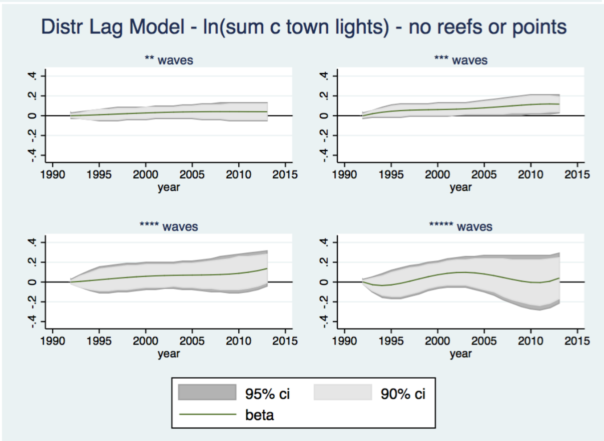
C Excluding certain wave types



i.

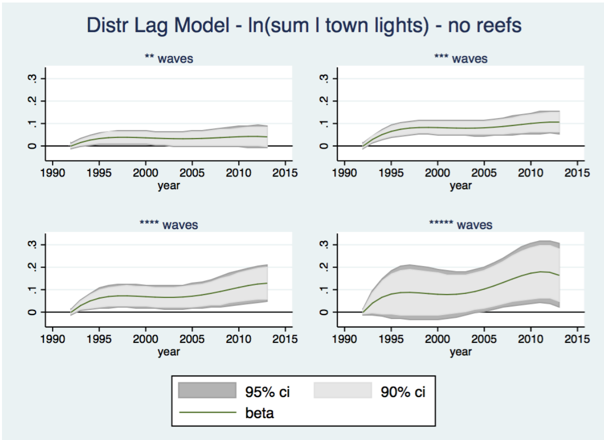


ii.

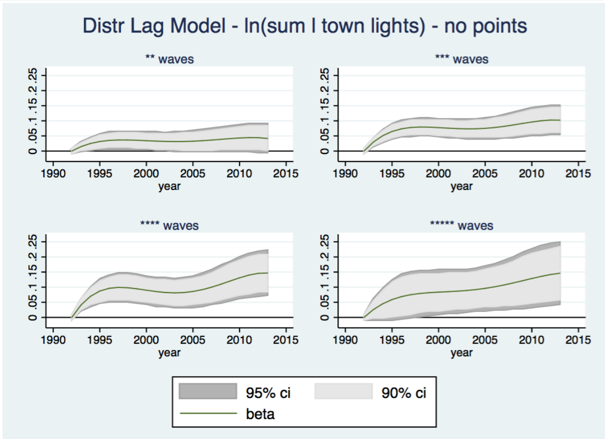


iii.

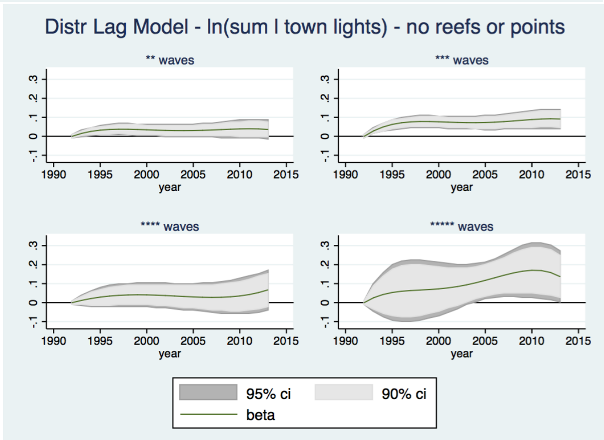
Figure C.1: Robustness test: excluding i. reefs, ii. points and iii. both from our analysis of illumination in the closest town.



i.



ii.



iii.

Figure C.2: Robustness test: excluding i. reefs, ii. points and iii. both from our analysis of illumination in the largest nearby town.

D Alternative baseline

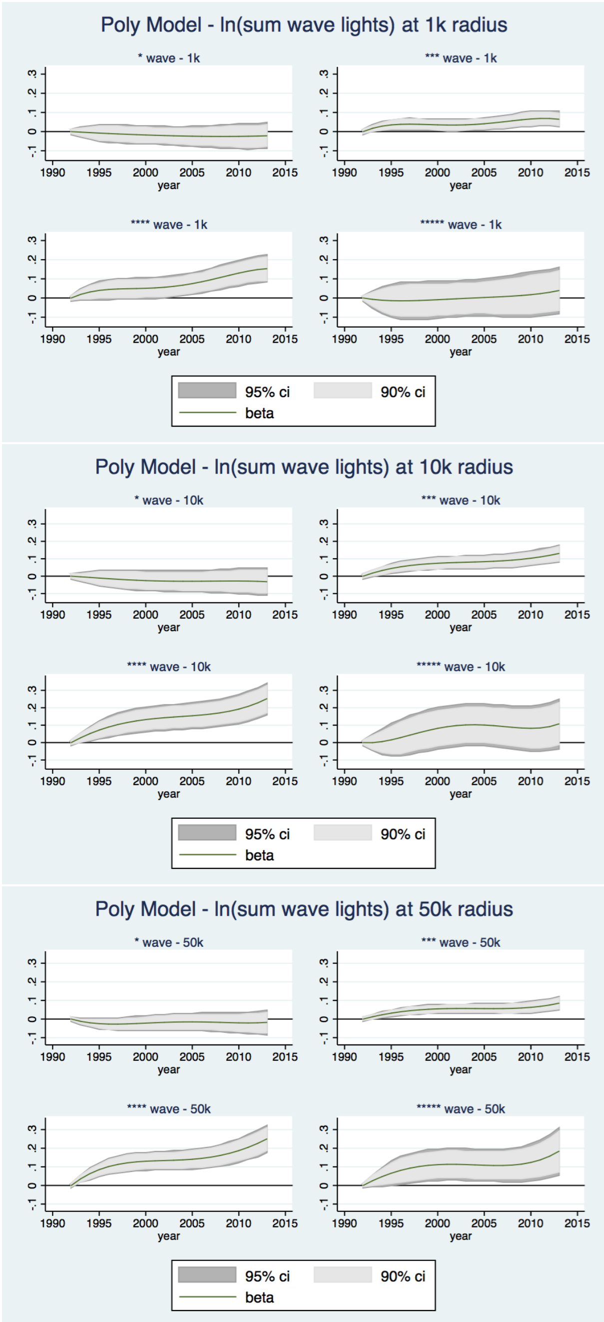


Figure D.1: Effect of waves on illumination within surrounding 1km, 10km and 50km, with quality 1 as baseline.

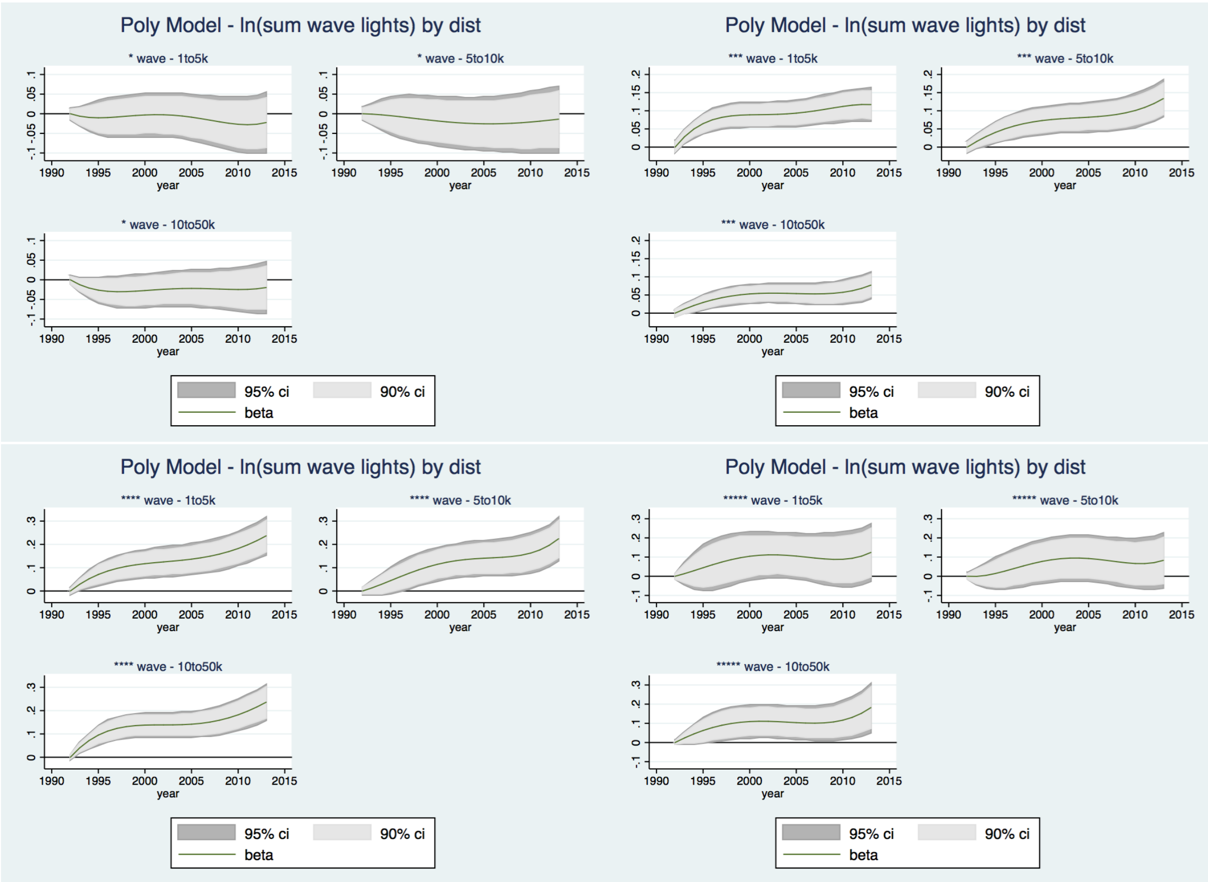


Figure D.2: Effect of waves on illumination at various distance buckets, quality 1 as baseline.