

Shedding light on aid:
Using night lights to analyse the effectiveness of
geocoded aid in Malawi

Daniel Schmid

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Daniel Schmid

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Abstract

This thesis uses two unique microeconomic datasets to analyse the effectiveness of foreign aid on economic activity, where economic activity is measured using night light intensity. First, I create an innovative night lights panel dataset for Malawi from 2005 to 2010. This dataset extracts individual pixel values from stable night light images captured from the Defense Meteorological Satellite Programme - Operational Linescan System (DMSP-OLS). The individual pixels values are then summed together in each town or village to represent a proxy for economic activity. Second, I use a dataset created by AidData that includes foreign aid projects in Malawi. This second dataset is geocoded, which means that longitude and latitude coordinates are attached to each aid project. Using ArcGIS 10, I overlay the geocoded aid projects on the stable night light images. This allows for analysis to be conducted at the town or village level.

I use both a random effects panel model and a spatial dynamic panel model, with a GMM estimator for the spatial dynamic panel model. I find that completed aid projects have a significant impact on the night light intensity in a town or village. The results with respect to the effectiveness of aid on night light intensity are sensitive to the type of econometric technique employed. In addition, I find a negative precipitation coefficient in a random effects panel model, which suggests that towns or villages with more cloud cover are associated with lower night light intensity levels. Finally, I find a negative spatial correlation in night light intensity between neighbouring towns or villages. This suggests that there is some form of mobility present with regards to commerce or resources.

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1. Introduction

The purpose of this thesis is to analyse the effectiveness of foreign aid on economic activity, where economic activity is measured using night light intensity. Over the past 60 years, more than US\$1 trillion of foreign development aid has been directed to Africa (Moyo, 2009). Too often, there is little accountability and transparency of most foreign assistance. In addition, up-to-date information is difficult to obtain. There are still many issues facing researchers when estimating the effectiveness of foreign aid.

Night lights have been used across many disciplines, mainly as a proxy for population growth or economic activity. This thesis uses night light intensity as a proxy for economic activity in a town or village. Some studies that use night lights as proxy for economic activity will be presented in the literature review of this thesis.

This thesis identifies towns or villages in Malawi from 2005 to 2010 using stable night light images from the Defense Meteorological Satellite Program - Operational Linescan System (DMSP-OLS). Based on these images, 21×21 pixel grids are created and centred on the brightest pixel of every town or village that emits light. I create a proxy for the level of economic activity by summing each pixel value within every 21×21 pixel grid in Malawi from 2005 to 2010.

Malawi is a landlocked country located in southern Africa. Malawi shares borders with Tanzania to the north, Mozambique to the south-east and Zambia to the west. In addition, Malawi has a sizeable lake located to east of the country, Lake Malawi. Malawi comprises of 28 districts, the capital being Lilongwe. The World Bank estimated the population to be 14,901,000 in 2010.¹ The population of Malawi is particularly rural, with approximately 90 percent residing in rural areas (CIA, 2012). Over the sample period, Malawi

¹ Data available from: <http://data.worldbank.org/country/malawi>

experienced persistent real gross domestic product (GDP) growth equal to 2.57 percent in 2005, 2.06 percent in 2006, 9.49 percent in 2007, 8.34 percent in 2008, 9.04 percent in 2009 and 6.53 percent in 2010.² More than half of export revenue in Malawi is produced from tobacco, sugar, tea and coffee (FAO, 2012).

When determining whether foreign aid inflows to developing nations are effective, the literature shows that results are sensitive to both how aid is measured and the econometric method that is applied. The debate on aid effectiveness has been growing since the 1970s, as more countries continue to deliver more foreign assistance to developing countries in a perpetual manner. Unfortunately, after 40 years of aid effectiveness literature, researchers are still shaping methods to reduce poverty in developing countries.

Foreign assistance to developing nations can come in many forms. An official measure and the most commonly used term to define development aid flow from donor to recipient is Official Development Assistance (ODA), identified by the Development Assistance Committee (DAC) of the Organisation for Economic Co-operation and Development (OECD). The aid dataset that I use in this thesis is geocoded, meaning that longitude and latitude coordinates are attached to aid projects. This means that each geocoded aid project is included in the sample if it falls in the vicinity of a town or village. This dataset represents approximately 80 percent of foreign assistance to Malawi since 2000, which is over US\$5.3 billion of foreign aid provided by 31 donors.³ All donors in this dataset distribute aid either bilaterally or multilaterally.⁴

This thesis examines the effectiveness of geocoded aid on the intensity of night light emissions in Malawi from 2005 to 2010. As a dependant variable, I use the natural logarithm of night light intensity in each town or village in Malawi. As explanatory variables, I include combinations of ongoing aid and completed aid that is directed into towns or villages. Using strictly positive values of light, a random effects panel model and a spatial dynamic panel model are presented. In the random effects panel model, aid is treated as exogenous with respect to night light intensity. I find a negative rainfall coefficient, which suggests that towns

² Data available from: <http://www.imf.org/external/pubs/ft/weo/2012/02/weodata/index.aspx>

³ Date available from: <http://www.aiddata.org/content/index/AidData-Raw/geocoded-data>

⁴ Bilaterally distributed aid is defined as government-to-government aid flows. Multilaterally distributed aid is defined as aid that is pooled together by different donors, such as the African Development Bank or International Monetary Fund, and then distributed to a recipient country.

or villages with more cloud cover may have lower levels of night light intensity. In the spatial dynamic panel model, aid is treated as both exogenous and endogenous with respect to night light intensity. I find that completed aid projects have a significant impact on night light intensity. Moreover, I find a negative spatial correlation in night light intensity between neighbouring towns or villages. This suggests that there is a random allocation of resources between towns or villages.

This thesis will be presented throughout the following chapters. Chapter 2 will examine the literature on night lights and aid effectiveness. Chapter 3 will describe how the data for this thesis were collected. Chapter 4 will analyse the econometric methods used to model the effectiveness of aid on night light intensity. Chapter 5 will present the results of a random effects panel model and a spatial dynamic panel model. Chapter 6 will present a summary of this thesis and conclude.

2. Background and literature review

This chapter comprises of two sections. The first section reviews the literature on night lights. The second section reviews the literature on aid effectiveness. The specific theme throughout this chapter is the accountability and transparency of foreign aid at a microeconomic level. This theme complements both the disaggregated nature of the night lights dataset and the foreign aid dataset.

2.1 Stable night lights

This section of the literature review will introduce and detail some of the recent applications of night lights. First, I will introduce the stable night light satellite and the background of the stable night light images. Second, I will explain how night lights are used as a proxy for economic activity. Third, I will explain the implications of low intensity lighting in Malawi. Finally, I will present the literature on night lights and politics.

2.1.1 *DMSP-OLS stable night lights*

The Earth Observation Group (EOG) at the National Oceanic and Atmospheric Administration (NOAA) is home to the DMSP. The DMSP was initially launched by the United States Department of Defense (USDOD) during the Cold War in the early 1960s, as photoreconnaissance satellites “...depended on accurate and timely meteorological forecasts of the Sino-Soviet landmass” (Hall 2001, p. 1). Nowadays, the current purpose of the DMSP is for the US Air Force to expose moonlit clouds; however in doing so it also exposes lighting on the Earth’s surface (Small, Elvidge, Balk and Montgomery, 2011).

The USDOD did not construct a digital archive of night light imagery until 1992 when the images became declassified. The stable night light dataset is derived from the DMSP-

OLS.⁵ The data can be retrieved from a number of satellites, which include the F10 satellite launched from 1992 to 1994, the F12 satellite launched from 1994 to 1999, the F14 satellite launched from 1997 to 2002, the F15 satellite launched from 2001 to 2003, the F16 satellite launched from 2004 to 2009 and the F18 satellite launched from 2010.

The stable night lights data are clean of cloud cover and any ephemeral lights (such as fires). The result is a set of composite images that provide a measure of light intensity from the Earth's surface for each 30 arc-second cell between -65 to -70 degrees latitude and -180 to 180 degrees longitude. At the equator, the size of the cell is approximately 1 square kilometre. However, as you move north or south from the equator, the size of the cell decreases (Florida, Gulden and Mellander, 2008). Each pixel within the stable night light images provides an annual average brightness level (pixel intensity) in units of 6 bit Digital Numbers (DNs) that range from 0 to 63, where 0 is black and 63 is bright white (Small et al., 2011).

DMSP-OLS stable night lights have been referenced in a number of economic research papers since they were declassified. The use of night lights as a measure for Gross Domestic Product (GDP) or other economic proxies becomes insightful when analysing developing countries. A number of developing countries have inaccurate, outdated and poorly aggregated data, leading to the unavailability of economic measurements. In contrast, DMSP-OLS stable night lights are accurate, updated yearly, disaggregated and have been made publicly accessible. Furthermore, they are an inexpensive method of extracting data at the town or village level where it would otherwise be too expensive, dangerous, or time-consuming to obtain.

2.1.2 *Using night lights as a proxy for economic activity*

Croft (1973) was the first to recognise that night lights could be used as a means for detecting human presence and hence as a proxy for economic activity. Although this study was the first to recognise such a relationship, no significant economic research could be conducted until the night lights dataset was publically released. Of the studies that use night lights as a proxy for economic activity, the majority are scaled to a global or national level. There has been little investigation into sub-national night lights for economic activity until recently. This

⁵ Data available from: <http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html>

thesis is unique in the sense that night light images are used to analyse economic activity at the town or village level.

One study of interest that examines the correlation of sub-national night lights to economic activity is Bhandari and Roychowdhury (2011) who used DMSP-OLS stable night lights throughout India in 2008 at a sub-national level. Their results suggest that district level stable light correlates to district level GDP for India. Likewise, Doll, Muller and Morley (2006) find a strong relationship between night light and Gross Regional Product (GRP) for 11 European Union (EU) countries and the US. Results like this are interesting, because this means that there is now an accepted proxy for sub-national economic activity. The general theme from the night light literature is that the relationship between stable night lights and GDP is stronger for larger cities, yet slightly weaker when analysing the relationship at a regional level.

Ghosh, Powell, Elvidge, Baugh, Sutton and Anderson (2010) adopted a similar technique to the method used in this thesis by summing DNs over each specific town or village. In addition, they take into account estimates of population and economic activity. These additional measures are utilised to help provide a proxy for measuring global economic activity. Not surprisingly, they deduce that many African countries have economic activity located in less illuminated areas, suggesting there is a reliance on agriculture (Ghosh et al., 2010). The results from this study are worth mentioning when analysing the locations of night light in Malawi as it is an agriculturally intensive nation.

Lastly, Chen and Nordhaus (2011) test whether night light data are a suitable proxy for measuring economic output at a regional level. They find a strong relationship between DSMP-OLS stable night lights and economic activity in countries with poor statistical institutions. They conclude that stable night lights tend to overestimate luminosity as a proxy for economic activity (Chen and Nordhaus, 2011). Therefore, based on these findings, one could hypothesise that low pixel values emitted in Malawi may overestimate the effect of foreign aid.

2.1.3 *Low intensity lighting in Malawi*

Small (2004) estimated that 2 percent of the human population clusters in densities of less than ten people per square kilometre on 50 percent of the potentially habitable land area on

Earth. DMSP-OLS stable night lights are a sensible proxy for human location estimates on Earth (Elvidge, Baugh, Dietz, Bland, Sutton and Kroehl, 1999). However, Elvidge, Safran, Tuttle, Sutton, Cinzano, Pettit, Arvesen and Small (2007) explains that night lights are primarily related to outdoor lighting, as opposed to the leakage of indoor lighting. Nonetheless, one would assume that infrastructure producing outdoor lighting suggests that there is some form of human presence in the vicinity of the night light.

A shortcoming of using night lights is the fact that not all rural villages have access to electricity. “Much of sub-Saharan Africa is densely populated but not detected in the night lights” (Small et al. 2011, p. 278). Elvidge, Baugh, Kihn, Kroehl, Davis and Davis (1997) suggest that DSMP-OLS stable night lights do not provide a direct observation of rural populations across a large land mass. Therefore, the use of night lights as a proxy for rural population estimates appears to be inaccurate.

Small (2004) analysed low lit pixels produced by DMSP-OLS stable night light satellites. He argues that large rural areas of intermediate population densities contain only small, isolated illumination and “...many small settlements are not detected or even illuminated at night” (Small 2004, p. 9). Small et al. (2011) found that although night lights and population density are correlated at high valued DN, this relationship is weaker with lower DN values. Their two conclusions are that either: (i) lower DN may relate to lower built area density with dimmer outdoor lighting; or (ii) that a small number of discrete lighted areas exist. The authors find a result that is relevant for this thesis. “The brightest pixels observed generally correspond to fully developed mixed use urban areas with near total outdoor illumination. Less brightly lit pixels may correspond to lower built area density with dimmer outdoor lighting throughout or to a small number of discrete lighted areas with somewhat brighter lighting” (Small et al. 2011, p. 271). In terms of this thesis, these results recommend exercising caution when making inference about the relationship between night lights and population. Therefore, in order to confirm the validity of the night light images, Google Earth was applied during the night light data collection phase in order to prove the physical locations of each night light image. As a result, I could prove that the major population centres in Malawi are accounted for.

Based on extracting the pixel information from the night light images, the majority of the pixels have DN values below 10. Most studies that use night lights do not go into detail

regarding the light intensity of each pixel. However, Elvidge et al. (2007) argue that the level of intensity of the night light is dependent on historical, political and socioeconomic factors. Moreover, due to the sub-Saharan developing nation status of Malawi, it is not surprising to see low DN values in most night light images. As will be explained in the data collection chapter, DNs are summed together within each town or village instead of analysing each individual pixel.

A drawback of using night light data to detect rural areas is that small emissions of light represent the whole pixel. “One of the consequences of this extremely low detection limit and coarse spatial resolution is the detection of extensive areas of dim lighting in what are largely rural environments. The sources of this that diffuse light are far smaller than the pixel footprint but their aggregate emission is detected nonetheless” (Small et al. 2011, p. 278). Again, this issue is mitigated because DNs are summed together over each town or village.

2.1.4 Night light and Malawian politics

Malawi became a democratically administered political system in 1995. Min (2010) analysed the relationship between stable night lights and democracy in 2003 for 148 countries. The motivation for this study was to test whether democratic political leaders provide more public goods to their citizens than do autocratic leaders. Min finds that democratisation is related to a significant increase in the use of electricity. These results could suggest that Malawi emits more light than that of an autocracy, due to its democratic status.

Hodler and Raschky (2010) study whether foreign aid encourages favouritism by analysing the birthplaces of current political leaders and night light emissions from those birthplaces. Using night light as the dependant variable, Hodler and Raschky find that foreign aid has a significantly higher effect on night light in the current political leader’s birth region. Therefore, included in this thesis is a *minister* variable which attempts to account for a possible aid flow bias to the birthplace or electorate of a Malawian minister. This will be discussed in more depth below in the aid effectiveness section of the literature review.

2.1.5 Conclusion

This section of the literature review has analysed a number of factors that are relevant for this thesis. First, I introduced the DMSP-OLS stable night lights and their background. Second, I showed how night lights have been used to analyse economic activity. There has been little research conducted at a sub-national level using night lights. Nonetheless, there are benefits of using night light as a proxy for economic activity as the data in this thesis are disaggregated and available at a sub-national level. Third, I showed that there has been little research using less intense DNs. A drawback is that Malawi produces low intensity lighting and this can lead to less accurate interpretation of results.⁶ Also, as not all Malawians have constant access to electricity, this method could potentially exclude some smaller human settlements. However, I confirm that the key population centres are included in the night light images. Finally, the argument for including a political dummy variable was highlighted.

2.2 Aid effectiveness

This section of the literature review aims to provide a broad account of the aid effectiveness literature and the recent methodologies adopted by various stakeholders. Many argue that the main area that needs improving is with respect to the accountability and transparency measures of foreign aid. Many donors are now setting a trend of publishing up-to-date data in order for the global aid community to achieve common goals. Indirectly, this places a form of pressure on recipients to improve their behaviour with the foreign aid they receive. The disaggregated nature of the night lights and the foreign aid datasets means that results can be produced that are fundamentally based on the principles of accountability and transparency.

2.2.1 Aid effectiveness literature

The aid effectiveness literature focuses on the effect of foreign aid on macroeconomic growth. Specifically:

$$\mu = \frac{\partial \text{economic growth}}{\partial \text{aid}} \quad (2.1)$$

⁶ Again, I will mitigate this by summing the DNs in a town or village to represent night light intensity.

where μ represents aid effectiveness (Doucouliagos and Paldam, 2009). This thesis sits between two extremes of the spectrum being microeconomic analysis and macroeconomic analysis. This literature review aims to provide a balance between these two spectrums. Ultimately, I will use both microeconomic and macroeconomic techniques to analyse the impact of foreign aid on the proxy for economic activity, night light intensity.

2.2.2 Geocoded aid literature

Geocoded aid encompasses the process of assigning coordinates to aid projects. More specifically, each individual aid project has respective longitudinal and latitudinal coordinates. Since 2011, AidData, Development Gateway and the World Bank have been working with the climate change and African political stability (CCAPS) program at the University of Texas to create an interactive mapping tool that overlays data on aid projects, climate change and conflicts (AidData, 2011). The fundamental purpose of the dataset is to provide improved transparency and accountability amongst the donor community.

The process of geocoding aid projects is a relatively new technique that uses the latitude and longitude of a specific project in order for it to be mapped. This method provides accountability and an auditing mechanism for aid projects. More specifically, donors now visually observe the output produced from their foreign aid investment, through software programmes such as Google Earth and ArcGIS. Subsequently, this puts a new form of pressure on the recipient to complete a physical aid project to a satisfactory level. No longer does the donor have to travel to a remote location in order to view the progress of the aid project as this can now be examined through satellite technology and software programmes.

As emphasised already, the accountability of foreign aid has become increasingly important over recent years. Too often, donors provide foreign aid to recipient countries, with little or no knowledge attained about how each project is set to be managed. It has become increasingly clear that recipient countries tend to lack transparency systems regarding how donor money is dispersed. The International Aid Transparency Initiative (IATI) was initiated in 2008. The IATI aims to promote the transparency of aid information between donor and recipient countries, one such country being Malawi.⁷ Currently, the IATI is the largest organisation attempting to increase transparency. As of May 2012, the United Nations Office

⁷ Data available from: <http://www.aidtransparency.net/about/whos-involved>

for Project Services (UNOPS) has become the first organisation to publish information transparently using the IATI format (IATI, 2012).

Findley, Powell, Strandow and Tanner (2011) use the same dataset that is used in this thesis. They analyse the relationship between geocoded aid projects and armed conflicts in Sierra Leone, Angola and Mozambique. They highlight that most data that has project-specific references ultimately becomes aggregated for econometric analysis. For this reason, they emphasise the value in disaggregated aid projects for research purposes.

2.2.3 *Micro-macro paradox*

The micro-macro paradox of aid effectiveness as suggested by Mosley (1986) is relevant for this thesis. Specifically, Mosley suggests that microeconomic data at the project level is effective in finding evidence of aid producing positive economic returns, yet when macroeconomic data is used to regress the effect of aid on growth at a national level it is ineffective. Recently, Doucouliagos and Paldam (2008) conducted a meta-study that found about half of projects succeed while the other half fail. However, the projects that failed did not significantly harm economic activity. Therefore, Doucouliagos and Paldam argue that when project level data are aggregated it will show a positive aid-growth effect. There are two reasons why this thesis somewhat aligns with the suggested micro-macro paradox. First, because of the disaggregated nature of the foreign aid dataset, microeconomic analysis can be conducted at a project level. However, the analysis in this thesis is not as microeconomic as a randomised controlled trial (RCT), as aid projects are aggregated in each town or village, instead of being analysed individually. Second, although the data used in this thesis are microeconomic, I use an econometric model similar to models published in the past that use macroeconomic data. Therefore, although the aid project data are aggregated in each town or village, I produce macroeconomic results that are effectively derived from a firm platform of microeconomic data.

2.2.4 *Randomised controlled trials*

RCTs are of interest at the microeconomic level of the aid effectiveness debate. A RCT attempts to gain knowledge about what types of foreign aid projects are effective, instead of relying on econometric-based theories or models. An attractive feature of RCTs is that they

circumvent the endogeneity problem with randomised trials (Deaton, 2010). This is different to the macroeconomic literature, where the endogeneity problem is managed by including suitable instruments. Banerjee (2007) describes RCTs as the most effective way of analysing the impact of an aid program. As a simple example, a randomised controlled trial of foreign aid could engage 100 towns or villages. However, 50 of those towns or villages will be controlled (no aid) and 50 will be treated (aid). The methodology for evaluating results from RCTs is still evolving.

As an example of a RCT, Miguel and Kremer (2003) evaluate a Kenyan school-based treatment of deworming drugs. In this RCT, the results were analysed at the school-level instead of the individual-level. This is because Miguel and Kremer believed that analysing the deworming drugs at an individual-level would underestimate any direct effects and would not account for any possible externalities. Their conclusion aligns somewhat with this thesis, in that instead of analysing individual aid projects in each town or village, I aggregate projects in each town or village. This approach should encompass any externalities of aid projects on economic activity.

2.2.5 *Early aid effectiveness theories*

Since the 1950s, the literature on aid effectiveness has been immense yet unconvincing that aid has a small positive effect on economic growth. Overall, it would seem that most of the literature on aid effectiveness has concluded that foreign aid has a slightly positive effect. Early theories on aid effectiveness included increasing economic growth through rapid increases in external capital investment (Chenery and Strout, 1966). Nonetheless, within this early literature, Chenery and Strout recognised that countries need to take steps with the aim of reducing their dependence of foreign aid in the future. Forty years later, aid flows between donor and recipient appear to be perpetual, with no policy on the recipient country becoming self-sufficient. Seemingly, a dependence on aid for recipient countries has been created with no end in sight.

Of particular interest is a study conducted by Papanek (1973) which was the first to “disaggregate inflows into their principle components” (p. 120). This disaggregation broke down foreign inflows into foreign aid, foreign investment and other inflows. Treating these as explanatory variables, Papanek found that foreign aid had a significant impact on growth

relative to the other explanatory variables. The foreign aid dataset employed throughout this thesis is also highly disaggregated but I do not categorise aid projects into principle components such as healthcare, education or infrastructure.

Cassen (1994) looks at the aid effectiveness debate since 1986. Cassen finds that the macroeconomic relationship between aid and growth is weak and ambiguous. Specifically, the effect of foreign aid on economic growth can be positive or negative, depending on the country groupings and the time periods in the macroeconomic model (Cassen 1994, pp. 15-16). In fact, the general theme of the aid effectiveness literature seems to have this conclusion. It was not until the Millennium Development Goals (MDGs) in 2000, the study by Burnside and Dollar (2000) and the Monterrey Consensus in 2002 that the aid effectiveness debate gathered some significant momentum.

2.2.6 Millennium Development Goals

Universal international development goals have laid the foundation for improving the economic standard of living in developing countries and one could argue they should set a benchmark in measuring the effectiveness of aid. The MDGs consist of eight goals. These eight goals were agreed upon by 189 nations at the United Nations Millennium Summit in September 2000, which were set to be achieved by 2015. They included improvements in the areas of:

- (i) *Poverty and hunger*
- (ii) *Universal education*
- (iii) *Gender equality*
- (iv) *Child health*
- (v) *Maternal health*
- (vi) *AIDS/HIV*
- (vii) *Environmental sustainability*
- (viii) *Global partnership*

These goals have seemingly become the main driving force when determining how foreign aid is allocated to developing nations and hence one could argue that the measure of

aid effectiveness should take into consideration these MDGs. One could argue that the UN General Assembly used a misguided approach in 1970 where goals were set for donor countries to contribute 0.7 percent of Gross National Income (GNI) to foreign aid. This argument of misguidance is supported by Sachs (2008) and his theory of clinical economics. He argues that each country is like a hospital patient, where each patient has a different diagnosis. A key driver of this theory is that donor countries were increasing their developmental assistance, when instead the diagnosis of the recipient country should have been addressed. Likewise, it was not until Dollar and Pritchett (1998) released a report through the World Bank that first emphasised that the situation of the recipient country needs to be taken into consideration when determining whether aid will be effective.

One can argue that donors should not be focusing on the quantity of aid they are allocating to recipient countries and instead place importance on various objectives that must be achieved in each recipient country in order to achieve the MDGs. For instance, donors should use a searching strategy to identify problems at an individual level in recipient countries, and then focus on how much aid is needed in order to achieve these goals (Easterly, 2007). This type of theory takes the importance away from the amount of aid allocated to a particular nation, and rather attempts to identify problems as determined by the communities within the developing nation. As an example, Isham, Narayan and Pritchett (1995) find that increasing community participation leads to improved project performance. Therefore, one could argue that recipient communities must place emphasis on defining which types of aid are the most effective. Consequently, this avenue has merit at a project level in the aid effectiveness debate.

Politically, the argument to make aid more effective gained momentum from the Monterrey Consensus in 2002, where political leaders came together to agree on delivery methods to make aid more effective. Since 2002, foreign aid stakeholders have been meeting around the world to discuss methods of delivering aid more effectively. These high-level forums took place in Rome in 2003, Paris in 2005, Accra in 2008 and Busan in 2011. These forums are significant for bringing together foreign aid stakeholders to discuss aid effectiveness and harmonisation. Harmonisation is difficult to achieve as all foreign aid stakeholders, bilateral or multilateral, need to accomplish common economic and social goals

such as the MDGs (Bourguignon and Sundberg, 2007). Therefore, complexity arises when these meetings require stakeholders to align on opposing values.

2.2.7 *Macroeconomic aid effectiveness*

Generally, the aid literature tends to focus on the impact of foreign aid on economic growth. For example, Burnside and Dollar (2000) concluded that the key factor that determines the effect foreign aid on growth was the macroeconomic policies implemented by the recipient country. Burnside and Dollar argued that countries that implemented weak macroeconomic policies exhibited poor growth with respect to foreign aid. However, these results have received much criticism, with researchers citing incorrect econometric methods and an incomplete dataset (Burnside and Dollar, 2004).

Furthermore, Easterly, Levine and Roodman (2004) used the same reconstructed dataset as the Burnside and Dollar (2000) study and concluded that statistically significant results will not be produced when countries have sound policies in place. A rebuttal from Burnside and Dollar (2004) uses new data to show that institutional quality was a key component when determining aid effectiveness. Based on these arguments, it becomes increasingly clear that the econometric treatment of aid determines its perceived effectiveness.

Shortly after the highly popular Burnside and Dollar (2000) study, Hansen and Tarp (2001) presented a paper that would go on to become another notable study in the literature.⁸ They analyse the impact of aid on real GDP per capita across countries. In addition, they include a squared aid term as an explanatory variable in their growth regressions which leads to decreasing marginal returns of aid flows (Hansen and Tarp 2001, p. 548). In sum, they find that when human capital and investment are added to the growth regressions, foreign aid does not have any impact on economic growth.

A further conception of foreign aid is that it comes in the form of either emergency or humanitarian assistance. Birdsall, Savedoff, Mahgoub and Vyborny (2011) argue that ‘cash on delivery aid’, which gives the recipient country more freedom in terms of how to reach their own defined output, is more likely to promote transparency, promote a results-based

⁸ Using a Google Scholar search, the Burnside and Dollar (2000) study is cited by 3,090 other studies as at 27/11/2012.

approach in terms of aid effectiveness and strengthen the relationships between donor and recipient countries.

Recently, Moyo (2011) added a more controversial perspective on the aid effectiveness debate, emphasising the negative effects associated with foreign aid. She concludes that foreign aid, excluding humanitarian assistance, to countries in Africa is doing more harm than good and needs to stop. In fact, a similar argument was heard at the fourth high-level forum in Busan in 2011, where there was an appeal to stop a culture of dependence arising from foreign aid. Moyo also argues that aid results in corrupt political regimes, as the political leaders have incentives to maintain relationships with donor countries as opposed to focusing on policy within their own countries. Therefore, her findings advocate that foreign aid has a negative impact on economic growth and that a political factor should be taken into consideration when determining the effectiveness of aid.

When one takes into account the amount of aid that a town or village receives, Acharya, De Lima and Moore (2006) find that increasing the amount of aid has an optimal point with respect to impact on economic growth. They find that aid has a greater effect on growth in regions where proliferation is less.⁹ A further perspective concerning aid allocation originated from John Maynard Keynes in the 1930s (Mercieca, 2010). Turning his view into an aid-related argument, donor countries should influence developing countries by using aid to close the gap between recipient country savings and the level of investment required to create a level of growth (Meier and Stiglitz, 2001). A number of gap models have also been developed in order to estimate the optimal allocation of aid. Overall, these models recognise that foreign aid can assist with savings deficits, exports and import gaps required for capital and the revenue gap of the recipient country (Mercieca, 2010). Nonetheless, no definitive recommendation is provided with respect to how aid should be distributed.

The conflicting results in the aid effectiveness literature are overwhelmingly based at a macroeconomic level when compared to studies using RCTs. Based on the view that Kosack

⁹ The first type of literature that econometrically models aid can be credited to Mckinlay and Little (1977). To date, there are now over 20 published studies of econometric aid allocation models (Fielding, 2010). Schraeder, Hook and Taylor (1998) modelled aid policies between the United States, Sweden, France and Japan in order to test the volume and direction of aid to Africa in the 1980s, which included aid as a lagged dependant variable. I also use an ongoing aid variable as a dependant variable to examine the suitability of a minister dummy variable, therefore testing for a political bias in the allocation of aid projects.

(2003) takes, this could suggest that the effectiveness of foreign assistance has potential to be measured at a microeconomic level.

2.2.8 *Publishing positive results*

As many researchers believe aid can reduce poverty, the interpretation of these results must be treated with caution as one could argue that there is an emotional bias when publishing results in favour of aid (Doucouliagos and Paldam, 2008). There is much discussion in the aid effectiveness debate regarding the publishing of positive aid-growth results due to different motives. Doucouliagos and Paldam (2009) refer to this as a ‘reluctance bias’, where the researcher is reluctant to publish results that suggest aid is ineffective. This may be due to a number of motives, including the researcher having a mindset that only significantly positive results will be published or even that the specific journal is reluctant to publish negative results. Doucouliagos and Stanley (2009) have found that the latter is becoming evident in that there is emerging evidence of a publication selection bias. Therefore, this is further noise surrounding the aid effectiveness literature that needs should be incorporated when interpreting results.

2.2.9 *Good governance*

Many studies debate whether good governance in the recipient country is a factor in determining the effectiveness of aid on economic growth. Hansen and Tarp (2000) study the macroeconomic impact of aid on growth. In doing so, they find evidence of a positive aid-growth relationship. Unlike the conclusion of Burnside and Dollar (2000) who suggest that good governance is required for a positive aid-growth effect, Hansen and Tarp find a positive aid-growth effect even in countries with poor governance.

A study by Minoiu and Reddy (2010) analyse the effect that ODA has on economic growth in developing nations. They first split aid into developmental and non-developmental categories, as each has distinctive effects on economic growth. Their results show that development aid has a statistically significant and positive impact on economic growth in the long-run, whereas non-development aid is neutral with respect to growth. Specifically, they find that aid from donor countries with sound policies and fiscal management are most effective in delivering growth-promoting assistance.

On the other hand, Boone (1996) conducted a study that analysed the relationship of foreign aid and the political regime of recipient nations. Boone concludes that foreign aid is ineffective in improving economic activity regardless of the political regime. Finally, Boone suggests that short-term aid projects may have had a better chance of promoting economic growth, although long-term aid projects had little impact on economic activity between 1971 and 1990.

2.2.10 Dutch disease

The Dutch disease effect refers to inflows of foreign aid resulting in an increased real exchange rate which in turn negatively affects exports and hence sacrifices economic growth. Recent studies tend to focus on the real exchange rate in analysing the effect of Dutch disease (see Fielding and Gibson, 2012; Rajan and Subramanian, 2011). The Dutch disease effect is now a plausible reason for the ineffectiveness of aid, yet it is not used as an explanatory variable when modelling the aid-growth relationship (Doucouliagos and Paldam, 2009).

2.2.11 Treating aid as endogenous

Papanek (1972) was one of the first researchers to treat aid as being endogenous with respect to economic growth. Specifically, an endogeneity issue can arise when aid is allocated to towns or villages with low economic growth. Econometrically, this can mean that there is correlation between foreign aid and the error term. Moreover, a study conducted by Dalgaard and Hansen (2001) find that there is a positive relationship between aid and economic growth, but their results indicate that aid should be treated as endogenous. Other studies that control for aid being endogenous include: Boone, 1996; Alesina and Dollar, 2000; Dalgaard, Hansen and Tarp, 2004 and Knack, 2004. In this thesis, aid is an explanatory variable that is treated as both exogenous and endogenous.

2.2.12 Foreign aid and Malawian politics

In terms of aid effectiveness, Isham, Kaufmann and Pritchett (1997) found that democracies are more productive with foreign aid compared to autocracies. Therefore, Malawi is a suitable candidate on which to conduct an aid effectiveness study. The relationship between foreign aid and African politics is often diagnosed as corrupt. Specific to Malawi, an example of this

occurring is when ex-Malawian president Bakili Muluzi, who served two terms from 1994 to 2004, was arrested on corruption charges (Moyo, 2009). Wright (2010) describes this relationship as personalism, which can be defined as politicians pursuing their own goals with respect to certain political constraints. During the course of his work, Wright highlights the continuous and problematic exploitation pattern of foreign aid being favoured for corrupt government activity as opposed to growth-promoting ventures. The issue is commonly referred to by researchers as ‘pork barrelling’ (see Herbst, 1990; Shepsle and Weingast, 1981). Hence, aid is most effective in nations with good governance and political stability.

Shikwati was interviewed by *Der Spiegel* newspaper to express his views on foreign aid to Africa, claiming that it does more harm than good (Spiegel, 2005). Throughout this consultation, Shikwati argued that Kenyan politicians often deliberately direct aid back to their electorate regions with the aim of winning votes. As an example, he argued that “a portion of the corn often goes directly into the hands of unscrupulous politicians who then pass it on to their own tribe to boost their next election campaign” (Spiegel, 2005). Instances like this suggest that politicians are motivated to preserve their electorate by distributing resources to their areas. Therefore, this indicates the necessity of including a variable that accounts for this aid allocation bias.

A recent study conducted by Nunnenkamp, Öhler and Andrés (2012) used a geocoded AidData dataset designed for India from 2006 to 2011. Their dependant variable is the number of World Bank projects within a particular district in India. They include a number of explanatory variables, including a spatially lagged dependant variable, as well as a political dummy variable. The intention of this political dummy variable is to evaluate whether the distribution of World Bank projects is biased by any political factors. For example, they mention that “Chief Ministers of states may direct projects primarily towards their own constituencies and home districts” (Nunnenkamp et al. 2012, p. 5). The majority of their results show that there is in fact no statistically significant political bias, except when the treatment of the dependant variable is changed to project-related observations.

A study by Kosack (2003) takes an another view on the effectiveness of aid on economic growth, and instead focuses on the quality-of-life. This is done by including an explanatory variable that focuses on the political regime of the recipient country. Kosack

(2003) finds that foreign aid is more effective at growing the quality-of-life in democracies than it is in autocracies.

2.2.13 Conclusion

In summary, the literature on aid effectiveness has covered a broad range of topics. The early literature on aid and growth supported foreign investment into recipient countries in order to increase growth. Since the study by Burnside and Dollar (2000), the aid effectiveness literature has been producing results based on macroeconomic data. In this literature review, I discussed the importance of the accountability and transparency of foreign aid, which seems to now be aligned with the goals of the aid community from the latest aid literature and high-level forums. However, as empirical analysis has evolved, some researchers have argued that aid is doing more harm than good. Whether aid is effective or not seems to be dependent on the econometric technique that is used. In saying that, there is still little evidence about exactly what types of aid projects are more effective than others in increasing economic. Of the few studies that have been conducted using an AidData dataset, none have directly attempted to econometrically model the relationship between disaggregated aid and economic growth. This will be the first study to econometrically model DMSP-OLS stable night lights and disaggregated geocoded aid.

3. Data collection

In this chapter I explain how the disaggregated nature of the night lights dataset used in this thesis allows for the measurement of economic activity in towns or villages over time. Likewise, the foreign aid dataset used in this thesis addresses some of the main issues that are highlighted in the aid effectiveness debate. Therefore, the night lights dataset complements the foreign aid dataset. Using ArcMap 10, I overlay the geocoded aid projects on the night light images. This allows for analysis to be conducted at the town or village level. First, the DMSP-OLS stable night lights dataset is analysed. Second, the geocoded aid dataset is analysed. Third, I report the techniques used to calculate the Malawian minister instrumental variable. Finally, I present how the precipitation data were collected and analysed.

3.1 DMSP-OLS stable night lights dataset

This section of the data collection chapter will explain how I created the dependant and spatial variables that are used in this thesis. First, I describe how the dependant variable is created, which is night light intensity. I will also describe the issues that I encountered in creating the dependant variable. Finally, I will describe how the two spatial variables are created.

Using night light images allows for the observation of towns or villages in Malawi from 2005 to 2010 using a software program. For every town or village that displayed night light in the images, the software program was able to calculate the intensity of the night light. Once a method to extract the information from the images was set, the process of finding every form of night light within the images of Malawi over a six year period took place. This method was both time-consuming and laborious. In the end, two separate methods of extracting the light intensity information were considered. Ultimately, what determined which method was used was based on the locations of the foreign aid project in the towns or villages.

The night light images were obtained from the NOAA's National Geophysical Data Center (NGDC). Specifically, the stable night light images of Malawi were obtained from the DMSP-OLS. Only specific satellites were used as the sample ranges from 2005 to 2010. The F16 satellite was used from 2005 to 2009 and the F18 satellite was used for 2010. These images were freely available for public use.¹⁰

3.1.1 Opening night light images

In order to extract information from these night light images, a student licence for ArcGIS Desktop 10 software was obtained from the Department of Surveying at the University of Otago. Once the night light images were opened using ArcMap 10, the night light clusters could be observed. In other words, the towns or villages that emitted night light could be seen using ArcMap 10. As an example of a night light cluster, Figure 3.1 shows the F18 stable night light satellite image over Kasungu, Malawi, in 2010. During the sample period, 80 night light clusters were discovered in Malawi using these images.¹¹ The locations of each night light cluster were referenced using their respective coordinates. Figure 3.2 presents the locations of all 80 night light clusters. Moreover, Google Earth was utilised for the purpose of identifying the town or village that a given night light cluster represented. This is detailed in Table A.1 in Appendix A. Throughout this thesis, the terms *night light cluster* and *town or village* are used interchangeably.

¹⁰ Data available from: <http://www.ngdc.noaa.gov/dmsp/maps.html>

¹¹ However, this purposely excludes both Lilongwe City and Blantyre City, as it is more difficult to locate where the light is coming from. Section 3.1.2 discusses this in detail.

Figure 3.1 Night light cluster of Kasungu, Malawi, 2010

F18 2010 DMSP stable night light image. Brightest DN = 60. Location of brightest DN: 33.478 and -13.038 decimal degrees.

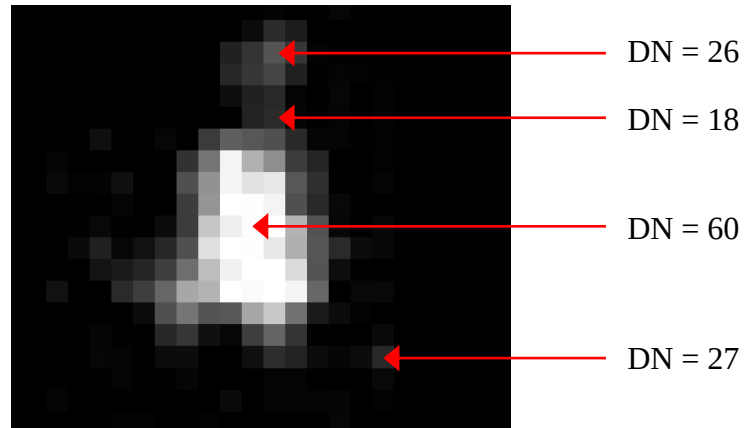
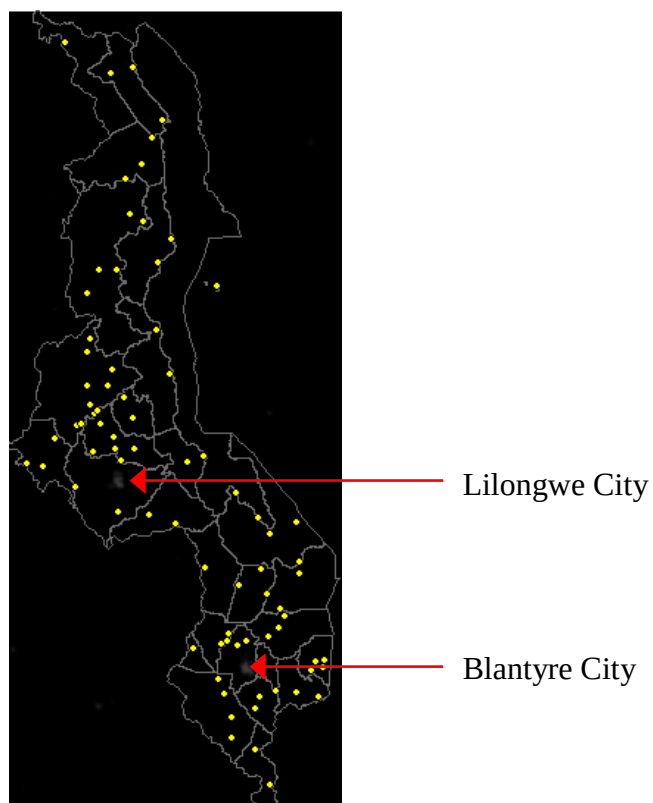


Figure 3.2 Night light cluster locations from 2005 to 2010

Yellow dots are centred on the brightest DN within the night light cluster. Note that both Lilongwe City and Blantyre City are excluded.



Further research was undertaken in order to comprehensively analyse the populations of each night light cluster. The most accurate data were extracted from the 2008 Population and Housing Census (PHC), conducted by the National Statistics Office of Malawi. I found that the locations of the night light clusters represented all of the major population centres as documented in the 2008 PHC. A list of regional and district population data based on the 2008 PHC are highlighted in Table A.2 in Appendix A.

When the night light clusters were displayed using ArcMap 10, it became apparent that some towns or villages display positive light only in certain years of the sample, while other years do not display any light at all. As a result, Table 3.1 shows that 379 night light clusters with positive light were recorded over Malawi for the sample period from 2005 to 2010.

Table 3.1 **Descriptive statistics of night light clusters for Malawi**

<i>Year</i>	<i>No light</i>	<i>Positive light</i>	<i>Total</i>
2005	24	56	80
2006	18	62	80
2007	22	58	80
2008	13	67	80
2009	18	62	80
2010	6	74	80
Total	101	379	480

3.1.2 Accuracy of night light clusters between years

Each yearly satellite image of stable night light over Malawi varied slightly in terms of projected coordinates. In other words, when observing the night light emitted from a town or village over the sample period, the night light image itself would shift in a south-easterly direction each year from 2005 onwards. Therefore, the overlay of the night light images for each year was not perfect. It has been documented that on average the geolocation accuracy is between $\pm$ one or two pixels, which equates to approximately two kilometres (Elvidge, Safran, Nelson, Tuttle, Hobson, Baugh, Dietz and Small, 2004). As a result, I could not analyse individual pixels within each night light cluster.

3.1.3 *Creating a 21 x 21 pixel grid*

Based on observing the size of the night light clusters and the locations of the aid projects, the most appropriate method to analyse each night light cluster was to place a 21 x 21 pixel grid over each singular cluster. Each pixel is 30 arc seconds, or approximately one square kilometre. Determining the size of this grid was based on observing the size of the night light clusters in ArcMap 10, alongside the locations of the geocoded aid projects. It must be noted that two major economic hubs of Malawi were excluded from this thesis, Lilongwe City and Blantyre City. This was due to the difficulty of determining where light is derived from in a large city. There will be more heterogeneity in the light sources from these larger cities, such as businesses or street lights, which is less likely to be the case in a small town or village.

3.1.4 *Extracting pixel information from night light clusters*

ArcMap 10 has the ability to extract pixel information from the night light images. The *Spatial Analyst* option within ArcMap 10 has a tool named *Pixel Inspector* which allows the user to extract light intensity information from every pixel of the stable night light images. The intensity of each night light pixel is known as a DN, which has a scale of zero to 63. Figure 3.3 displays a 21 x 21 pixel grid over Lilongwe City, Malawi, in 2005.

Figure 3.3 21 x 21 pixel grid, Lilongwe City, Malawi, 2005

F16 DMSP-OLS 2005 stable night light results centred on the highest DN of Lilongwe.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	0	0	6	9	15	20	23	23	23	23	26	25	23	18	12	8	0	0	0	0	0
2	0	0	6	11	17	21	24	25	26	28	31	31	28	23	15	9	0	0	0	0	0
3	0	0	6	12	18	26	30	34	36	37	38	38	34	30	18	13	7	0	0	0	0
4	0	0	8	13	21	29	36	43	46	48	49	48	44	36	23	16	9	5	0	0	0
5	0	0	9	14	24	35	47	52	54	54	53	52	47	38	28	16	10	6	0	0	0
6	0	5	9	15	26	38	49	54	55	55	53	51	47	39	27	17	10	7	6	0	0
7	0	5	9	15	25	38	49	56	58	55	51	46	40	32	24	15	11	7	6	0	0
8	5	5	8	16	25	38	51	56	57	55	52	47	40	32	25	16	10	7	5	0	0
9	5	6	8	14	22	35	48	55	58	58	54	51	46	36	28	19	10	6	0	0	0
10	6	7	9	12	20	30	44	53	58	59	58	56	54	47	35	24	13	8	0	0	0
11	8	10	12	13	19	26	36	46	55	59	60	59	58	53	40	29	17	10	0	0	0
12	12	15	16	16	17	20	27	39	45	55	59	59	58	55	46	33	21	11	5	0	0
13	15	17	18	17	16	17	20	30	38	47	54	55	54	50	42	30	19	12	6	0	0
14	16	18	19	18	15	12	14	19	26	36	44	45	44	40	33	24	17	10	6	0	0
15	15	16	16	15	13	10	9	12	17	23	31	33	32	29	24	18	11	6	0	0	0
16	12	13	13	12	10	8	7	9	12	14	18	19	19	15	13	9	6	0	0	0	0
17	9	9	9	7	7	0	0	7	8	9	12	12	11	10	8	6	0	0	0	0	0
18	6	6	6	0	0	0	0	0	0	7	9	9	9	8	6	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	6	6	6	6	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Each number within the grid represents a pixel, or a DN. Note that Lilongwe City is excluded from the sample, however it is used here as an example. This is because I want to give the reader an example of the variation in DN within a 21 x 21 pixel grid. In other words, if this pixel grid was placed on a rural village of Malawi, the 21 x 21 pixel grid would not offer much insight. Finally, the average night light cluster in the sample has a maximum DN of 11.13 while the average DN is 7.68.

As previously mentioned, this 21 x 21 pixel grid appeared to drift in a south-easterly direction between years. As a result, two separate methods were applied in order to extract the pixel information from the images:

1. The first method undertaken was to centre the 21 x 21 pixel grid on the highest DN within the night light cluster during the first year of light emission. Then, latitude and longitude coordinates were recorded from the centre of the grid. For every year thereafter, the 21 x 21 pixel grid was placed on these coordinates. This technique saw the night light clusters

move in a south-easterly direction. This would suggest that the satellites were not all in synchronisation with each other, as Elvidge et al. (2004) pointed out above.

2. The second method undertaken was to centre the 21×21 pixel grid on the highest DN within the night light cluster for each sample year. If there were two or more pixels with the highest DN within a night light cluster, the highest summation of orthogonal and diagonal neighbours was taken, and that pixel was used. This technique mitigated the problem of the satellite movement. However, this meant that the geocoded aid projects were located in different parts of the 21×21 pixel grid each year.

Overall, both methods produced similar results. The grid was large enough to take into account satellite movement. Nonetheless, the first method was ultimately used. The key advantage of this technique was that once the geocoded aid projects were located in the 21×21 pixel grid, they did not change positions over the sample period.

3.1.5 *Analysing pixel information from night light clusters*

The *Pixel Inspector* tool in ArcMap 10 was set to a 21×21 pixel grid for six satellite years from 2005 to 2010. This data were then transferred into Microsoft Excel. Once all 379 night light clusters were in Microsoft Excel, I compared different approaches of measuring light intensity inside the night light cluster:

Summation of DNs within each 21×21 grid. (3.1)

Maximum DN within each 21×21 grid. (3.2)

An indicator variable equal to one if there is any light in the 21×21 grid, and zero otherwise. (3.3)

The method used during this thesis to extract light intensity information was consistent with the technique used by Chen and Nordhaus (2011), however at a more disaggregated scale. Chen and Nordhaus compare luminosity data at a country specific level by setting a 1° longitude $\times$ 1° latitude grid cell, or a 120×120 pixel grid over 12 satellite years. Moreover, Chen and Nordhaus sum each DN value within the 120×120 pixel grid to create an aggregate

luminosity measure. In addition, Hodler and Raschky (2010) apply a similar technique in that they sum all night light pixels within each sub-region of a given country from 1992 to 2005. In sum, this thesis uses equation 3.1 to represent light intensity for each night light cluster, which is consistent with the method applied by Chen and Nordhaus (2011).

3.1.6 Great circle distance between night light clusters

In the results and discussion chapter, I will present a spatial dynamic panel model. Based on this, for the remainder of this section I will introduce the spatial variable, *wlsum*. This spatial variable is a weighted average of neighbouring night light clusters based on distance. Therefore, I will introduce the notion of great circle distance here.

Tobler's first law of geography is "everything is related to everything else, but near things are more related than distant things" (Tobler 1970, p. 236). This is the foundation for including a spatial variable. In order to create a spatial variable, a weights matrix needs to be calculated.

The dependant variable used in this thesis is night light intensity in a night light cluster. The spatial variable is the dependant variable as a function of a weights matrix. The weights matrix used in this thesis is similar to the spatial weights matrix as defined by Anselin, Gallo and Jayet (2008).

The distance between night light clusters was calculated using Great Circle Distance (GCD). This technique allows for the fact that the Earth is approximately spheroid. The distance calculated was between the centres of every night light cluster (the centre of every 21×21 pixel grid). The equation used to compute the GCD, which is relevant for small distances, is known as the Haversine formula:

$$\Delta\hat{\sigma} = 2 \arcsin \left(\sqrt{\sin^2 \left(\frac{\Delta\phi}{2} \right) + \cos\phi_s \cdot \cos\phi_f \cdot \sin^2 \left(\frac{\Delta\lambda}{2} \right)} \right) \quad (3.4)$$

where $\Delta\phi$ indicates a change in latitude and $\Delta\lambda$ indicates a change in longitude. GCD is then calculated by multiplying the earth's radius and $\Delta\hat{\sigma}$. Based on this, a $N \times N$ weights matrix was created to determine distance between any two night light clusters.

There are numerous approaches for creating a weights matrix. For example, some studies use common borders or physical distance as weighting factors (see Jacobs, Ligthart

and Vrijburg, 2009). I calculated two separate weights matrices for each spatial variable. When calculating both of these weight matrices, GCD was inversed. This means that more weight is given to night light clusters that are closer to night light cluster i , and less weight to night light clusters that are further away from night light cluster i . Next, I will present how these two spatial variables were calculated.

3.1.7 *Spatial dependant variable using all night light clusters*

In order to calculate a weighted average of night light intensity in neighbouring regions, the following formula was used to calculate a spatial dependant variable that takes into account all night light clusters and GCD:

$$wlsun1(i, t) = \sum_{k \neq i} \frac{lsum(k, t) \cdot w(k)}{N-1} \quad (3.5)$$

where $w(k) = 1/GCD(k)$. The reason for $N-1$ is so the distance of the night light cluster in question is not included. Therefore, $k \neq i$ where k is every other night light cluster. Furthermore, by turning this into an inverse distance function, ultimately more weight is given to variables closer to night light cluster i , and less weight is given to night light clusters further away from night light cluster i .

3.1.8 *Spatial dependant variable using nearest neighbour night light clusters*

A second light intensity measure for neighbouring towns or villages is calculated. The nearest neighbour distance (NND) method defines a neighbour by the shortest GCD between two night light clusters, i and j :

$$NND(i) = \sum_{i=1}^N \frac{1}{Min(GCD_{i,j})} \quad (3.6)$$

where the inverse GCD function allows more weight to be placed on night light clusters that are closer to night light cluster i . Table A.3 in Appendix A details the full list of night light clusters and their respective nearest neighbours by GCD. Equation (3.7) is used to calculate a second spatial dependant variable:

$$wls\text{um}2(i, t) = l\text{sum}(k, t) \cdot NND(i) \quad (3.7)$$

where $l\text{sum}(k, t)$ represents the light intensity within the nearest neighbouring night light cluster for every year in the sample.

3.1.9 Conclusion

This section of the data collection chapter has detailed how I created the dependant variable and the two spatial variables. First, I detailed how the night light images were analysed. Second, I detailed the reason for creating a 21×21 pixel grid. Third, I explained how I analysed the information within the night light clusters. Finally, I detailed how I created the two spatial variables.

3.2 Malawi geocoded aid dataset

This section of the data collection chapter will explain how I created the aid variables that are used in this thesis. First, I introduce the dataset that is used to create the aid variables. Second, I will describe how I created another spatial measurement that measures the distance between an aid project and the centre of a night light cluster. Third, I will describe how the aid variables are created. Finally, I will describe which aid variable combinations are the most appropriate to be used together as explanatory variables.

AidData provided their geocoded aid dataset for the purpose of this thesis.¹² The dataset contained 2523 geocoded aid project locations in Malawi that started as early as 1996 and some that were projected to be completed as far out as 2016. However, only projects with latitude and longitude coordinates attached were used. Furthermore, based on the night lights sample period, aid projects were excluded if they started after 2010. These conditions decreased the number of observations to 2113.

The AidData geocoded aid dataset came in the form of a spreadsheet and could be transferred into ArcMap 10 based on longitude and latitude coordinate systems provided for each aid project. After this process was completed, each aid project that was included in this

¹² Note that I obtained this data in a slightly different format before it was made publicly available at the following link in April 2012: http://strausscenter.org/form/5-malawi-download-registerhtml?dataset=2a&ndtm_pl=component

dataset for Malawi could be seen visually using ArcMap 10. This is presented in Figure 3.4. Also, Figure 3.5 displays both aid project and night light cluster locations.

Figure 3.4 Aid project locations

Green dots represent geocoded aid projects; 2113 in total. Note that one green dot can represent multiple aid projects. The earliest aid project start date is 1998 and latest aid project planned finish date is 2016.

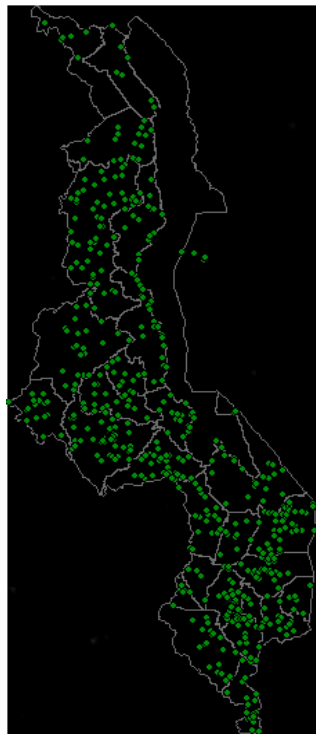
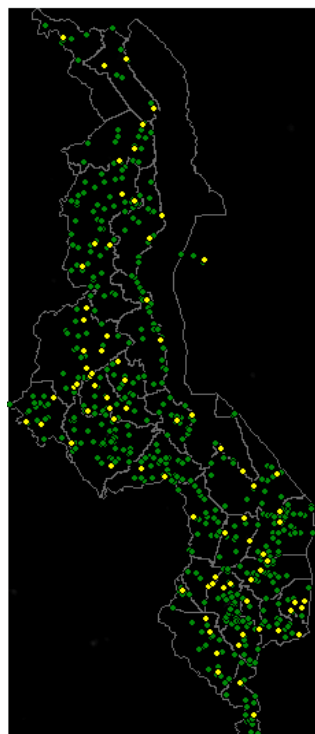


Figure 3.5 Aid and night light locations

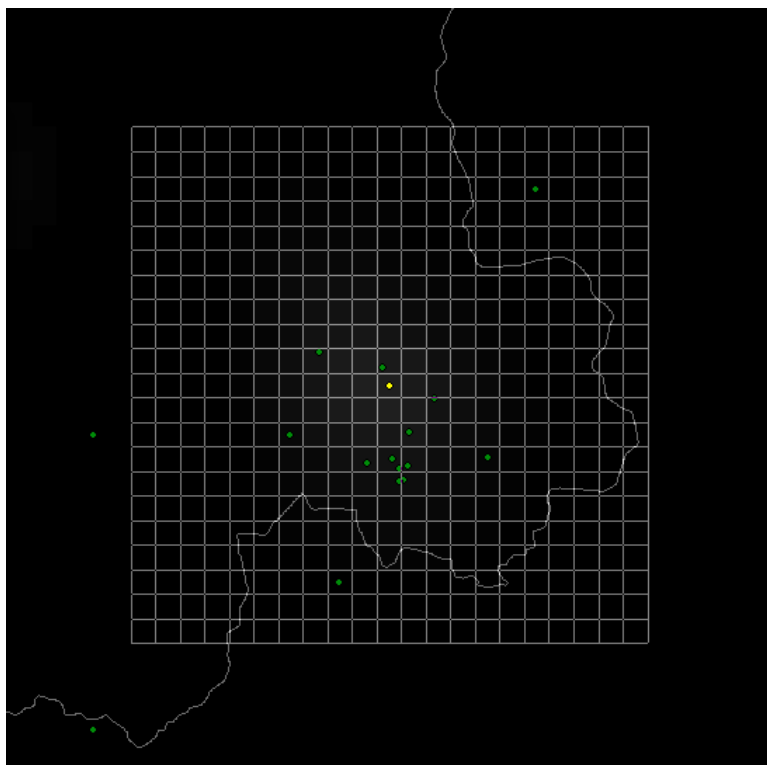
Green dots represent geocoded aid projects. Yellow dots are centred on the brightest DN within the night light cluster. Note that both Lilongwe City and Blantyre City are excluded.



Each individual aid project was recorded on the condition that it fell within a 21×21 pixel grid. In other words, each individual aid project was recorded on the condition that it fell within the vicinity of a town or village (approximately a 10 kilometre radius from the brightest DN). Refer to Figure 3.6 for a visual example of projects that fall within a 21×21 pixel grid. Overall, 990 aid projects fell within one of the eighty 21×21 pixel grids. Based on the locations of these projects, seven out of the 80 night light clusters did not receive any aid over the sample period (8.75 percent, or 8.54 percent if Lilongwe City and Blantyre City are included). Additionally, 32 aid projects had longitude and latitude attached, however they did not have a total amount spent value. Therefore, these projects were omitted. In total, the number of geocoded aid projects used in the analysis is 958.

Figure 3.6 Aid project locations within the night light cluster, Mzuzu, Malawi, 2005

F16 2005 stable night lights. Mzuzu, Malawi. 33.592 and -11.891 decimal degrees. Green dots represent aid projects. Only aid projects within the grid are included in the sample. The 21 x 21 pixel grid is centred on the brightest DN in 2005, which has a value of 31 here.



3.2.1 Descriptive statistics from the geocoded aid dataset

The geocoded aid dataset is extremely rich in content. Appendix B attempts to describe the level of detail in this dataset. Table B.1 in Appendix B lists all the donors within the aid dataset. The financing of the aid provided to Malawi in the full dataset was broken down into the categories displayed in Table B.2 in Appendix B. Moreover, aid was broken into sectors displayed in Table B.3 in Appendix B. Finally, an interactive mapping tool is available through the CCAPS website.¹³ In addition to aid, this interactive mapping tool is also used to map climate, governance and conflict.

¹³ Data available from: <http://www.strausscenter.org/ccaps>

3.2.2 Distance between aid projects and the maximum DN

Another weighting measurement was developed for each aid project within the night light cluster. It measures the distance from each geocoded aid project that fell within a 21×21 pixel grid to the centre of that same grid. In other words, it measures the distance from project j from the centre of night light grid i . The measurements for these distances were calculated through use of the *Measure* tool within ArcMap 10. I refer to this distance variable as d_j , which is the inverse distance of project j from the centre of pixel cluster i . Surprisingly, there are 16 aid projects that fall exactly within the centre of their respective 21×21 pixel grid. Therefore, I could not calculate the distances for these aid projects. Instead, aid projects that fell within the centre 21×21 pixel grids received distance values of 100 metres.

3.2.3 Deflating aid expenditure

Each individual aid project is deflated using the Malawian National Statistics Office data on the National Consumer Price Index.¹⁴ The following equation calculates the real amount of spending per year.¹⁵

Real amount of spending per year:

$$a_{j,t} = \frac{\text{Nominal amount spent}_j / T_j}{CPI_t} \quad (3.8)$$

where j is the geocoded aid project, T_j is the total length of project j and CPI_t is the Consumer Price Index (CPI) for Malawi in year t . Therefore, all values are in real terms with respect to the amount spent on each project.

3.2.4 Individual aid variables

Importantly, as this dataset provides a *start year* and *finish year* for most aid projects, it is possible to determine whether each aid project is completed or ongoing in any given year. Below, j represents a geocoded aid project in year t , s_j is the start year and f_j is the finish year. In addition, $G_{j,t}$ is an indicator variable equal to 1 if the project is ongoing, otherwise

¹⁴ Data available from: <http://www.nsomalawi.mw/>

¹⁵ This equation implicitly assumes that there is a uniform distribution of expenditure across the length of the aid project.

zero. Likewise, $I_{j,t}$ is an indicator variable equal to 1 if the project is completed, zero otherwise. Finally, recall that d_j is the inverse distance of project j from the centre of pixel cluster i :

If started:

$$G_{j,t} = \begin{cases} 1 & \text{if } s_j \leq t \\ 0 & \text{otherwise} \end{cases} \quad (3.9)$$

If finished:

$$I_{j,t} = \begin{cases} 1 & \text{if } f_j \leq t \\ 0 & \text{otherwise} \end{cases} \quad (3.10)$$

Total length of the project in years:

$$T_j = f_j - s_j + 1 \quad (3.11)$$

Time if started:

$$H_{j,t} = \begin{cases} t - s_j + 1 & \text{if } t - s_j \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (3.12)$$

Time if finished:

$$K_{j,t} = \begin{cases} t - f_j + 1 & \text{if } t - f_j \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (3.13)$$

Now that these variables are available, I create both completed and ongoing aid variables. First, I present how the completed aid variables are calculated:

The value of a completed aid project which is scaled by inverse distance to the centre of the night light cluster i :

$$x_{j,t}^1 = a_{j,t} \cdot I_{j,t} \cdot d_j \quad (3.14)$$

The value of a completed aid project in night light cluster i :

$$x_{j,t}^2 = a_{j,t} \cdot I_{j,t} \quad (3.15)$$

The value of a completed aid project which is scaled by time since completion in night light cluster i:

$$x_{j,t}^3 = a_{j,t} \cdot I_{j,t} \cdot K_{j,t} \quad (3.16)$$

The years since completion of an aid project which is scaled by inverse distance to the centre of night light cluster i:

$$x_{j,t}^4 = I_{j,t} \cdot K_{j,t} \cdot d_j \quad (3.17)$$

The completed aid variables are important. Specifically, $K_{j,t}$, will capture whether completed aid projects make a difference and if so, whether their importance decays (or increases) over time. Second, I describe how the ongoing aid variables are calculated:

The value of an ongoing aid project which is scaled by inverse distance to the centre of night light cluster i:

$$y_{j,t}^1 = a_{j,t} \cdot [G_{j,t} - I_{j,t}] \cdot d_j \quad (3.18)$$

The value of an ongoing aid project in night light cluster i:

$$y_{j,t}^2 = a_{j,t} \cdot [G_{j,t} - I_{j,t}] \quad (3.19)$$

An indicator variable for an ongoing aid project in night light cluster i:

$$y_{j,t}^3 = G_{j,t} - I_{j,t} \quad (3.20)$$

3.2.5 Aid variables

The following equations represent a summation of aid projects conditional on night light clusters. The individual aid variables were summed together if they fell in night light cluster i :

$$x_{i,t}^k = \sum_{j \in i} x_{j,t}^k, j = 1, \dots, n(i) \quad (3.21)$$

$$y_{i,t}^k = \sum_{j \in i} y_{j,t}^k, j = 1, \dots, n(i) \quad (3.22)$$

where $n(i)$ is the number of projects in night light cluster i . This creates an aggregate aid variable within each night light cluster. Based on this, I now have four completed aid variables and three ongoing aid variables:

Completed aid variables:

$x_{i,t}^1, x_{i,t}^2, x_{i,t}^3$ and $x_{i,t}^4$.

Ongoing aid variables:

$y_{i,t}^1, y_{i,t}^2$ and $y_{i,t}^3$.

3.2.6 Combinations of aid variables used as explanatory variables

Here, I create four different combinations of completed and ongoing aid. These combinations will be used together as explanatory variables. Using the above equations, the following combinations of $x_{i,t}^k$ and $y_{i,t}^k$ are used as explanatory variables for aid:

Aid combination 1:

$$x_{i,t}^2 \text{ and } x_{i,t}^3 \tag{3.23}$$

Aid combination 2:

$$x_{i,t}^2, x_{i,t}^3 \text{ and } y_{i,t}^2 \tag{3.24}$$

Aid combination 3:

$$x_{i,t}^1 \text{ and } x_{i,t}^4 \tag{3.25}$$

Aid combination 4:

$$x_{i,t}^1, x_{i,t}^4 \text{ and } y_{i,t}^1 \tag{3.26}$$

Each type of aid combination will be used in the results and discussion chapter to measure the effectiveness of foreign aid on night lights. For example, the *aid combination 1*

model will include $x_{i,t}^2$ and $x_{i,t}^3$ as explanatory variables, while the *aid combination 4* model will include $x_{i,t}^1$, $x_{i,t}^4$ and $y_{i,t}^1$ as explanatory variables.

3.2.7 Conclusion

This section of the data collection chapter explained how I created the aid variables that are used in this thesis. First, I introduced the dataset that was used to create the aid variables. Second, I described how I created a further spatial measurement that measures the distance between an aid project and the centre of a night light cluster. Third, I described how the aid variables are created. I have separated aid into either ongoing or completed. Finally, I described which aid variable combinations are the most appropriate to be used together as explanatory variables.

3.3 Malawian minister instrumental variable

A further dataset is collected for Malawian ministers over the sample period with respect to which district they were born in. The purpose of this is to determine if there is any bias towards the amount of aid received in a Malawian minister's birthplace or electorate. The motivation for this comes from Hodler and Raschky (2010), who find significantly more light in presidential birthplaces. Data were collected from shuffles in the Malawian government in August 2005, November 2007, June 2009 and August 2010. A detailed examination of all Malawian ministers in these periods is shown in Table C.1 in Appendix C. Based on this, the variable $minister(i,t)$ is constructed which is an indicator variable equal to one if a current Malawian minister was born in the same district as night light cluster i at time t , and zero otherwise. The results for each district are shown in Table C.2 in Appendix C.

3.4 Precipitation control variable

Malawi is often economically setback as a result of poor weather (Booth, Cammack, Harrigan Kanyongolo, Mataure and Ngwira, 2009). A precipitation control variable is calculated, assuming agriculture production in Malawi is reliant on rainfall. Rainfall data from 2005 to 2010 over Malawi are publicly available in a 10-day format during the October to April growing season from the World AgroMeteorological Information Service. This data are available for multiple weather stations in Malawi. Each weather station can be placed in a

district using Google Earth. However, certain districts do not have a weather station. Therefore, when allocating a district to a weather station, the nearest neighbour approach is used. This approach involved assigning the precipitation data from the closest available weather station to the district that did not have a weather station. Furthermore, there were some districts that have more than one weather station. In such cases, the average precipitation across all stations in a district from a district is calculated. Overall, an annual rainfall dataset over Malawi was produced from 2005 to 2010. The data are presented in Table D.1 in Appendix D.

4. Econometric methods

This chapter will explain the models and estimators that are used in the results and discussion chapter of this thesis. This thesis uses two types of econometric models, a random effects panel model and the spatial dynamic panel model. First, the random effects model will be introduced. This is the simpler of the two models, although there may be some ambiguity in interpreting the estimated coefficients of the model. Second, the spatial dynamic panel model will be introduced with the generalised method of moments (GMM) estimator. This model will be the main focus in the results and discussion chapter.

4.1 Random effects panel model

First, I introduce the random effects panel model. The explanatory variables are all treated as exogenous. Moreover, I included a lagged dependant variable as an explanatory variable. The random effects panel model takes into account changes in light intensity across all towns or villages:

$$Y_{i,t} = \beta Y_{i,t-1} + EX_{i,t} + u_i + \varepsilon_{i,t} \quad (4.1)$$

where $Y_{i,t-1}$ is the lagged dependant variable in a $N \times 1$ vector, $EX_{i,t}$ is a $N \times p$ matrix of p exogenous explanatory variables, u_i is a random town or village effect that is assumed to be normally distributed and $\varepsilon_{i,t}$ is a normally distributed error term conditional on u_i .

The presentation of the random effects model will be brief, and the majority of the effort will be placed into the spatial dynamic panel model, which is effectively a fixed effects panel model. I will explain here three key features of the model. First, a key feature of using a random effects panel model is that the estimated coefficients on each variable are weighted

averages of a cross-sectional effect and a time-series effect. In this thesis, the cross-sectional effect refers to variation in night light intensity across night light clusters, while the time-series effect refers to changes in night light intensity in each night light cluster over time. Second, the random effects panel model includes an individual-specific effect, which is random in the sense that it is not correlated with the explanatory variables. Finally, there are fewer parameters to be estimated in a random effects panel model when compared to the spatial dynamic panel model (Nickell, 1981). In contrast, the main drawback of making inferences from the estimated coefficients in the random effects panel model is that the lagged dependant variable might be correlated with a fixed effect, even though I have instrumented for it through $\widehat{lsunf}_{i,t-1}$.

Recalling to the micro-marco paradox as suggested by Mosley (1986), the disaggregated datasets are well suited for analysis at an individual level.¹⁶ This is contrasting to empirical aid effectiveness literature, which tends to analyse data at a macroeconomic level. A fixed effects panel model will focus specifically on a town or village over time, separate from effects related to cross-sectional variation. Therefore, a fixed effects panel model is the most suitable model for the purpose of this thesis.

4.2 Spatial dynamic panel model

4.2.1 Introduction

Dynamic panel models imply having a lagged dependant variable as an explanatory variable. However, spatial panel models having a spatial variable as an explanatory variable. This spatial variable in the context of this thesis is used to measure changes in light intensity in a night light cluster that may be correlated to changes in light intensity in another night light cluster. Therefore, spatial dynamic panel models imply having a combination of the above two models. Specifically, spatial dynamic panel models include a spatial variable and a lagged dependant variable as explanatory variables. Below, I follow Kukenova and Monteiro (2009) for a straightforward example of a spatial dynamic panel model for a given cross section i ($i = 1, \dots, N$) at time t ($t = 1, \dots, T$):

¹⁶ In this thesis, the individual level refers to a town or village.

$$Y_{i,t} = \beta Y_{i,t-1} + \varphi_1 WY_{i,t} + \varphi_2 WY_{i,t-1} + EX_{i,t} + EN_{i,t}\gamma + u_i + \varepsilon_{i,t} \quad (4.1)$$

where Y_t is the dependant variable in a $N \times 1$ vector, $Y_{i,t-1}$ is the lagged dependant variable is a $N \times 1$ vector, $EX_{i,t}$ is a $N \times p$ matrix of p exogenous explanatory variables, $EN_{i,t}$ is a $N \times q$ matrix of q endogenous variables, u_i is the town or village fixed effect and $\varepsilon_{i,t}$ is a normally distributed error term.

The spatial component in the model comes from W , which represents an $N \times N$ nonnegative spatial matrix, where the diagonal elements are zero. The spatial weighting matrix in this thesis was detailed in section 3.1.6.¹⁷

Based on equation 4.1, I will explain the difference between a dynamic panel model and a spatial panel model. A dynamic model would require $\varphi_1 = \varphi_2 = 0$. On the other hand, a spatial panel model would require $\beta = \varphi_2 = 0$. According to Elhorst (2011), these two models have been discussed extensively in the econometrics literature, however a combination of them in the form of a spatial dynamic panel model has had little attention to date.

In the last ten years, a specialised econometrics literature that has begun to emerge is that of dynamic models based on spatial panels (Elhorst, 2011). Much academic attention has been invested around dynamic panel models, however very little research has been put into spatial dynamic panel models. Cliff and Ord (1972) were among the first to develop a model that included spatial features, generating a model that could be used to test for correlation among geographically located error terms that resulted from least squares regressions. The attractive feature of spatial panel models is that they allow the researcher to control for unknown heterogeneity by allowing cross-sectional dependence as well as sectional dependence (Lee and Yu 2010, p. 255). The first paper to present a dynamic model in both space and time was presented by Elhorst (2001).

The inclusion of this lagged dependant variable more often than not displays an estimated coefficient that is highly statistically significant. However the purpose of this variable is to properly identify dynamic effects. Unlike ordinary least squares, a spatial dynamic panel model has the ability to analyse the impact of aid in both the short-run and

¹⁷ However, certain explanatory aid variables in this thesis are also a function of distance from each aid project to the centre of the night light cluster as detailed in section 3.2.3.

long-run. However, a drawback of using a spatial dynamic panel model is that the fixed effects do not allow for comparison between night light clusters.¹⁸

4.2.2 Generalised method of moments

There have been many estimation methods for spatial dynamic panel models, including maximum likelihood (ML) or quasi-maximum likelihood (QML), Bayesian Markov chain Monte Carlo (MCMC) and generalised method of moments (GMM) (Elhorst, 2011). The most appropriate estimator to use in this thesis is based on the system-GMM estimator which was developed by Arellano and Bover (1995) and Blundell and Bond (1998) as it corrects for potential endogeneity using internal and/or external instruments (Kukenova and Monteiro, 2009).¹⁹ The set of potentially endogenous explanatory variables includes the lagged dependant variable, spatial variable and aid. The estimator corrects for any potential endogeneity by using explanatory variables that are not correlated with the error term as potential instruments (Greene, 2003).

There are two common forms of GMM estimators, difference-GMM and system-GMM. The difference-GMM estimator was developed first by Arellano and Bond (1991) and it only uses a differenced equation instrumented by lagged levels of the endogenous variables. The inclusion of a lagged dependant variable could lead to inconsistent estimates. A common strategy is to first difference the model to eliminate any individual effects. The difference-GMM estimator developed by Arellano and Bond (1991) eliminates any individual effects from the first difference transformation (Arellano and Bover, 1995). However, instrumental variables are needed for the estimation of parameters. The lagged differenced dependant variable is instrumented using lagged levels of the dependant variable, assuming a serially uncorrelated error term. Identification is based on the restriction that higher-order lags of the endogenous explanatory variables are uncorrelated with the error term in each cross-section of the panel.²⁰ For example, the lagged level of the dependant variable in period zero is uncorrelated with the difference of the error term in period two. The lagged level of the

¹⁸ Arguably, this can be achieved through the spatial variable.

¹⁹ In this thesis, I apply a system-GMM estimator to linear spatial dynamic panel models using the Stata 11 *xtdpd* command. Out of the available estimators in the literature, system-GMM appears to be the most suitable in the context of this thesis (see Kukenova and Monteiro, 2009).

²⁰ Within but not between towns or villages.

dependant variable in period one is uncorrelated with the difference in the error term in period three. Similarly, the lagged level of the dependant variable in period two is uncorrelated with the difference in the error term in period four. This process continues for the remaining time periods in the dataset (see Baltagi, 2009). Following Bouayad-Agha and Védrine (2010), this creates the following instrument matrix:

$$Z_i = \begin{bmatrix} y_{i,1} & 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ 0 & y_{i,1} & y_{i,2} & 0 & 0 & \dots & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & y_{i,1} & y_{i,2} & y_{i,3} & \dots & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \dots & \vdots & \vdots & \vdots & \dots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \dots & y_{i,1} & y_{i,2} & y_{i,3} & \dots & y_{i,T-2} \end{bmatrix} \quad (4.2)$$

where the rows in Z_i correspond to the first differenced equations for period $t=3,4,\dots,T$ for individual i , assuming the moment conditions $E(y_{is}\Delta\epsilon_{it}) = 0$ for $s = 1, \dots, T-2$ and $t = 2, \dots, T$. Hansen and Tarp (2001) use a difference-GMM estimator to analyse the effect of aid on growth and suggest that is a “...reasonably robust solution to the problems of possible mis-specification” (p. 556).

The system-GMM estimator includes the restrictions made by Arellano and Bond (1991), as well as a second set of restrictions. The system-GMM estimator was developed by Blundell and Bond (1998) and uses both differenced and levels equations, with instruments comprising of lagged levels and lagged differences, respectively. These second set of restrictions imposes orthogonality between the lagged difference in the dependant variable in period one and the level of the error term in period three.²¹ Likewise, the lagged difference in the dependant variable in period two is uncorrelated with the level of the error term in period four, and so on. Again, this process continues for the remaining time periods in the dataset.

The key advantage of the system-GMM estimator is its ability to handle unobserved heterogeneity by incorporating night light cluster fixed effects. This is equivalent to analysing the effect of changes in aid in a town or village on night light intensity.

²¹ Note that it starts at $t = 1$ and not $t = 0$. This is because it is the difference in the dependant variable, not the level.

4.2.3 Instruments and tests

The system-GMM estimator requires specifying instruments to be used. The number of instruments used must be at least as large as the number of explanatory variables in the spatial dynamic panel model.²² There are two types of tests that are recommended by Arellano and Bond (1991) to verify the validity of the model. First, the Sargan test confirms whether there were too many restrictions made or not.²³

Sargan test:

H_0 : *The overidentifying restrictions are valid.*

Hence, it is important that each model does not reject this null hypothesis. Second, the Arellano and Bond test is a test for autocorrelation in the residuals.²⁴

Arellano and Bond test:

H_0 : $\Delta \varepsilon_{i,t}$ is 1st order correlated but is not 2nd order correlated.

Likewise, it is important that each model does not reject this null hypothesis in order for the moment conditions to be valid. In the results and discussion chapter, I will confirm the validity of the models presented using both the Sargan and Arellano and Bond tests.

4.2.4 Conclusion

This is a unique econometric model in the sense that it is dealing with endogeneity from the dynamic, spatial and aid components in the spatial dynamic panel model. It is difficult to find an estimator that accounts for different types of endogeneity in the explanatory variables. However, the system-GMM estimator appears to be the most trusted within the econometric literature when dealing with spatial dynamic panel data. In fact, the system-GMM estimator is the most suitable in applied research for estimating time-space models that include endogeneity of the lagged dependent variable, spatial lag and other potentially endogenous

²² Typically, the GMM estimator entails are more instruments than there are endogenous regressors, so the model is over-identified.

²³ Stata command: *estat sargan*

²⁴ Stata command: *estat abond, artests(2)*

variables (Kukenova and Monteiro, 2009). Therefore, the system-GMM estimator is well suited for the purpose of estimating spatial dynamic panel models.

5. Results and discussion

In this chapter, a random effects panel model and a spatial dynamic panel model is presented. Each of these models attempts to estimate the impact of aid on night light intensity. The aid variables are either ongoing or completed. Moreover, each model uses a different combination of ongoing or completed aid, which I refer to as an *aid combination*.

I present four types of random effects panel models, each using a different *aid combination*. In each of these models, aid is treated as exogenous. The random effects panel model is the simplest model for analysing the impact of aid on night light intensity, however there may be some ambiguity in interpreting the coefficients. Therefore, I focus mainly on two types of spatial dynamic panel model. The first type treats aid as exogenous and the second type treats aid as endogenous. Moreover, each type of spatial dynamic panel model includes two forms of spatial variable as an explanatory variable. The first spatial variable measures light intensity for all neighbouring night light clusters. The second spatial variable measures light intensity for only the nearest neighbouring night light cluster. Also, to address the endogeneity problem, I include the dependant variable, the spatial variable and aid as instruments using the system-GMM estimator.

First, I will present Table 5.1 and Table 5.2, which are a summary of the models and variables, respectively. Second, I will then present a section that provides a foundation for interpreting the results of this chapter. Third, I will present the results of the random effects panel model and the spatial dynamic panel model. Finally, I will discuss these results in more detail.

Table 5.1 Summary of models

This table presents a summary of the models used in this chapter.

Models	Tables	Equations	Standard instruments	GMM levels equation instruments	GMM differenced equation instruments
Random effects panel model including:					
<i>Exogenous aid and a fitted value of the lagged dependant variable.</i>	5.4	5.1,5.2, 5.3,5.4	$lsum_0,$ $minister_t,$ $rainfall_t.$	-	-
Spatial dynamic panel model including:					
<i>Exogenous aid and a neighbouring light intensity spatial variable.</i>	5.5	5.5,5.6, 5.7,5.8	$aid_t, minister_t,$ $rainfall_t, year_t.$	$lsum_{t-3},$ $wlsum1_{t-3}.$	$lsum_{t-3}$ onwards, $wlsum1_{t-3}$ onwards.
<i>Exogenous aid and a nearest neighbour light intensity spatial variable.</i>	5.6	5.5,5.6, 5.7,5.8	$aid_t, minister_t,$ $rainfall_t, year_t.$	$lsum_{t-3},$ $wlsum2_{t-3}.$	$lsum_{t-3}$ onwards, $wlsum2_{t-3}$ onwards.
<i>Endogenous aid and a neighbouring light intensity spatial variable.</i>	5.8	5.5,5.6, 5.7,5.8	$minister_t,$ $rainfall_t,$ $year_t.$	$lsum_t,$ $wlsum1_t,$ $aid_t.$	$lsum_{t-2},$ $wlsum1_{t-3}$ onwards, aid_{t-3} onwards.
<i>Endogenous aid and a nearest neighbour light intensity spatial variable.</i>	5.9	5.5,5.6, 5.7,5.8	$minister_t,$ $rainfall_t,$ $year_t.$	$lsum_t,$ $wlsum2_t,$ $aid_t.$	$lsum_{t-3}$ onwards, $wlsum2_{t-3}$ onwards, aid_{t-3} onwards.

Here, aid refers to the respective aid variable that is used in an equation. The GMM levels equation uses differences of variables to form instruments. Likewise, the GMM differenced equation uses the levels of variables to form instruments.

Table 5.2 Summary of variables

The table presents a summary of the variables used in this chapter. Note that the terms ‘night light cluster’ and ‘town or village’ are used interchangeably.

Variable	Variable description	Mean	Within s.d.	Between s.d.
$lsum(i,t)$	The natural logarithm of the summation of DNs in night light cluster i .	5.143	0.376	1.068
$ifsum(i,t)$	An indicator variable equal to 1 if night light cluster i has positive light, otherwise zero.	0.861	0.226	0.349
$wlsum1(i,t)$	A spatial variable which measures light intensity for all neighbouring night light clusters.	1.328	0.167	0.098
$wlsum2(i,t)$	A spatial variable which measures light intensity in the nearest neighbour night light cluster.	0.250*	0.087*	0.200*
$minister(i,t)$	An indicator variable equal to 1 if a minister was born in town or village i , otherwise zero.	0.438	0.347	0.376
$rainfall(i,t)$	A control variable measuring precipitation in town or village i in units of 100 millimetres.	9.757*	2.271*	2.159*
$year(t)$	A year dummy variable.	-	-	-
$x^1(i,t)$	The value of all completed aid projects where each project is scaled by inverse distance to the centre of the night light cluster i , in units of \$100,000.	0.010*	0.020*	0.030*
$x^2(i,t)$	The value of all completed aid projects in night light cluster i , in units of \$1,000,000.	0.186*	0.207*	0.262*
$x^3(i,t)$	The value of all completed aid projects where each project is scaled by time since completion in night light cluster i , in units of \$1,000,000.	0.425*	0.572*	0.628*
$x^4(i,t)$	A summation of years since completion of all aid projects where each project is scaled by inverse distance to the centre of night light cluster i .	2.528*	4.209*	3.651*
$y^1(i,t)$	The value of all ongoing aid projects where each project is scaled by inverse distance to the centre of night light cluster i , in units of \$100,000.	0.062*	0.100*	0.134*
$y^2(i,t)$	The value of all ongoing aid projects in night light cluster i , in units of \$1,000,000.	0.116*	0.057*	0.126*
$y^3(i,t)$	The number of ongoing aid projects in night light cluster i .	6.1	1.6	6.6

** Note that these values are after data scaling has taken place in order for the estimated coefficients and standard errors to be interpretable. However this will not affect the t -statistics or the inference itself.*

5.1 Interpreting the impact of aid on night lights

This section provides a platform for interpreting the estimated coefficients in each model presented in this chapter. First, I will present the conclusion of a sample selection model. Second, I will describe the implications of including a lagged dependant variable in each model. Third, I will define how shocks to the level of economic activity are measured. Fourth, I will describe the endogeneity problem. Finally, I will explain the amount of observations in each model.

5.1.1 *Sample selection bias*

Controlling for sample selection bias in any panel model is difficult to achieve. Due to the nature of the variables used in this thesis, there is potential for some form of sample selection bias to be present. Appendix E considers the Semykina and Wooldridge (2010) estimator, which corrects for sample selection bias in the presence of endogenous explanatory variables. This involves fitting year-specific Probit regressions for the selection outcome. Based on the selection outcome, I find that initial light intensity ($ifsum_{i,0}$), plus other exogenous explanatory variables, perfectly predict the outcome ($ifsum_{i,t}$). Therefore, the selection is exogenous, so there is no need to be concerned about sample selection bias.

5.1.2 *Lagged dependant variable*

Each random effects panel model and spatial dynamic panel model includes a lagged dependant variable as an explanatory variable. A drawback of including a lagged dependant variable as an explanatory variable is an upward bias on the coefficient of the lagged dependant variable and a downward bias on the coefficients of the other explanatory variables (Achen, 2000). Based on this, one would expect the coefficient on the lagged dependant variable to be below one if light intensity increases over each year in the sample. However, it could still be inflated due to the upward bias. Therefore, the size of the coefficients should be interpreted carefully.

5.1.3 *Shocks to economic activity*

The estimated coefficient on the lagged dependant variable allows one to analyse the persistence of shocks to the level of economic activity through the correlation of β and $\varepsilon_{i,t}$.

The estimated persistence of a unit shock to the level of economic activity can be measured using half-life, which calculates the time it takes for half of a unit shock to wear off. Starting at the steady state, a one unit shock to the initial level of economic activity ($\varepsilon_{i,0} = 1$), the half-life measure attempts to solve for a value of t such that: $\beta^t = 0.5$, where β is an estimated coefficient of the lagged dependant variable. An approximation of half-life is defined as: $t = \frac{\ln(1/2)}{\ln(\beta)}$. Therefore, the greater the half-life measure the greater the persistence of the shock. This puts into context the difference between short-run and long-run effects. I will not present the half-life measure in the random effects panel model because of how $\widehat{lsun}f_{i,t-1}$ is constructed. However, I will present the half-life measure in the spatial dynamic panel model.

5.1.4 Endogeneity problem

An endogeneity problem arises when the lagged dependant variable and other explanatory variables are potentially correlated to the error term (Nickell, 1981). Moreover, a potential endogeneity problem may arise from relatively poorer towns or villages receiving more foreign aid over time. This is a selection issue that causes endogeneity. For this type of endogeneity to happen, when allocating aid to a town or village, one would have to know what towns or villages are actually poorer. This is unlikely to be the case unless one was to allocate aid to towns or villages that have lower light intensity levels from observing the satellite images. In general terms, both aid and economic activity could be jointly endogenous when time averages are taken into account (Dalgaard, Hansen and Tarp, 2004). However, there is less chance of this type of endogeneity problem occurring in a fixed effects model. This means that permanent differences in the amount of foreign aid between towns or villages will be factored out. To address the endogeneity issue, the *minister* variable was calculated and tried as an instrument for aid that was ongoing. The hypothesis was that a minister of the Malawian government may be able to influence which towns or villages receive aid projects (see Herbst, 1990; Shepsle and Weingast, 1981 and Wright, 2010). Unfortunately, it was found that this was a weak instrument (see Appendix F).

5.1.5 Observations in each model

I have identified 80 towns or villages over six years in the dataset, meaning there are 480 potential night light clusters. However, 101 of these night light clusters do not produce any night light. Each random effects panel model and spatial dynamic panel model use strictly positive values of light. Therefore, the sample reduces to 379 night light clusters. Based on extracting the night light data in ArcMap 10 and referencing each night light cluster using Google Earth, the clusters which do not produce any night light are in fact the smaller towns or villages in Malawi.

Most towns or villages in the sample emit light from 2005 to 2010. However, for example, a night light cluster may only begin to emit light from 2007 onwards. Due to using a one period lag on some explanatory variables, this means that the spatial dynamic panel model will only include observations from 2008 onwards. As a result, the number of observations in the random effects panel model is greater than the number of observations in the spatial dynamic panel model, 323 and 278, respectively. Table 5.3 shows the changes in average light intensity for each night light cluster from 2005 to 2010. The pattern in night light intensity over time is consistent with the timing of the ‘global financial crisis’ (GFC) of 2007 and 2008.

Table 5.3 Average night light intensity for all night light clusters

In total, there are 379 positive night light observations over the sample period. Below, ‘sum’ represents the average summation of DNs in a night light cluster for all positive night light observations and ‘lsum’ is the average natural logarithm of ‘sum’ in each night light cluster

Variable	2005	2006	2007	2008	2009	2010
<i>sum</i>	242.9	277.2	304.4	290.9	271.8	393.8
<i>lsum</i>	4.938	5.047	5.140	5.173	5.051	5.428
<i>Observations</i>	56	62	58	67	62	74

5.2 Random effects panel model

The random effects panel model presented here includes four types of *aid combination* as explanatory variables. Each *aid combination* used here treats aid as exogenous. As a potential solution for the endogeneity problem, I include $minister_{i,t}$, as well as $lsum_{i,0}$ and $rainfall_{i,t}$, as standard instruments:

$$lsum_{i,t} = \alpha + \beta \cdot \widehat{lsum}_{i,t-1} + \varphi \cdot ifsum_{i,t-1} + \vartheta \cdot x_{i,t}^2 + \omega \cdot x_{i,t}^3 + \theta \cdot rainfall_{i,t} + u_i + \varepsilon_{i,t} \quad (5.1)$$

$$lsum_{i,t} = \alpha + \beta \cdot \widehat{lsum}_{i,t-1} + \varphi \cdot ifsum_{i,t-1} + \vartheta \cdot x_{i,t}^2 + \omega \cdot x_{i,t}^3 + \tau \cdot y_{i,t}^2 + \theta \cdot rainfall_{i,t} + u_i + \varepsilon_{i,t} \quad (5.2)$$

$$lsum_{i,t} = \alpha + \beta \cdot \widehat{lsum}_{i,t-1} + \varphi \cdot ifsum_{i,t-1} + \xi \cdot x_{i,t}^1 + \delta \cdot x_{i,t}^4 + \theta \cdot rainfall_{i,t} + u_i + \varepsilon_{i,t} \quad (5.3)$$

$$lsum_{i,t} = \alpha + \beta \cdot \widehat{lsum}_{i,t-1} + \varphi \cdot ifsum_{i,t-1} + \xi \cdot x_{i,t}^1 + \delta \cdot x_{i,t}^4 + \eta \cdot y_{i,t}^1 + \theta \cdot rainfall_{i,t} + u_i + \varepsilon_{i,t} \quad (5.4)$$

where the variable $ifsum_{i,t-1}$ is an indicator variable equal to one if there was positive light from town or village in year $t-1$, $x_{i,t}^k$ is a completed aid variable, $y_{i,t}^k$ is an ongoing aid variable and $\varepsilon_{i,t}$ is an error term conditional on u_i .

Table 5.4 Random effects panel model from 2005 to 2010

<i>lsum</i>	<i>Aid combination 1</i>				<i>Aid combination 2</i>				<i>Aid combination 3</i>				<i>Aid combination 4</i>			
	<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>	
<i>constant</i>	1.117	0.222	0.000	***	1.110	0.222	0.000	***	1.148	0.224	0.000	***	1.167	0.225	0.000	***
$\widehat{lsun}(i,t-1)$	0.849	0.040	0.000	***	0.853	0.040	0.000	***	0.839	0.040	0.000	***	0.834	0.041	0.000	***
$ifsum(i,t-1)$	3.104	0.220	0.000	***	3.122	0.220	0.000	***	3.065	0.221	0.000	***	3.044	0.223	0.000	***
$x^1(i,t)$									-0.643	0.975	0.510		-0.754	0.988	0.446	
$x^2(i,t)$	-0.122	0.253	0.628		-0.017	0.276	0.951									
$x^3(i,t)$	0.162	0.097	0.096	*	0.142	0.100	0.156									
$x^4(i,t)$									2.250	0.704	0.002	***	2.290	0.707	0.001	***
$y^1(i,t)$													0.175	0.245	0.474	
$y^2(i,t)$					-0.270	0.284	0.344									
$rainfall(i,t)$	-2.049	1.074	0.057	**	-2.026	1.074	0.060	**	-1.901	1.069	0.076	**	-1.909	1.070	0.075	**
Observations	323				323				323				323			
Regression s.e.	0.569				0.569				0.567				0.567			
Adjusted R-squared	0.726				0.726				0.729				0.728			

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level

5.2.1 Lagged dependant variable

In each random effects panel model, the coefficients on $\widehat{lsum}_{i,t-1}$ are highly statistically significant. The results suggest that a 0.01 unit increase in the fitted value of the lagged dependant variable will increase the summation of night light intensity by approximately 0.84 percent. The lagged dependant variable is describing the dynamics of light intensity as well as cross cluster fixed effects. Specifically, $\widehat{lsum}_{i,t-1}$ is the fitted value from a regression of $lsum_{i,t-1}$ on $lsum_{i,0}$, $minister_{i,t-1}$ and $rainfall_{i,t-1}$. Recall I have previously mentioned that *minister* was a weak instrument for ongoing aid. In terms of $\widehat{lsum}_{i,t-1}$, the variable that is providing most of the explanatory power here is $lsum_{i,0}$.

5.2.2 Light indicator variable

The coefficients on the variable $ifsum_{i,t-1}$ are also highly significant in each random effects panel model. This is a binary variable, so as $ifsum_{i,t-1}$ goes from zero to one, the expected increase in night light intensity is approximately 3 percent. This positive and significant coefficient on $ifsum_{i,t-1}$ is not surprising, as one would expect a town or village that uses electricity in year $t-1$ to continue using electricity in year t .

5.2.3 Precipitation control variable

The coefficients on *rainfall* in each random effects panel model are statistically significant at the 5 percent level of significance. The results show that high rainfall is associated with lower light intensity. Specifically, an increase in precipitation by 100 millimetres decreases the log of light intensity by approximately 2. Or, an increase in precipitation by 1 millimetre decreases the log of light intensity by approximately 0.02, which decreases the level of light intensity by approximately 0.02 percent. As shown in Table 5.2, the between effect is slightly less than the within effect. Nonetheless, this coefficient is a function of both the within and between effects. The negative coefficient could suggest that towns or villages with consistent cloud cover, and hence precipitation, have lower levels of night light intensity than other towns or villages. In other words, consistent cloud cover may limit the ability of the DMSP-OLS satellite to observe a town or village.

5.2.4 Exogenous aid variables

Next, I describe the coefficients on each aid variable. The coefficient on $x_{i,t}^3$ is significant at the 10 percent level of significance in the *aid combination 1* model. Also, each coefficient on $x_{i,t}^4$ is significant at the 1 percent level of significance in the *aid combination 3* and *4* models. Both $x_{i,t}^3$ and $x_{i,t}^4$ display positive coefficients, indicating that completed aid has a positive impact on increasing night light intensity. Each of these completed aid variables are functions of time since completion. Interestingly, $x_{i,t}^3$ is a function of the value of all aid projects in night light cluster i , whereas $x_{i,t}^4$ is not. The significance of $x_{i,t}^4$ could suggest that aid projects themselves have a significant impact on economic activity, regardless of the total amount spent on them.

The size of the effect of aid on light intensity is of interest. The variable $x_{i,t}^3$ is the real value of all completed aid projects, where each aid project is scaled by time since completion in night light cluster i . Interpreting $x_{i,t}^3$ in the *aid combination 1* model, a \$10,000,000 increase in completed aid, as a function of time since completion for each aid project, increases the log of night light intensity by 1.62. Or, a \$100,000 increase in completed aid, as a function of time since completion for each aid project, increases night light intensity by approximately 0.0162 percent. Likewise, $x_{i,t}^4$ is the summation of years since completion of all aid projects, where each aid project is scaled by inverse distance to the centre of night light cluster i . Interpreting $x_{i,t}^4$ in the *aid combination 3* and *aid combination 4* models, a 0.01 unit increase in $x_{i,t}^4$ increases night light intensity by approximately 0.02 percent.

Therefore, two of the three completed aid variables that are functions of the total amount spent on aid projects were not statistically significant. There is some support as to why there are conflicting results in each random effects panel model. Rajan and Subramanian (2008) find that foreign aid cannot consistently produce economic growth. However, the spatial dynamic panel models will look into the effectiveness of aid on night light intensity in more detail.

5.3 Spatial dynamic panel model

The next section presents a set of spatial dynamic panel models. Once more, the purpose of each model is to analyse the effect of aid on night light intensity. The spatial dynamic panel

models include, among other variables, a lagged dependant variable and two spatial variables. The lagged dependant variable is $lsum_{t-1}$ and the spatial variables are $wlsum1_{i,t}$ and $wlsum2_{i,t}$. These two spatial variables are included as separate explanatory variables. I present two versions of the spatial dynamic panel model. First, a spatial dynamic panel model is presented that treats aid as exogenous. Second, a spatial dynamic panel model is presented that treats aid as endogenous.

5.4 Spatial dynamic panel model with exogenous aid

I present four types of spatial dynamic panel models that estimate the effectiveness of aid on night light intensity. These models treat aid as exogenous:

$$lsum_{i,t} = \alpha_i + \beta \cdot lsum_{i,t-1} + \varphi_1 \cdot wlsum_{i,t} + \varphi_2 \cdot wlsum_{i,t-1} + \vartheta_1 \cdot x_{i,t}^2 + \vartheta_2 \cdot x_{i,t-1}^2 + \omega_1 \cdot x_{i,t}^3 + \omega_2 \cdot x_{i,t-1}^3 + \theta \cdot rainfall_{i,t} + \psi_t + \varepsilon_{i,t} \quad (5.5)$$

$$lsum_{i,t} = \alpha_i + \beta \cdot lsum_{i,t-1} + \varphi_1 \cdot wlsum_{i,t} + \varphi_2 \cdot wlsum_{i,t-1} + \vartheta_1 \cdot x_{i,t}^2 + \vartheta_2 \cdot x_{i,t-1}^2 + \omega_1 \cdot x_{i,t}^3 + \omega_2 \cdot x_{i,t-1}^3 + \tau_1 \cdot y_{i,t}^2 + \tau_2 \cdot y_{i,t-1}^2 + \theta \cdot rainfall_{i,t} + \psi_t + \varepsilon_{i,t} \quad (5.6)$$

$$lsum_{i,t} = \alpha_i + \beta \cdot lsum_{i,t-1} + \varphi_1 \cdot wlsum_{i,t} + \varphi_2 \cdot wlsum_{i,t-1} + \xi_1 \cdot x_{i,t}^1 + \xi_2 \cdot x_{i,t-1}^1 + \delta_1 \cdot x_{i,t}^4 + \delta_2 \cdot x_{i,t-1}^4 + \theta \cdot rainfall_{i,t} + \psi_t + \varepsilon_{i,t} \quad (5.7)$$

$$lsum_{i,t} = \alpha_i + \beta \cdot lsum_{i,t-1} + \varphi_1 \cdot wlsum_{i,t} + \varphi_2 \cdot wlsum_{i,t-1} + \xi_1 \cdot x_{i,t}^1 + \xi_2 \cdot x_{i,t-1}^1 + \delta_1 \cdot x_{i,t}^4 + \delta_2 \cdot x_{i,t-1}^4 + \eta_1 \cdot y_{i,t}^1 + \eta_2 \cdot y_{i,t-1}^1 + \theta \cdot rainfall_{i,t} + \psi_t + \varepsilon_{i,t} \quad (5.8)$$

where $wlsum_{i,t}$ can take either $wlsum1_{i,t}$ or $wlsum2_{i,t}$, $x_{i,t}^k$ is a completed aid variable, $y_{i,t}^k$ is an ongoing aid variable, ψ_t is a year fixed effect and $\varepsilon_{i,t}$ is an error term.

Table 5.5 Spatial dynamic panel model with exogenous aid from 2005 to 2010

A spatial dynamic panel model using $lsum_{t-3}$ and $wlsum1_{t-3}$ as GMM differenced instruments and $lsum_{t-3}$ onwards and $wlsum1_{t-3}$ onwards as GMM levels instruments.

<i>lsum</i>	<i>Aid combination 1</i>				<i>Aid combination 2</i>				<i>Aid combination 3</i>				<i>Aid combination 4</i>			
	<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>	
<i>constant</i>	30.208	24.705	0.221		34.539	26.135	0.186		-9.391	25.817	0.716		1.109	29.429	0.970	
<i>lsum (i,t-1)</i>	0.750	0.118	0.000	***	0.736	0.130	0.000	***	0.734	0.127	0.000	***	0.700	0.151	0.000	***
<i>wlsum1 (i,t)</i>	-1.892	0.213	0.000	***	-1.923	0.192	0.000	***	-1.884	0.202	0.000	***	-1.942	0.172	0.000	***
<i>wlsum1 (i,t-1)</i>	1.902	0.238	0.000	***	1.898	0.236	0.000	***	1.877	0.243	0.000	***	1.850	0.266	0.000	***
$x^1(i,t)$									9.933	8.232	0.228		5.946	24.366	0.807	
$x^1(i,t-1)$									-3.070	4.654	0.510		-0.952	24.955	0.970	
$x^2(i,t)$	0.393	3.624	0.914		0.488	3.638	0.893									
$x^2(i,t-1)$	-0.022	0.238	0.928		0.057	0.241	0.813									
$x^3(i,t)$	-0.433	3.552	0.903		-0.616	3.573	0.863									
$x^3(i,t-1)$	0.481	3.272	0.883		0.644	3.300	0.845									
$x^4(i,t)$									0.004	0.036	0.913		0.002	0.038	0.961	
$x^4(i,t-1)$									0.003	0.043	0.951		0.005	0.045	0.905	
$y^1(i,t)$													0.266	0.545	0.626	
$y^1(i,t-1)$													0.039	0.474	0.934	
$y^2(i,t)$					-0.177	0.335	0.597									
$y^2(i,t-1)$					0.255	0.257	0.321									
<i>rainfall(i,t)</i>	-0.007	0.007	0.329		-0.008	0.008	0.329		-0.007	0.007	0.329		-0.008	0.009	0.389	
2005																
2006									41.410	4.642	0.000	***	41.299	4.823	0.000	***
2007	-41.868	4.604	0.000	***	-41.972	4.400	0.000	***								
2008	11.319	2.846	0.000	***	11.879	2.814	0.000	***	52.862	5.449	0.000	***	53.965	4.808	0.000	***
2009	-58.019	7.337	0.000	***	-57.814	7.329	0.000	***	-15.808	3.199	0.000	***	-14.921	3.721	0.000	***
2010	37.408	6.554	0.000	***	38.654	6.331	0.000	***	78.963	8.554	0.000	***	81.514	7.243	0.000	***

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 5.5 (Continued)

	<i>Aid combination 1</i>		<i>Aid combination 2</i>		<i>Aid combination 3</i>		<i>Aid combination 4</i>	
Observations	278		278		278		278	
Sargan test ¹	<i>chi2(12)</i>	<i>p-value</i>	<i>chi2(10)</i>	<i>p-value</i>	<i>chi2(12)</i>	<i>p-value</i>	<i>chi2(10)</i>	<i>p-value</i>
	14.546	0.267	13.961	0.175	13.487	0.335	12.910	0.229
Arellano and Bond test ²	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>
Order 1	-0.759	0.448	-0.878	0.380	-0.849	0.396	-1.210	0.226
Order 2	0.280	0.780	0.587	0.557	0.489	0.625	0.705	0.481

¹ The null hypothesis is that the instrumental variables are not correlated with the residuals.

² The null hypothesis is that the errors in the first differenced equation display no second order autocorrelation.

Table 5.6 Spatial dynamic panel model with exogenous aid from 2005 to 2010

A spatial dynamic panel model using $lsum_{t-3}$ and $wlsum2_{t-3}$ as GMM differenced instruments and $lsum_{t-3}$ onwards and $wlsum2_{t-3}$ onwards as GMM levels instruments.

<i>lsum</i>	<i>Aid combination 1</i>				<i>Aid combination 2</i>				<i>Aid combination 3</i>				<i>Aid combination 4</i>			
	<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>	
<i>constant</i>	2.123	0.761	0.005	***	3.255	1.299	0.012	**	2.429	0.684	0.000	***	3.411	1.082	0.002	***
<i>lsum(i,t-1)</i>	0.636	0.123	0.000	***	0.551	0.135	0.000	***	0.588	0.120	0.000	***	0.516	0.114	0.000	***
<i>wlsum2(i,t)</i>	0.191	0.748	0.799		-0.712	1.312	0.587		0.089	0.894	0.921		-0.574	1.242	0.644	
<i>wlsum2(i,t-1)</i>	-0.615	0.859	0.474		-0.096	1.250	0.939		-0.787	0.963	0.413		-0.356	1.143	0.755	
$x^1(i,t)$									-20.902	21.900	0.340		-99.611	71.943	0.166	
$x^1(i,t-1)$									16.503	22.953	0.472		82.079	67.598	0.225	
$x^2(i,t)$	15.227	8.315	0.067	*	10.948	9.821	0.265									
$x^2(i,t-1)$	1.075	0.564	0.056	*	0.789	0.476	0.098	*								
$x^3(i,t)$	-15.305	8.296	0.065	*	-11.037	9.813	0.261									
$x^3(i,t-1)$	14.102	7.732	0.068	*	10.225	9.133	0.263									
$x^4(i,t)$									0.161	0.067	0.016	**	0.201	0.067	0.003	***
$x^4(i,t-1)$									-0.186	0.085	0.029	**	-0.238	0.085	0.005	***
$y^1(i,t)$													-0.917	1.463	0.531	
$y^1(i,t-1)$													1.583	1.290	0.220	
$y^2(i,t)$					0.758	0.567	0.182									
$y^2(i,t-1)$					0.404	0.473	0.393									
<i>rainfall(i,t)</i>	-0.012	0.011	0.273		-0.013	0.015	0.382		-0.007	0.011	0.523		-0.014	0.016	0.371	
2005																
2006									0.036	0.172	0.833		0.085	0.162	0.601	
2007	-0.057	0.155	0.712		-0.035	0.196	0.859									
2008	0.176	0.175	0.314		0.105	0.227	0.643		0.272	0.108	0.011	**	0.174	0.103	0.091	*
2009	-0.197	0.193	0.307		-0.206	0.251	0.411		-0.132	0.115	0.254		-0.206	0.113	0.069	*
2010	0.576	0.214	0.007	***	0.597	0.338	0.077	*	0.606	0.146	0.000	***	0.551	0.168	0.001	***

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 5.6 (Continued)

	<i>Aid combination 1</i>		<i>Aid combination 2</i>		<i>Aid combination 3</i>		<i>Aid combination 4</i>	
Observations	278		278		278		278	
Sargan test ¹	<i>chi2(16)</i>	<i>p-value</i>	<i>chi2(14)</i>	<i>p-value</i>	<i>chi2(16)</i>	<i>p-value</i>	<i>chi2(14)</i>	<i>p-value</i>
	22.995	0.114	19.162	0.159	19.774	0.231	16.967	0.258
Arellano and Bond test ²	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>
Order 1	-2.735	0.006	-2.331	0.020	-2.861	0.004	-2.385	0.017
Order 2	0.997	0.319	1.026	0.305	1.228	0.219	1.198	0.231

¹ The null hypothesis is that the instrumental variables are not correlated with the residuals.

² The null hypothesis is that the errors in the first differenced equation display no second order autocorrelation

5.4.1 Validity of the GMM estimator

Equations 5.5, 5.6, 5.7 and 5.8 use two sets of GMM-instruments. First, the models in Table 5.5 use levels of $lsum_{t-3}$ onwards and $wlsum1_{t-3}$ onwards are used in the differenced equations. Likewise, differences of $lsum$ and $wlsum1$ are used in the levels equations. Second, the models in Table 5.6 use levels of $lsum_{t-3}$ onwards and $wlsum2_{t-3}$ onwards in the differenced equations. Similarly, differences of $lsum$, $wlsum2$ are used in the levels equations. The standard instruments used are *aid*, *minister*, *rainfall* and *year*. The over-identifying moment conditions in the models presented in both Tables 5.5 and 5.6 are all valid at the 5 percent level of significance, based on not rejecting the null hypothesis of the Sargan test in each model. The Arellano and Bond test for no second-order autocorrelation in the first differenced errors is not significant, suggesting that the moment conditions in the models displayed in Tables 5.5 and 5.6 are valid at the 5 percent level of significance.

5.4.2 Half-life measure

Using the estimated coefficient on the lagged dependant variable makes it possible to estimate the degree of persistence to a shock in the level of economic activity. When aid is treated as exogenous, the coefficient on $lsum_{i,t-1}$ is highly significant. Table 5.5 shows the half-life of a shock to economic activity is equal to 2.41, 2.26, 2.24 and 1.94 years for each *aid combination 1-4* model. Likewise, Table 5.6 shows the half-life of a shock is equal to 1.53, 1.16, 1.31 and 1.05 years for each *aid combination 1-4* model. Again, this means that it will take approximately two or three years for half of a shock to the level of economic activity to wear off. This result is important when comparing the differences between short-run and long-run effects in the spatial dynamic panel model.

5.4.3 Spatial variables

The spatial measures that represent neighbouring light intensity from all towns or villages, $wlsum1_{i,t}$ and $wlsum1_{i,t-1}$, all have highly significant coefficients in the models presented in Table 5.5. This variable is a measure of light intensity for all neighbouring towns or villages. The significance of $wlsum1_{i,t}$ and $wlsum1_{i,t-1}$ indicates that there is a high spatial

correlation to changes in neighbouring light intensity from all towns or villages.²⁵ However, the negative coefficient on $wlsum1_{i,t}$ and the positive coefficient on $wlsum1_{i,t-1}$ are approximately the same size in absolute terms. Based on this, the effect of this variable on night light intensity appears to be in differences and not levels. The negative coefficient on $wlsum1_{i,t}$ indicates that there is a significant short-run effect on economic activity ($lsum_{i,t}$). The negative spatial correlation of neighbouring night light intensity between all towns or villages ($wlsum1_{i,t}$) could indicate that resources, trade, or commerce is randomly reallocated across towns or villages. This suggests that there may be some form of mobility present.

5.4.4 Exogenous aid variables

I do not find any exogenous aid coefficients that are statistically significant when $wlsum1$ are included as an explanatory variable (Table 5.5). However, there are some statistically significant exogenous aid coefficients when $wlsum2$ is included as an explanatory variable (Table 5.6). In the *aid combination 1* model of Table 5.6, the coefficients $x_{i,t}^2$ and $x_{i,t}^3$, along with their respective lags, are significant at the 10 percent level of significance.

The completed aid variable $x_{i,t}^2$ is the value of all completed aid projects in night light cluster i . The coefficients on $x_{i,t}^2$ and $x_{i,t-1}^2$ suggests that completed aid projects have a positive impact on the level of economic activity. Specifically, a \$1,000,000 increase in completed aid is expected to increase the log of night light intensity in a town or village by 15.227. Or, a \$10,000 increase in completed aid is expected to increase night light intensity in a town or village by approximately 0.15 percent.

Recall, $x_{i,t}^3$ is the value of all completed aid projects, where each is scaled by the time since completion in night light cluster i . The coefficient on $x_{i,t}^3$ is negative and the coefficient on $x_{i,t-1}^3$ is positive. The negative coefficient on $x_{i,t}^3$ suggests that a \$1,000,000 increase in completed aid, as a function of time since completion, will decrease the log of night light intensity in a town or village by 15.305. Or, a \$10,000 increase in completed aid, as a function of time since completion, is expected to decrease night light intensity in a town or village by approximately 0.15 percent.

²⁵ There are fixed effects contributing to this fit and it washes out the cross-cluster variation.

Finally, the *aid combination 3* and *aid combination 4* models in Table 5.6 display statistically significant coefficients on $x_{i,t}^4$ and $x_{i,t-1}^4$. In both of these models, $x_{i,t}^4$ has a positive coefficient and $x_{i,t-1}^4$ has a negative coefficient. The coefficient on $x_{i,t}^4$ suggests that completed aid projects significantly impact economic activity in a town or village, regardless taking the value of completed aid projects into account.

5.4.5 Long-run effect

Tables 5.7A and 5.7B display long-run effects of each *aid combination* on economic activity.²⁶ Table 5.7A treats aid as exogenous and uses a spatial variable that is a function of light intensity of all neighbouring towns or villages. Table 5.7B also treats aid as exogenous, although it uses the nearest neighbour light intensity measure.

Table 5.7 Long-run impact of exogenous aid in a spatial dynamic panel model

Where the values in bold represent the aid variables that were statistically significant in their respective models.

Table 5.7A: Exogenous aid and a total spatial variable

<i>lsum</i>	<i>Aid combination 1</i> Steady state	<i>Aid combination 2</i> Steady state	<i>Aid combination 3</i> Steady state	<i>Aid combination 4</i> Steady state
$x^1(i,t)$			25.845	16.653
$x^2(i,t)$	1.486	2.062		
$x^3(i,t)$	0.192	0.106		
$x^4(i,t)$			0.025	0.024
$y^1(i,t)$				1.016
$y^2(i,t)$		0.294		

Table 5.7B: Exogenous aid and a nearest neighbour spatial variable

<i>lsum</i>	<i>Aid combination 1</i> Steady state	<i>Aid combination 2</i> Steady state	<i>Aid combination 3</i> Steady state	<i>Aid combination 4</i> Steady state
$x^1(i,t)$			-10.685	-36.238
$x^2(i,t)$	44.828	26.148		
$x^3(i,t)$	-3.308	-1.808		
$x^4(i,t)$			-0.063	-0.078
$y^1(i,t)$				1.377
$y^2(i,t)$		2.589		

²⁶ The long-run impact is equal to: $\frac{(\text{Coefficient on aid measure}_{i,t} + \text{Coefficient on aid measure}_{i,t-1})}{(1 - \text{Coefficient on } lsum_{i,t-1})}$

Interestingly, three of the four significant aid coefficients suggest that completed aid has a negative impact on economic activity in a town or village in the long-run. The only aid coefficient that has a positive impact on long-run economic activity in a town or village is $x_{i,t}^2$ in the *aid combination 1* model in Table 5.7B. This result is consistent with Minoiu and Reddy (2010) who find that development aid has a positive long-run effect on growth. The difference in these the aid coefficients in the short-run and the long-run highlights the sensitivity of aid to how it is measured. In other words, these results emphasise the sensitivity of aid effectiveness to the econometric measure used.

5.5 Spatial dynamic panel model with endogenous aid

Another four types of spatial dynamic panel models estimate the effectiveness of aid on night light intensity. These models treat aid as endogenous. The primary equations are still 5.5, 5.6, 5.7 and 5.8; however they use different GMM-instruments and standard instruments in order to treat aid as endogenous.

Table 5.8 Spatial dynamic panel model with endogenous aid from 2005 to 2010

A spatial dynamic panel model using $lsum_{t-3}$, $wlsum1_{t-3}$ and aid_{t-3} as GMM differenced instruments and $lsum_{t-2}$, $wlsum1_{t-3}$ onwards and aid_{t-3} onwards as GMM levels instruments.

<i>lsum</i>	<i>Aid combination 1</i>				<i>Aid combination 2</i>				<i>Aid combination 3</i>				<i>Aid combination 4</i>			
	<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>	
<i>constant</i>	36.815	6.327	0.000	***	39.551	5.643	0.000	***	-12.177	5.794	0.036	**	-8.898	6.646	0.181	
<i>lsum(i,t-1)</i>	1.010	0.029	0.000	***	0.996	0.027	0.000	***	1.006	0.035	0.000	***	0.999	0.029	0.000	***
<i>wlsum1(i,t)</i>	-2.232	0.100	0.000	***	-2.254	0.100	0.000	***	-2.201	0.104	0.000	***	-2.261	0.111	0.000	***
<i>wlsum1(i,t-1)</i>	2.220	0.106	0.000	***	2.220	0.097	0.000	***	2.192	0.109	0.000	***	2.222	0.112	0.000	***
$x^1(i,t)$									-10.692	16.690	0.522		6.723	20.438	0.742	
$x^1(i,t-1)$									7.144	13.923	0.608		-4.892	18.024	0.786	
$x^2(i,t)$	-1.717	1.565	0.273		-1.374	1.349	0.308									
$x^2(i,t-1)$	0.088	0.165	0.594		0.050	0.090	0.577									
$x^3(i,t)$	1.715	1.548	0.268		1.365	1.351	0.312									
$x^3(i,t-1)$	-1.611	1.441	0.264		-1.282	1.255	0.307									
$x^4(i,t)$									0.008	0.012	0.484		-0.009	0.019	0.633	
$x^4(i,t-1)$									-0.009	0.016	0.556		0.011	0.025	0.656	
$y^1(i,t)$													-0.009	0.311	0.977	
$y^1(i,t-1)$													-0.033	0.295	0.911	
$y^2(i,t)$					-0.024	0.111	0.826									
$y^2(i,t-1)$					0.032	0.116	0.781									
<i>rainfall(i,t)</i>	-0.004	0.003	0.212		-0.004	0.003	0.146		-0.003	0.003	0.221		-0.005	0.003	0.141	
2005																
2006									48.249	2.310	0.000	***	49.058	2.386	0.000	***
2007	-48.887	2.233	0.000	***	-48.991	2.091	0.000	***								
2008	13.757	0.877	0.000	***	14.118	0.867	0.000	***	61.768	2.910	0.000	***	63.260	3.062	0.000	***
2009	-67.469	3.239	0.000	***	-67.392	2.927	0.000	***	-18.371	1.059	0.000	***	-18.378	1.100	0.000	***
2010	44.721	2.318	0.000	***	45.550	2.352	0.000	***	92.291	4.363	0.000	***	94.833	4.654	0.000	***

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 5.8 (Continued)

	<i>Aid combination 1</i>		<i>Aid combination 2</i>		<i>Aid combination 3</i>		<i>Aid combination 4</i>	
Observations	278		278		278		278	
Sargan test ¹	<i>chi2(31)</i>	<i>p-value</i>	<i>chi2(37)</i>	<i>p-value</i>	<i>chi2(36)</i>	<i>p-value</i>	<i>chi2(42)</i>	<i>p-value</i>
	44.595	0.054	40.784	0.308	46.327	0.116	41.784	0.480
Arellano and Bond test ²	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>
Order 1	-2.512	0.012	-2.608	0.009	-2.485	0.013	-2.700	0.007
Order 2	1.768	0.077	1.914	0.056	1.700	0.089	1.879	0.060

¹ The null hypothesis is that the instrumental variables are not correlated with the residuals.

² The null hypothesis is that the errors in the first differenced equation display no second order autocorrelation.

Table 5.9 Spatial dynamic panel model with endogenous aid from 2005 to 2010

A spatial dynamic panel model using $lsum_{t-3}$, $wlsum2_{t-3}$ and aid_{t-3} as GMM differenced instruments and $lsum_{t-2}$ onwards, $wlsum2_{t-3}$ onwards and aid_{t-3} onwards as GMM levels instruments.

<i>lsum</i>	<i>Aid combination 1</i>				<i>Aid combination 2</i>				<i>Aid combination 3</i>				<i>Aid combination 4</i>			
	<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>	
<i>constant</i>	1.646	0.658	0.012	**	1.767	0.758	0.020	**	1.763	0.710	0.013	**	2.357	0.735	0.001	***
<i>lsum(i,t-1)</i>	0.700	0.110	0.000	***	0.750	0.091	0.000	***	0.599	0.148	0.000	***	0.663	0.109	0.000	***
<i>wlsum2(i,t)</i>	0.471	0.642	0.463		0.281	0.665	0.672		0.781	0.685	0.254		-0.009	0.706	0.989	
<i>wlsum2(i,t-1)</i>	-0.460	0.618	0.456		-0.169	0.706	0.811		-0.463	0.601	0.442		-0.222	0.582	0.703	
$x^1(i,t)$									35.096	106.060	0.741		-145.769	114.077	0.201	
$x^1(i,t-1)$									-39.962	92.210	0.665		128.853	104.653	0.218	
$x^2(i,t)$	12.538	6.994	0.073	*	6.603	5.541	0.233									
$x^2(i,t-1)$	1.211	0.652	0.063	*	0.875	0.537	0.103									
$x^3(i,t)$	-13.163	6.899	0.056	*	-7.383	5.580	0.186									
$x^3(i,t-1)$	12.189	6.463	0.059	*	6.887	5.226	0.188									
$x^4(i,t)$									0.152	0.102	0.136		0.165	0.072	0.022	**
$x^4(i,t-1)$									-0.196	0.133	0.140		-0.210	0.095	0.027	**
$y^1(i,t)$													-1.981	2.212	0.370	
$y^1(i,t-1)$													2.088	2.066	0.312	
$y^2(i,t)$					-0.361	0.654	0.581									
$y^2(i,t-1)$					1.428	0.705	0.043									
<i>rainfall(i,t)</i>	-0.015	0.011	0.169		-0.014	0.012	0.217		-0.017	0.011	0.144		-0.016	0.013	0.223	
2005																
2006									0.236	0.128	0.064		0.323	0.127	0.011	**
2007	-0.182	0.149	0.221		-0.228	0.165	0.168									
2008	0.010	0.167	0.951		-0.005	0.167	0.976		0.187	0.095	0.049	**	0.129	0.087	0.138	
2009	-0.348	0.188	0.064		-0.436	0.201	0.030	**	-0.185	0.106	0.079	*	-0.279	0.095	0.003	***
2010	0.422	0.199	0.034		0.367	0.233	0.115		0.529	0.142	0.000	***	0.478	0.124	0.000	***

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

Table 5.9 (Continued)

	<i>Aid combination 1</i>		<i>Aid combination 2</i>		<i>Aid combination 3</i>		<i>Aid combination 4</i>	
Observations	278		278		278		278	
Sargan test ¹	<i>chi2(27)</i>	<i>p-value</i>	<i>chi2(33)</i>	<i>p-value</i>	<i>chi2(32)</i>	<i>p-value</i>	<i>chi2(38)</i>	<i>p-value</i>
	37.074	0.094	36.880	0.294	40.089	0.154	46.204	0.170
Arellano and Bond test ²	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>	<i>z</i>	<i>p-value</i>
Order 1	-2.649	0.008	-2.927	0.003	-2.320	0.020	-2.448	0.014
Order 2	1.270	0.204	1.646	0.100	0.953	0.340	1.203	0.229

¹ The null hypothesis is that the instrumental variables are not correlated with the residuals.

² The null hypothesis is that the errors in the first differenced equation display no second order autocorrelation.

5.5.1 Validity of the GMM estimator

Equations 5.5, 5.6, 5.7 and 5.8 use two sets of GMM-instruments. First, the models in Table 5.8 use levels of $lsum_{t-2}$, $wlsum1_{t-3}$ onwards and aid_{t-3} onwards in the differenced equations. Likewise, differences of $lsum$, $wlsum1$ and aid are used in the levels equations. Second, the models in Table 5.9 use levels of $lsum_{t-3}$ onwards, $wlsum2_{t-3}$ onwards and aid_{t-3} onwards in the differenced equations. Similarly, differences of $lsum$, $wlsum2$ and aid are used in the levels equations. In the models presented in Tables 5.8 and 5.9, the variables *minister*, *rainfall* and *year* are the standard instruments used. The over-identifying moment conditions in the models presented both Table 5.8 and 5.9 are all valid at the 5 percent level of significance, based on not rejecting the null hypothesis of the Sargan test in each model. The Arellano and Bond test for no second-order autocorrelation in the first differenced errors is not significant, suggesting that the moment conditions in the models displayed in Tables 5.8 and 5.9 are valid at the 5 percent level of significance.

5.5.2 Half-life measure

When aid is treated as endogenous, the coefficient on $lsum_{i,t-1}$ is highly significant. However, Table 5.8 shows that the size of the estimated coefficients on the lagged dependant variable is approximately equal to unity ($\beta \approx 1$). Based on this, Appendix G presents a fixed effects model in differences. Table 5.9 shows the half-life of a shock is equal to 1.94, 2.41, 1.35 and 1.69 years in each *aid combination 1-4* model. Again, this means that it will take approximately two years for half of a shock to the level of economic activity to wear off. This result is important when comparing the differences between short-run and long-run effects in the spatial dynamic panel model.

5.5.3 Spatial variables

Again, every coefficient on $wlsum1_{i,t}$ and $wlsum1_{i,t-1}$ is highly significant in the models presented in Table 5.8. The significance of $wlsum1_{i,t}$ and $wlsum1_{i,t-1}$ indicates that there is a high spatial correlation to changes in night light emission from all towns or villages in Malawi. The signs on this spatial coefficient are consistent with the results above where aid is treated as exogenous. Also, the size of this effect is of greater magnitude than when aid is treated as exogenous in Table 5.5.

5.5.4 Endogenous aid variables

I do not find any aid coefficients that are statistically significant when $wlsum1$ are included as an explanatory variable (Table 5.8). However, there are some statistically significant aid coefficients when $wlsum2$ is included as an explanatory variable (Table 5.9). In Table 5.9, the *aid combination 1* and *aid combination 4* models display significant coefficients only on some endogenous aid variables. In the *aid combination 1* model, $x_{i,t}^2$ and $x_{i,t}^3$, along with their lags, are significant at the 10 percent level of significance. In the *aid combination 4* model, $x_{i,t}^4$, along with its lag, is significant at the 5 percent level of significance.

The completed aid variable $x_{i,t}^2$ is the value of all completed aid projects in night light cluster i . The coefficients on $x_{i,t}^2$ and $x_{i,t-1}^2$ suggests that completed aid projects have a positive impact on the level of economic activity. Specifically, a \$1,000,000 increase in completed aid is expected to increase the log of night light intensity in a town or village by 12.538. Or, a \$10,000 increase in completed aid is expected to increase night light intensity in a town or village by approximately 0.13 percent.

Recall again, $x_{i,t}^3$ is the value of all completed aid projects, where each is scaled by the time since completion in night light cluster i . The coefficient on $x_{i,t}^3$ is negative and the coefficient on $x_{i,t-1}^3$ is positive. The negative coefficient on $x_{i,t}^3$ suggests that a \$1,000,000 increase in completed aid, as a function of time since completion, will decrease the log of night light intensity in a town or village by approximately 13.163. Or, a \$10,000 increase in completed aid, as a function of time since completion, is expected to decrease night light intensity in a town or village by approximately 0.13 percent.

Finally, the *aid combination 4* model in Table 5.9 displays statistically significant coefficients on $x_{i,t}^4$ and $x_{i,t-1}^4$. In both of these models, $x_{i,t}^4$ has a positive coefficient and $x_{i,t-1}^4$ has a negative coefficient. Similarly to the spatial dynamic panel model with exogenous aid (Table 5.6), the coefficient on $x_{i,t}^4$ suggests that completed aid projects significantly impact economic activity in a town or village, regardless taking the value of completed aid projects into account.

5.5.5 Long-run effect

The two tables below describe the long-run impact of aid on night light intensity. Table 5.10A treats aid as endogenous and uses a spatial variable that is a function of light intensity of all

neighbouring towns or villages. Table 5.10B also treats aid as endogenous and includes the nearest neighbour light intensity variable as explanatory variables.

Table 5.10 Long-run impact of endogenous aid in a spatial dynamic panel model

Where the values in bold represent the aid variables that were statistically significant in their respective models.

Table 5.10A: Endogenous aid and a total spatial variable from 2005 to 2010

<i>lsum</i>	<i>Aid combination 1</i> Steady state	<i>Aid combination 2</i> Steady state	<i>Aid combination 3</i> Steady state	<i>Aid combination 4</i> Steady state
$x^1(i,t)$			572.297	1290.935
$x^2(i,t)$	161.317	-373.321		
$x^3(i,t)$	-10.346	-0.013		
$x^4(i,t)$			0.165	1.346
$y^1(i,t)$				-29.438
$y^2(i,t)$		2.230		

Table 5.10B: Endogenous aid and a total spatial variable from 2005 to 2010

<i>lsum</i>	<i>Aid combination 1</i> Steady state	<i>Aid combination 2</i> Steady state	<i>Aid combination 3</i> Steady state	<i>Aid combination 4</i> Steady state
$x^1(i,t)$			-12.133	-50.199
$x^2(i,t)$	45.820	29.966		
$x^3(i,t)$	-3.244	-1.986		
$x^4(i,t)$			-0.110	-0.134
$y^1(i,t)$				0.318
$y^2(i,t)$		4.274		

Again, some endogenous aid coefficients suggest that completed aid can be harmful to economic activity in a town or village in the long-run, specifically when the nearest neighbour spatial variable is used. The size of the impact of completed aid on long-run economic activity in a town or village appears to be slightly larger in Table 5.10 than in Table 5.7, with the exception of $x_{i,t}^3$.

5.6 Discussion of results

The random effects panel model takes into account the variation in night light intensity between towns or villages. However, the estimated coefficients produced from the random effects model may be subject to ambiguity in terms of interpretation. The spatial dynamic panel model incorporates fixed effects, which allows for the interpretation of coefficients

within towns or villages. The results produced from the spatial dynamic panel model will be the main focus throughout this discussion.

5.6.1 *Quality of estimators*

Two tests are used in the spatial dynamic panel models to confirm the quality of the estimators. Both the Sargan and Arellano and Bond tests confirm that the moment conditions are valid at the 5 percent level of significance in every spatial dynamic panel model. As suggested by Roodman (2009), a necessary condition for the validity of the instruments is that the lagged dependant variable should have an absolute coefficient of less than unity. This is consistent with convergence to the steady state. This is the case in every spatial dynamic panel model, with the exception of those models presented in Table 5.8 where aid is treated as endogenous and a neighbouring light intensity spatial variable is included as explanatory variables. Based on the results in Table 5.8, a fixed effect in differences model is applied in Appendix G.

5.6.2 *Overall shocks to economic activity*

The coefficient on the lagged dependant variable is highly significant in every model which was expected. It is well known that the shortcoming of including a lagged dependant variable as an explanatory variable is that it can lead to biased coefficient estimates. Therefore, interpretation of this coefficient should be treated with caution. The half-life of a shock is approximately two to three years. As the sample period is only six years, it is possible that the full impact of a completed aid project on night light intensity will not appear in these results. Generally, completed aid projects has a positive impact on economic activity in a town or village in the short-run, however negatively impacted economic activity in a town or village in the long-run. The half-life measurement suggests a time frame for the difference between the short-run and the long-run.

5.6.3 *Comparing spatial variables*

Looking at the two spatial variables used as explanatory variables, it was clear to see that the coefficients on *wlsum1* were consistently significant while the coefficients on *wlsum2* were insignificant in the spatial dynamic panel models. The significance of *wlsum1* is not surprising given other studies have found a significant spatial effect. Franzese and Hays

(2007) find a negative spatial correlation in labour market training spending per unemployed worker across countries in Europe. They suggest that there could be some form of mobility of unemployed workers crossing borders in order to receive free labour market training in some countries. However, Lottmann (2012) finds a positive significant spatial correlation in regional unemployment in Germany. Likewise, Madariaga and Poncet (2007) find a positive significant correlation between income per capita and FDI-to-GDP ratio in a given city and surrounding cities.²⁷ The negative coefficient on *wlsum1* suggests that there is a negative spatial correlation effect happening. Again, this suggests there could be a random movement of people or resources, suggesting that mobility is present. On the other hand, *wlsum2* measures light intensity in the nearest neighbouring town or village. As this measure is not statistically significant, no inference can be made on this coefficient.

5.6.4 *Discussing the control variable*

A control variable for precipitation was included as an explanatory variable to control for increasing rainfall subsequently increasing agriculture production, and hence increasing the proxy for economic activity (*lsum*). The negative coefficient on the control variable *rainfall_{i,t}* is statistically significant at the 5 percent level in the random effects panel model only. This may be due to the coefficient being based on a cross-sectional correlation between night light intensity and precipitation. However, the spatial dynamic panel model does show time-series correlation of rainfall within a night light cluster. In other words, the random effects results take into account changes in rainfall across all towns or villages that emit night light, whereas the spatial dynamic panel model only takes into account changes in a town or village. The negative *rainfall_{i,t}* coefficient could mean that towns or villages that have more rainfall also have more cloud cover. For this reason, this will lower the night light intensity as the DMSP-OLS satellite will not be able to observe the town or village through the cloud cover.

5.6.5 *Ongoing aid projects*

The coefficients on the ongoing aid variables in every model are found to be insignificant. The original hypothesis was that electricity was a function of an ongoing aid project, either

²⁷ Madariaga and Poncet (2007) also control for any potential endogeneity problems through the use of a system-GMM estimator.

directly or indirectly. For example, electricity is needed to complete the aid project or the revenue that the aid project provides enables more electricity to be consumed. In other words, I find there is no spill-over effect of foreign aid projects. As an example, this suggests that building a school does not impact economic activity in a town or village until the school is opened. However, because this thesis did not categorise every aid project, I could not directly test for which types of aid projects directly impact night light intensity in a town or village. For example, with the results from this thesis, it is not possible to say that an ongoing healthcare project will result in improved night light intensity in a town or village. Therefore, this is a measurement error. Looking forward, the categorisation of aid projects is an avenue that merits investigation.

5.6.6 Completed aid projects

The coefficient on *wlsum1* is found to be highly statistically significant. This, coupled with the statistical significance of a lagged dependant variable, leaves no room for the aid variables to be significant. The coefficient on the nearest neighbour spatial variable (*wlsum2*) is not significant in any spatial dynamic panel model. Only in these spatial dynamic panel models, where *wlsum2* is included as an explanatory variable, were the coefficients on completed aid project variables statistically significant.

In each random effects panel model and spatial dynamic panel model, only the coefficients on the completed aid project variables have a statistically significant impact on economic activity. I found more significant aid coefficients when aid was treated as endogenous as opposed to exogenous. However, the results also suggest that completed aid has a negative impact on long-run night light intensity in a town or village. Overall, the significance of the completed aid variables is evidence that aid projects do not impact economic activity until after they are completed.

5.6.7 Comparing studies

The aid effect in each random effects model and spatial dynamic panel model is comparable to other studies that have analysed the impact of aid on economic activity. For example, a meta-study conducted by Doucouliagos and Paldam (2008) found that of the 68 aid-growth studies analysed, 46 percent had a statistically significant positive effect, while 54 percent were not statistically significant or negative. I compare the results from this thesis to that of

RCTs. I present a summary of a selection of RCTs, including their main details and results in Table 5.11. In order to estimate the effect of a RCT at the town or village level, I find the cost of each RCT intervention per person and assume a town or village population of 66,777.²⁸

Table 5.11 Comparing randomised controlled trials

Dependant variable	Description	Explanatory variable	Cost	Results	Author
School participation.	A mass treatment of deworming drugs was randomly phased into 75 Kenyan schools.	Deworming drugs.	\$0.49 US dollars per child. Alternatively, \$32,721 US dollars per town or village.	The deworming program increase school participation by 0.14 years per child. Therefore, \$3.50 US dollars spent per child on deworming leads to an additional year of school participation. Overall, the deworming program led to a 7.5 percent increase in school participation.	Miguel and Kremer (2003).
School participation.	A program that paid for uniforms that Kenyan school children were required to wear to school.	School uniforms.	\$6 US dollars per child. Alternatively, \$400,662 US dollars per town or village.	On average, students in comparison schools remained enrolled for 3.8 years, while those in treatment schools remained enrolled for 4.3 years, a 0.5 year or 13 percent increase.	Kremer, Moulin and Namunyu (2002).
Water sanitation behaviours.	An educational intervention to improve water sanitation and hence prevent diarrhoea in developing countries using 937 intervention and 986 control families in Bangladesh.	Education in the form of basic primary health care services.	Assuming that schools provide the education.	The rate of diarrhoea (per 100 person-weeks) in children under six years of age was 4.3 in the intervention communities and 5.8 in the control communities, which equates to a 26 percent change.	Stanton and Clemens (1987).
Secondary school completion rates.	Secondary school vouchers offered to children in low socioeconomic areas of Columbia.	Secondary school vouchers covering half the cost of education.	\$190 US dollars per voucher. Alternatively, \$12,687,624 US dollars per town or village.	The program was estimated to increase secondary school completion rates by 15-20 percent.	Angrist, Bettinger and Kremer (2006).

The results in this thesis are deduced from disaggregated datasets. Based on this, it is more appropriate to compare these results with RCTs as opposed to results from the aid

²⁸ I assume a town or village population of 66,777. This is based on taking the average of the urban population numbers in Table A.2 in Appendix A. I take the average of the urban populations and not the rural populations because the night light clusters are more likely to represent an urban area.

effectiveness literature that are interpreted at a macroeconomic level. Table 5.11 shows a variation in the amount spent on RCT in a town or village assuming a population of 66,777. Ideally, the results from this thesis would be categorised in order to directly compare the results of the RCTs. For example, this would allow for the comparison of healthcare aid projects to healthcare RCTs. Instead, one can estimate how much needs to be spent on a project in order to see a given percentage change in some dependant variable.

The average amount spent on an aid project is \$4,320,000 US dollars per year. I will use the coefficients on $x_{i,t}^2$ in Tables 5.6 and 5.9 to estimate the impact of an extra aid project on a percentage change in night light intensity. I use the coefficients on $x_{i,t}^2$ because this variable is the value of all completed aid projects in night light cluster i . Based on this, I find that an extra completed aid project costing \$4,320,000 in a town or village is associated with an increase in the log of night light intensity by approximately 14. Or, an extra completed aid project costing \$43,200 in a town or village is associated with an increase in night light intensity by approximately 0.14 percent. The RCT results presented in Table 5.11 suggest that the school uniform program has a similar sized impact to the results of completed aid in this thesis.

5.6.8 Limitations and future research

The findings from the random effects panel model and spatial dynamic panel model suggest that completed aid projects have a significant impact on short-run and long-run effect on economic activity. Many studies argue that the econometric treatment of aid will determine whether aid is effective or not in impacting economic activity. The results in this thesis highlight the sensitivity of aid to changes in the way it is measured. For example, ongoing aid and completed aid have displayed different coefficients. The coefficients on all ongoing aid variables were insignificant in each random effects panel model and spatial dynamic panel model. On the other hand, some completed aid variables displayed statistically significant coefficients. Interestingly, I find a positive short-run impact of completed aid on night light intensity and a negative long-run impact of completed aid on night light intensity. At this time, there are no direct studies to compare these results to in terms of the effect that aid has on night light intensity. The results on the effectiveness of aid are best compared to the findings from RCTs as opposed to the findings from macroeconomic data due the disaggregated nature of the datasets used in this thesis. However, one could argue that

aggregating aid to the town or village level may have an externality impact on economic activity, which may not occur in a RCT.

The foreign aid dataset used in this thesis has some inaccuracies that need to be mentioned. The first inaccuracy is with respect to the precision of the geocoded locations of the aid projects. Each aid project has a precision scale. Therefore, the coordinates of each aid project may be subject to some form of measurement error. However, this was mitigated by incorporating the 21×21 pixel grid in each town or village, and subsequently aggregating projects within each 21×21 pixel grid. Moreover, although the foreign aid dataset covers a large time frame, there is a noticeable increase in aid projects from 2004 onwards. One must point out that this is not due to a larger increase in aid flows from 2004 onwards, but instead an improvement in accountability and transparency of aid which allows for the geocoding of aid projects. As the aid industry changes their culture into creating an up-to-date database, future analysis of aid projects at a microeconomic level will become increasingly possible. Nonetheless, the increase in aid flows from 2004 onwards is likely to undervalue the estimated effectiveness of foreign aid on economic activity. There is merit in categorising aid projects as a possible avenue for further study in this topic. In addition, more statistics could be used in order to correctly account for the missing aid data.

6. Conclusion

Based on the amount of time, money and resources devoted to foreign aid in order to improve the standard of living in developing countries, there is still little evidence about the effectiveness of foreign aid on economic growth. Even so, foreign aid seems to be increasing in scale and in a perpetual manner.

This thesis is unique in the sense that it draws conclusions from disaggregated or microeconomic datasets. First, the night lights dataset for Malawi from 2005 to 2010 is a major contribution to the literature. The techniques applied to this dataset are scalable in the sense that they are applicable to any country producing night light. Second, the geocoded aid dataset provided by AidData provides an up-to-date description of foreign aid that encourages accountability and transparency.

Most conclusions on aid effectiveness come from a macroeconomic level. A large amount of aid effectiveness literature constructs models based on macroeconomic data. In addition, the macroeconomic literature on aid effectiveness seems to be emphasising the need to find the correct instruments to account for possible endogeneity. However, there is an emerging literature deduced from RCTs. RCTs are important, as they circumvent the endogeneity problem of foreign aid with randomised trials (Deaton, 2010).

Recently, stakeholders in the aid effectiveness debate have emphasised the need for greater accountability and transparency of foreign aid. This has meant that stakeholders are beginning to align values in order to achieve common goals. Moreover, the new transparency initiatives being implemented by aid stakeholders allow for an up-to-date database of aid projects. There needs to be improved knowledge on what types of foreign aid projects are effective, instead of relying on econometric-based models or instruments.

To analyse the impact of aid on night light intensity, I fit two types of models using strictly positive values of light. First, I present a random effects panel model which treats aid as exogenous. Second, I present two versions of the spatial dynamic panel model, one that

treats aid as exogenous and one that treats aid as endogenous with respect to economic activity.

The results from both models are aligned with the aid effectiveness literature. First, the random effects panel model finds that some completed aid project variables have statistically significant coefficients which are associated with a positive impact on the level of economic activity. However, the impact on the level of economic activity appears to be negative in the long-run. Second, the spatial dynamic panel model found that the coefficients on completed aid projects were statistically significant when the nearest neighbour spatial variable was insignificant. The sensitivity of these results to the econometric method employed confirms there is no strong evidence on the effectiveness of aid on night light intensity. Moreover, I find a statistically significant coefficient on the precipitation variable in the random effects panel model. This could suggest that the towns or villages that have constant cloud cover also have lower night light intensity. Finally, I find a negative spatial correlation in night light intensity between neighbouring towns or villages. This could suggest some form of random mobility exists for resources, trade or commerce between towns or villages.

Future research using this foreign aid dataset should consider categorising aid projects in order to observe which types of aid impact economic activity. The night lights dataset and the geocoded aid dataset used in this thesis allows for more development questions to be investigated at a microeconomic level.

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Appendices

Appendix A. Night light data

Table A.1 Night light cluster locations

Town or village names were collected using Google Earth. Longitude and latitude are displayed in decimal degrees. All of the main population centres are covered with these night light clusters. Note that Mwanza district includes Neno district.

<i>Night light cluster</i>	<i>District</i>	<i>Town or village</i>	<i>Longitude</i>	<i>Latitude</i>	<i>Night light cluster</i>	<i>District</i>	<i>Town or village</i>	<i>Longitude</i>	<i>Latitude</i>
1	Chitipa	Chitipa	33.267	-9.690	41	Salima	Salima	34.450	-13.766
2	Karonga	Karonga	33.925	-9.923	42	Salima	Senga	34.609	-13.716
3	Karonga	Karonga	33.700	-9.990	43	Dedza	Tete	34.076	-14.288
4	Karonga	Chilomba	34.209	-10.441	44	Dedza	Dedza	34.326	-14.368
5	Rumphi	Livingstonia	34.103	-10.613	45	Ntchisi	Ntcheu	34.625	-14.800
6	Rumphi	N'Gonga	34.009	-10.874	46	Mangochi	Monkey Bay	34.918	-14.067
7	Rumphi	Rumphi	33.850	-11.007	47	Mangochi	Nkopola	35.133	-14.308
8	Mzimba	Ekwendeni	33.883	-11.358	48	Mangochi	Mangochi	35.251	-14.470
9	Mzimba	Mzuzu	34.017	-11.433	49	Mangochi	Namwera	35.500	-14.347
10	Mzimba	Mzimba	33.592	-11.891	50	Balaka	Kalembo	35.158	-14.817
11	Mzimba	Chikangawa	33.758	-11.899	51	Balaka	Balaka	34.950	-14.974
12	Mzimba	Loudon	33.474	-12.124	52	Machinga	Liwonde	35.217	-15.058
13	Nkhata Bay	Nkhata Bay	34.292	-11.592	53	Machinga	Ntaja	35.525	-14.858
14	Nkhata Bay	Chintheche	34.164	-11.824	54	Machinga	Thomo	35.527	-14.736
15	Likoma	Likoma	34.734	-12.058	55	Zomba	Likwenu	35.351	-15.200
16	Kasungu	Kasungu	33.483	-13.025	56	Zomba	Malosa	35.392	-15.267
17	Kasungu	Cipeta	33.724	-12.866	57	Zomba	Zomba City	35.325	-15.375
18	Kasungu	Kaluluma	33.508	-12.566	58	Zomba	Malajira	35.225	-15.473
19	Kasungu	Cavura	33.478	-12.696	59	Mwanza	Tedzani	34.776	-15.542
20	Kasungu	Kamuzu	33.674	-13.025	60	Mwanza	Walkers Ferry	34.826	-15.508
21	Kasungu	Santhe	33.383	-13.416	61	Mwanza	Zalewa	34.851	-15.442
22	Kasungu	Kanyundo	33.508	-13.216	62	Mwanza	Mwanza	34.508	-15.583
23	Kasungu	Santhe	33.417	-13.392	63	Blantyre	Lunzu	35.017	-15.517
24	Lilongwe	Chika	33.550	-13.300	64	Blantyre	Chileka	34.938	-15.555
25	Kasungu	Chika	33.570	-13.271	65	Chiradzulu	Chiradzulu	35.176	-15.692
26	Dowa	Madisi	33.600	-13.400	66	Thyolo	Luchenza	35.309	-16.000
27	Dowa	Mponela	33.733	-13.525	67	Mulanje	Mulanje	35.509	-16.009
28	Dowa	Dowa	33.933	-13.642	68	Mulanje	Thornwood	35.718	-16.059
29	Dowa	Lumbadzi	33.800	-13.759	69	Phalombe	Phalombe	35.643	-15.792
30	Dowa	Miwale	33.528	-13.671	70	Phalombe	Phodgoma	35.759	-15.767
31	Dowa	Dzoole	33.753	-13.646	71	Phalombe	Likangaria	35.776	-15.700
32	Ntchisi	Ntchisi	33.916	-13.340	72	Phalombe	Siana	35.684	-15.717
33	Ntchisi	Mbobo	33.840	-13.141	73	Thyolo	Thyolo	35.142	-16.058
34	Nkhotakota	Kanyenda	34.141	-12.486	74	Thyolo	Chingazi	35.101	-16.167
35	Nkhotakota	Nkhotakota	34.282	-12.916	75	Chikwawa	Maganga	34.750	-15.884
36	Mchinji	Chikoto	33.163	-13.534	76	Chikwawa	Chikwawa	34.801	-16.026
37	Mchinji	Mchinji	32.885	-13.785	77	Chikwawa	Nchalo	34.875	-16.251
38	Mchinji	Nkotakata	33.041	-13.816	78	Chikwawa	Ngabu	34.876	-16.459
39	Mchinji	Namitete	33.357	-14.016	79	Nsanje	Bangula	35.109	-16.568
40	Lilongwe	Mitundu	33.775	-14.250	80	Nsanje	Nsanje	35.251	-16.909

Table A.2 Malawi 2008 Population and Housing Census

Note that each district below is represented by one of the 80 night light clusters, excluding Lilongwe City and Blantyre City, which are excluded from the analysis.

Region and district	Total	Urban	Rural
Malawi	13,077,160	2,003,309	11,073,851
Northern region	1,708,930	240,515	1,468,415
Chitipa	178,904	14,753	164,151
Karonga	269,890	40,334	229,556
Nkhata Bay	215,789	11,269	204,520
Rumphi	172,034	17,845	154,189
Mzimba	727,931	20,994	706,937
Likoma	10,414	1,352	9,062
Mzuzu City	133,968	133,968	N/A
Central region	5,510,195	832,113	4,678,082
Kasungu	627,467	39,640	587,827
Nkhotakota	303,659	24,726	278,933
Ntchisi	224,872	7,918	216,954
Dowa	558,470	4,765	553,705
Salima	337,895	27,852	310,043
Lilongwe	1,230,834	0	1,230,834
Lilongwe City	674,448	674,448	0
Mchinji	456,516	17,881	438,635
Dedza	624,445	20,241	604,204
Ntcheu	471,589	14,642	456,947
Southern region	5,858,035	930,681	4,927,354
Mangochi	797,061	50,821	746,240
Machinga	490,579	24,147	466,432
Zomba	579,639	N/A	579,639
Zomba City	88,314	88,314	N/A
Chiradzulu	288,546	2,348	286,198
Blantyre	340,728	N/A	340,728
Blantyre City	661,256	661,256	N/A
Mwanza	92,947	14,226	78,721
Thyolo	587,053	18,589	568,464
Mulanje	521,391	14,497	506,894
Phalombe	313,129	4,935	308,194
Chikwawa	434,648	6,987	427,661
Nsanje	238,103	20,179	217,924
Balaka	317,324	22,733	294,591
Neno	107,317	1,649	105,668

Source: 2008 Population and Housing Census, National Statistical Office, Malawi. Retrieved from:
http://unstats.un.org/unsd/demographic/sources/census/2010_PHC/Malawi/Malawi_Report.pdf

Table A.3 Nearest neighbour great circle distances

Where nearest neighbour distance is calculated using the shortest great circle distance between night light clusters.

<i>Night light cluster</i>	<i>Nearest neighbour</i>	<i>Distance</i>	<i>Night light cluster</i>	<i>Nearest neighbour</i>	<i>Distance</i>
1	3	57.990	41	42	18.050
2	3	25.740	42	41	18.050
3	2	25.740	43	44	28.370
4	5	22.360	44	45	57.820
5	4	22.800	45	51	39.930
6	7	22.800	46	47	35.430
7	6	22.800	47	48	22.050
8	9	16.820	48	47	22.050
9	8	16.820	49	48	30.100
10	11	18.080	50	52	27.540
11	10	18.080	51	50	28.360
12	10	28.910	52	55	21.360
13	14	29.320	53	54	13.570
14	13	29.320	54	53	13.570
15	14	67.250	55	56	8.650
16	20	20.690	56	55	8.650
17	20	18.490	57	56	13.990
18	19	14.820	58	57	15.290
19	18	14.820	59	60	6.560
20	17	18.490	60	59	6.560
21	23	4.540	61	60	7.810
22	25	9.080	62	59	29.070
23	21	4.540	63	64	9.460
24	25	3.880	64	63	9.460
25	24	3.880	65	63	25.860
26	24	12.370	66	67	21.400
27	31	13.630	67	66	21.400
28	29	19.380	68	67	23.020
29	31	13.550	69	72	9.420
30	31	24.470	70	71	7.670
31	27	13.630	71	70	7.670
32	33	23.610	72	70	9.760
33	32	23.610	73	74	12.890
34	35	50.200	74	73	12.890
35	34	50.200	75	76	16.700
36	38	34.020	76	75	16.700
37	38	17.190	77	78	23.130
38	37	17.190	78	77	23.130
39	38	40.720	79	78	27.640
40	43	32.710	80	79	40.820

Appendix B. Aid data

Table B.1 List of donors for all geocoded aid to Malawi from 1996 to 2016

	<i>Donor</i>	<i># of projects</i>	<i>% of total projects</i>
1	African Development Bank (AfDB)	242	9.59%
2	Arab Bank for Economic Development in Africa (BADEA)	26	1.03%
3	Australian Agency for International Development (AusAid)	17	0.67%
4	Canadian International Development Agency (CIDA)	15	0.59%
5	European Union (EU)	603	23.90%
6	Flemish International Cooperation Agency (FICA)	67	2.66%
7	Food and Agriculture Organization (FAO)	91	3.61%
8	German Agency for International Cooperation (GIZ)	94	3.73%
9	Global Fund	6	0.24%
10	Icelandic International Development Agency (ICEIDA)	9	0.36%
11	International Fund for Agricultural Development (IFAD)	30	1.19%
12	Irish Aid	30	1.19%
13	Japan	9	0.36%
14	Japan International Cooperation Agency (JICA)	20	0.79%
15	KFW Bankengruppe	12	0.48%
16	Kuwait Fund	11	0.44%
17	Multi-Donor Trust Fund	3	0.12%
18	Norwegian Agency for Development Cooperation (NORAD)	304	12.05%
19	OPEC Fund	19	0.75%
20	People's Republic of China	2	0.08%
21	Republic of India	1	0.04%
22	UK Department for International Development (DfID)	215	8.52%
23	UNAIDS	18	0.71%
24	UNDP	133	5.27%
25	UNESCO	26	1.03%
26	UNHCR	8	0.32%
27	UNIDO	9	0.36%
28	US Agency for International Development	283	11.22%
29	US Center for Disease Control and Prevention (US CDC)	40	1.59%
30	World Bank	134	5.31%
31	World Food Program (WFP)	46	1.82%
	Total projects	2523	100%

Table B.2 Type of assistance for all geocoded aid to Malawi from 1996 to 2016

	<i>Type of assistance</i>	<i># of projects</i>	<i>% of total projects</i>
1	<i>Grant</i>	2210	87.59%
2	<i>Loan</i>	282	11.18%
3	<i>Technical assistance</i>	31	1.23%
	Total projects	2523	100%

Table B.3 Type of sector for all geocoded aid to Malawi from 1996 to 2016

Note that further sub-parts to these sectors are available within the dataset, where the creators have ultimately attempted to describe in detail the exact use of the funds for every project.

	<i>Type of sector</i>	<i># of projects</i>	<i>% of total projects</i>
1	<i>Agriculture</i>	431	17.08%
2	<i>Democratic governance</i>	116	4.60%
3	<i>Economic governance</i>	81	3.21%
4	<i>Education</i>	172	6.82%
5	<i>Energy and mining</i>	15	0.59%
6	<i>Environment, lands and natural resources</i>	94	3.73%
7	<i>Gender, youth development and sports</i>	97	3.84%
8	<i>Health</i>	455	18.03%
9	<i>Information technology</i>	6	0.24%
10	<i>Integrated rural development</i>	346	13.71%
11	<i>Other</i>	1	0.04%
12	<i>Public administration</i>	3	0.12%
13	<i>Roads, public works and transport</i>	371	14.70%
14	<i>Tourism, wildlife and culture</i>	21	0.83%
15	<i>Trade, industry and private sector development</i>	22	0.87%
16	<i>Vulnerability, disaster and risk management</i>	122	4.84%
17	<i>Water, sanitation and irrigation</i>	170	6.74%
	Total projects	2523	100%

Appendix C. Minister data

Table C.1 Malawian minister birthplaces from August 2005 to August 2010

Note that if birthplaces were unavailable, the district of the minister's electorate was used instead. N/A represents the information was not available or a new ministerial position was created.

Minister position	August 2005	Birthplace/electorate	November 2007	Birthplace/electorate
President of the Republic of Malawi	Bingu wa Mutharika	Thyolo	Bingu wa Mutharika	Thyolo
Vice President	Dr Cassim Chilumpha	Nkhata Bay	Dr Cassim Chilumpha	Nkhata Bay
2nd Vice President	N/A	N/A	N/A	N/A
Irrigation and Water Development	Sidik Mia	Chikwawa	N/A	N/A
Finance	Goodall Gondwe	Mzimba	Goodall Gondwe	Mzimba
Economic Planning and Development	David Faiti	Chikwawa	Ted Kalebe	N/A
Local Government and Rural Development	George Chaponda	Mulanje	George Chaponda	Mulanje
Justice and Constitutional Affairs	Henry Phoya	N/A	Henry Dama Phoya	N/A
Industry, Science and Technology	Khumbo Chirwa	N/A	Bingu wa Mutharika	Thyolo
Agriculture and Food Security	Uladi Mussa	N/A	Bingu wa Mutharika	Thyolo
Education and Human Resources	Kate Kainja	Dedza	Bingu wa Mutharika	Thyolo
Lands, Housing and Surveys	Bazuka Mhango	Karonga	Khumbo Chirwa	N/A
Transport and Public Works	Henry Mussa	Chiradzulu	Henry Mussa	Chiradzulu
Tourism, Wildlife and Culture	Patricia Kaliyati	Mulanje	Callista Chimombo	Zomba
Labour and Vocational Training	Ken Lipenga	Phalombe	Anna Kachikho	Phalombe
Trade and Private Sector Development	Martin Kansichi	Lilongwe	Ken Lipenga	Phalombe
Health	Hetherwick Ntaba	Lilongwe	Marjory Ngaunje	N/A
Foreign Affairs	Davis Katsonga	Mwanza	Joyce Banda	Zomba
Home Affairs and Internal Security	Anna Kachikho	Phalombe	Ernest Malenga	N/A
Mines, Natural Resources and Environmental Affairs	Henry Chimunthu Banda	Nkhotakota	Chimunthu Banda	Nkhotakota
Women, Child Welfare and Community Services	Joyce Banda	Zomba	Patricia Kaliati	Mulanje
Youth, Sports and Culture	Jaffalie Mussa	N/A	Khumbo Kachali	Mzimba
Presidential and parliamentary affairs	N/A	N/A	Davies Katsonga	N/A
Social Development and Persons with Disabilities	Clement Chiwaya	Mangochi	N/A	N/A
Defence	N/A	N/A	Bob Khamisa	N/A
National Coordinator, Maternal Infant and Child Health, HIV/Nutrition/Malaria and Tuberculosis	N/A	N/A	N/A	N/A
Development, Planning and Cooperation	N/A	N/A	N/A	N/A

This information is based on an internet search.

Table C.9 (CONTINUED)

Minister Position	June 2009		August 2010	
	Name	Birthplace/electorate	Name	Birthplace/electorate
<i>President of the Republic of Malawi</i>	Bingu wa Mutharika	Thyolo	Bingu wa Mutharika	Thyolo
<i>Vice President</i>	Joyce Banda	Zomba	Joyce Banda	Zomba
<i>2nd Vice President</i>	N/A	N/A	Nicholas Dausi	N/A
<i>Irrigation and Water Development</i>	Ritchie Bizwick Muyewa	Mulanje	N/A	N/A
<i>Finance</i>	Ken Kandodo	Kasungu	Ken Kandodo	Kasungu
<i>Economic Planning and Development</i>	N/A	N/A	Abbie Shaba	Mzimba
<i>Local Government and Rural Development</i>	Anna Kachikho	Phalombe	Anna Kachikho	Phalombe
<i>Justice and Constitutional Affairs</i>	Peter Mutharika	Thyolo	George Chaponda	Mulanje
<i>Industry, Science and Technology</i>	George Chaponda	Mulanje	Peter Mutharika	Thyolo
<i>Agriculture and Food Security</i>	Bingu wa Mutharika	Thyolo	Peter Mwanza	Mzimba
<i>Education and Human Resources</i>	Leckford Thotho	Dowa	Vuwa Symon Kaunda	N/A
<i>Lands, Housing and Surveys</i>	Peter Mwanza	Mzimba	John Bande	N/A
<i>Transport and Public Works</i>	Khumbo Kachali	Mzimba	Sidik Mia	Chikwawa
<i>Tourism, Wildlife and Culture</i>	N/A	N/A	Ken Lipenga	Phalombe
<i>Labour and Vocational Training</i>	Yunus Mussa	Zomba	Yunus Mussa	Zomba
<i>Trade and Private Sector Development</i>	Eunice Kazembe	Chiradzulu	Eunice Kazembe	Chiradzulu
<i>Health</i>	Moses Chirambo	Rumphi	Jean Kalilani	Dowa
<i>Foreign Affairs</i>	Etta Elizabeth Banda	Nkhata Bay	Etta Elizabeth Banda	Nkhata Bay
<i>Home Affairs and Internal Security</i>	Aaron Sangala	Blantyre	Aaron Sangala	Blantyre
<i>Mines, Natural Resources and Environmental Affairs</i>	Grey Malunga	N/A	Grain Malunga	N/A
<i>Women, Child Welfare and Community Services</i>	Patricia Kaliati	Mulanje	Theresa Mwale	Mchinji
<i>Youth, Sports and Culture</i>	Lucius Kanyumba	Ntcheu	Simon Vuwa Kaunda	N/A
<i>Presidential and parliamentary affairs</i>	N/A	N/A	N/A	N/A
<i>Social Development and Persons with Disabilities</i>	Bessie Reen Kachere	Neno	Reen Kachere	Neno
<i>Defence</i>	Sidik Mia	Chikwawa	Leckford Thotho	Dowa
<i>National Coordinator, Maternal Infant and Child Health, HIV/Nutrition/Malaria and Tuberculosis</i>	Callista Mutharika	Zomba	Callista Mutharika	Zomba
<i>Development, Planning and Cooperation</i>	Abbie Shaba	Mzimba	N/A	N/A

This information is based on an internet search.

Table C.2 Indicator variable for Malawian minister birthplaces from 2005 to 2010

An indicator variable for each district is equal to 1 if any current Malawian minister was born in district i, otherwise zero. If this information was unavailable, then that minister's electorate was used instead. Note that Neno and Mwanza are included here, despite the fact that they were used as one district in the night light cluster analysis.

	<i>District</i>	<i>August 2005</i>	<i>November 2007</i>	<i>June 2009</i>	<i>August 2010</i>
1	Dedza	1	0	0	0
2	Dowa	0	0	1	1
3	Kasungu	0	0	1	1
4	Lilongwe	1	0	0	0
5	Mchinji	0	0	0	1
6	Nkhotakota	1	1	0	0
7	Ntcheu	0	0	0	0
8	Ntchisi	0	0	0	0
9	Salima	0	0	0	0
10	Chitipa	0	0	0	0
11	Karonga	0	0	0	0
12	Likoma	0	0	0	0
13	Mzimba	1	1	1	1
14	Nkhata Bay	1	0	1	1
15	Rumphi	0	0	1	0
16	Balaka	0	0	0	0
17	Blantyre	0	0	1	1
18	Chikwawa	1	0	1	1
19	Chiradzulu	1	1	1	1
20	Machinga	0	0	0	0
21	Mangochi	1	0	0	0
22	Mulanje	1	1	1	0
23	Mwanza	1	0	0	0
24	Nsanje	0	0	0	0
25	Thyolo	1	1	1	1
26	Phalombe	1	1	1	1
27	Zomba	0	1	1	1
28	Neno	0	0	1	1

Note that August 2005 is used for 2005 and 2006, November 2007 is used for 2007 and 2008, June 2009 is used for 2009 and August 2010 is used for 2010.

Appendix D. Rainfall data

Table D.1 Precipitation data over Malawi from 2005 to 2010

Rainfall data measured in millimetres. Note that precipitation data for a given year includes January-April and October-December precipitation only. Note that Neno district is included in Mwanza district.

	<i>District</i>	<i>2005</i>	<i>2006</i>	<i>2007</i>	<i>2008</i>	<i>2009</i>	<i>2010</i>
1	<i>Dedza</i>	612.3	894.9	884.8	1349.8	878.2	1034.1
2	<i>Dowa</i>	602.4	825.0	962.3	909.9	768.7	882.5
3	<i>Kasungu</i>	505.5	830.0	1100.5	583.7	730.3	831.6
4	<i>Lilongwe</i>	599.4	1014.8	996.0	921.7	945.6	895.4
5	<i>Mchinji</i>	717.0	990.1	1099.3	1032.0	1098.3	877.1
6	<i>Nkhotakota</i>	880.4	1262.3	1415.2	1243.0	1298.2	1172.3
7	<i>Ntcheu</i>	816.7	1195.2	967.1	1299.4	898.0	961.1
8	<i>Ntchisi</i>	424.8	756.3	1208.1	921.9	967.5	800.9
9	<i>Salima</i>	661.1	1725.5	1520.4	1351.7	850.1	2486.4
10	<i>Chitipa</i>	785.2	1019.6	779.7	699.7	1035.2	853.2
11	<i>Karonga</i>	824.4	1187.7	870.5	1267.7	1201.4	922.9
12	<i>Likoma</i>	632.6	906.4	1016.3	862.5	927.1	714.7
13	<i>Mzimba</i>	632.6	906.4	1016.3	862.5	927.1	714.7
14	<i>Nkhata Bay</i>	877.0	1493.1	969.6	1405.1	1252.3	1227.7
15	<i>Rumphi</i>	582.1	630.2	875.0	668.2	777.4	517.7
16	<i>Balaka</i>	657.3	1166.7	1026.9	1020.7	988.2	962.5
17	<i>Blantyre</i>	607.1	1179.6	1115.2	916.4	1027.7	1370.5
18	<i>Chikwawa</i>	462.0	757.8	1514.2	632.9	535.3	842.4
19	<i>Chiradzulu</i>	583.8	1162.8	1121.0	814.6	940.6	1276.1
20	<i>Machinga</i>	655.8	1044.0	1121.4	964.5	985.4	1034.5
21	<i>Mangochi</i>	546.6	1156.3	1062.1	1059.5	954.3	750.4
22	<i>Mulanje</i>	1128.8	1994.0	2052.9	1646.6	1751.8	1388.0
23	<i>Mwanza</i>	719.1	757.8	1274.9	1009.4	932.7	1025.6
24	<i>Nsanje</i>	488.1	732.6	1336.7	802.3	681.7	652.5
25	<i>Thyolo</i>	518.8	1397.2	1518.4	891.2	1107.2	1136.7
26	<i>Phalombe</i>	637.2	1516.7	1095.7	1152.5	1119.3	1249.6
27	<i>Zomba</i>	805.7	1276.5	1379.2	933.4	1073.9	1056.2

Source: World AgroMeteorological Information Service

<http://www.wamis.org/countries/malawi.php>

Appendix E. Sample selection model

A recent methodology developed by Semykina and Wooldridge (2010) could be applied to the panel dataset in order to correct for sample selection bias caused from unobserved heterogeneity and endogenous explanatory variables. In this case, the endogenous explanatory variables are the lagged dependant variable and aid. The Semykina and Wooldridge methodology is conducted in two steps. First, year-specific Probit regressions are run on the binary dependant variable, $ifsum_{i,t}$. Second, a pooled two-stage least squares model using strictly positive values of light is estimated. However, the perfect fit of the Probit equations means that the selection is exogenous, so there is no sample selection bias. Therefore, I stop short of applying the Semykina and Wooldridge methodology. The following year-specific Probit regressions are used to model the dependant binary variable, $ifsum_{i,t}$ which is equal to 1 if $lsum_{i,t} > 0$, otherwise 0:

$$P(ifsum_{i,t} = 1) = \Phi(E[y_{i,t}]), \quad (E.1)$$

$$ifsum_{i,t} = \alpha_t + \beta \cdot ifaid_{i,t} + \varphi \cdot minister_{i,t} + \chi \cdot ifsum0_{i,0} + u_{i,t} \quad (E.2)$$

where $\Phi(\cdot)$ is a cumulative normal density function and $ifaid_{i,t}$ is an indicator variable equal to one if a geocoded aid project is in night light cluster i in year t , otherwise zero. Normally, an inverse Mills ratio (IMR) is produced from the year-specific Probit regression. An IMR is a ratio of the normal density function and the cumulative normal density function (Greene, 2003). An IMR variable would be included as an explanatory variable in the remainder of the Semykina and Wooldridge methodology. However, it is found that $lsum0_{i,0}$, along with $ifaid_{i,t}$ and $minister_{i,t}$, perfectly predicts $ifsum_{i,t}$. This result is the same across each year of the sample period. As the explanatory variables in equation E.2 are exogenous, the sample selection effect is weakly exogenous. There is no need to adjust any model fitted to strictly positive values of $lsum_{i,t}$ for sample selection bias. In other words, there is no need to apply the methodology developed by Semykina and Wooldridge (2010) based on the perfect prediction results in the year-specific Probit regressions.

Appendix F. Malawian minister instrument

I attempted to create an instrumental variable to control for any potential endogeneity. However, a problem arises when the instrumental variable is weak and has no correlation with the endogenous variable (Wooldridge, 2009). The motivation for creating this instrument came from Hodler and Raschky (2010) who study whether foreign aid encourages favouritism by analysing the birthplaces of current political leaders and night light emissions from those birthplaces. Therefore, included in this thesis is a *minister* variable which attempts to account for a possible aid flow bias to the birthplace or electorate of a Malawian minister.

A dynamic panel model is fitted for each *ongoing aid* variable on the *minister_{i,t}* indicator variable, plus *rainfall_{i,t}* and *year_t*. The purpose is to assess the strength of the *minister_{i,t}* as an instrument. The motivation for this is that the allocation of aid may be influenced by which minister is currently holding a position in the Malawian cabinet:

$$y_{i,t}^1 = \alpha_i + \beta \cdot y_{i,t-1}^1 + \varphi_1 \cdot \text{minister}_{i,t} + \varphi_2 \cdot \text{minister}_{i,t-1} + \theta \cdot \text{rainfall}_{i,t} + \psi_t + \varepsilon_{i,t} \quad (\text{F.1})$$

$$y_{i,t}^2 = \alpha_i + \beta \cdot y_{i,t-1}^2 + \varphi_1 \cdot \text{minister}_{i,t} + \varphi_2 \cdot \text{minister}_{i,t-1} + \theta \cdot \text{rainfall}_{i,t} + \psi_t + \varepsilon_{i,t} \quad (\text{F.2})$$

$$y_{i,t}^3 = \alpha_i + \beta \cdot y_{i,t-1}^3 + \varphi_1 \cdot \text{minister}_{i,t} + \varphi_2 \cdot \text{minister}_{i,t-1} + \theta \cdot \text{rainfall}_{i,t} + \psi_t + \varepsilon_{i,t} \quad (\text{F.3})$$

where ψ_t is a year fixed effect and ε_t is an error term. Here, only one lag is used on the *ongoing aid* variables and *minister* in order to maximise the number of observations in the sample. Equations F.1, F.2 and F.3, two sets of GMM-instruments are used. First, the models in Table F.1 use *lsum* and *wlsum1* as GMM-instruments for both the differenced and level equations. Second, the models in Table F.2 use *lsum* and *wlsum2* as GMM-instruments for both the differenced and level equations. In the differenced equation, levels of *lsum* and each of the two *wlsum* variables are used with their lags from 3 onwards. In the levels equation, differences of the first lags from *lsum* and each of the two *wlsum* variables are used. In each

differenced and level equation, each respective *ongoing aid* variable, *minister*, *rainfall* and *year* are instruments. The over-identifying moment conditions in the models presented in Tables F.1 and F.2 are all valid at the 5 percent level of significance, based on not rejecting the null hypothesis of the Sargan test in each model. The Arellano and Bond test for no autocorrelation at order two in the first differenced errors is not significant, suggesting that the moment conditions in the models displayed in Tables F.1 and F.2 are valid at the 5 percent level of significance.

The results from this model allow one to examine the suitability of *minister* as an instrumental variable for ongoing aid. I find that $minister_{i,t}$ is a weak instrument for ongoing aid. Not surprising is the coefficients on the lagged dependant variables, which all display values close to unity. Of interest is $minister_{i,t}$ and $minister_{i,t-1}$. These variables are not significant even at the 10 percent level of significance. Based on this, there is little evidence to show that $minister_{i,t}$ is a suitable instrument for ongoing aid. This is consistent with Nunnenkamp, Öhler and Sosa Andrés (2012), whose dependant variable is the number of World Bank aid projects within a particular district in India from 2006 to 2011. They find that the inclusion of a *minister* dummy variable, named ‘Chief Minister constituency’ for possible political patronage is not significant.

Therefore, ongoing aid is regressed on *minister* due to the hypothesis that a minister of the Malawian government may be able to influence which towns or villages receive aid projects. In the models shown in Tables F.1 and F.2, I find that all 2009 dummies are statistically significant and display a negative coefficient. This means that the amount of aid projects in a town or village post 2009 was significantly lower than the amount of aid projects in a town or village prior to 2009. A possible answer to this discovery is the GFC of 2007/2008 that may have had an indirect and negative effect on aid projects in Malawi.

Table F.1 Dynamic panel model for ongoing aid from 2005 to 2010

A dynamic panel model using lsum and wsum1 as GMM-instruments for the differenced and level equations.

Ongoing aid	Ongoing aid: y1				Ongoing aid: y2				Ongoing aid: y3			
	<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>	
<i>constant</i>	0.007	0.027	0.803		0.006	0.064	0.920		-0.011	0.013	0.412	
$y^1(i,t-1)$	0.922	0.061	0.000	***								
$y^2(i,t-1)$					1.129	0.094	0.000	***				
$y^3(i,t-1)$									1.055	0.031	0.000	***
<i>minister(i,t)</i>	0.034	0.027	0.199		0.028	0.021	0.190		0.007	0.006	0.285	
<i>minister(i,t-1)</i>	-0.012	0.015	0.425		-0.060	0.037	0.108		-0.019	0.012	0.126	
<i>rainfall(i,t)</i>	-0.003	0.002	0.101		-0.002	0.002	0.236		-0.001	0.000	0.220	
<i>2005</i>												
<i>2006</i>	-0.033	0.043	0.439		-0.006	0.019	0.759		0.004	0.004	0.235	
<i>2007</i>												
<i>2008</i>	0.007	0.007	0.266		0.026	0.014	0.065		0.002	0.004	0.658	
<i>2009</i>	-0.022	0.011	0.042	**	-0.047	0.020	0.020	**	-0.017	0.005	0.001	***
<i>2010</i>	-0.017	0.011	0.120		-0.039	0.016	0.016		-0.010	0.005	0.049	
Observations			278				278				278	
Sargan test ¹	<i>chi2(17)</i>		<i>p-value</i>		<i>chi2(17)</i>		<i>p-value</i>		<i>chi2(17)</i>		<i>p-value</i>	
	0.914		1.000		5.483		0.996		11.549		0.827	
Arellano and Bond test ²	<i>z</i>		<i>p-value</i>		<i>z</i>		<i>p-value</i>		<i>z</i>		<i>p-value</i>	
<i>Order-1</i>	-1.898		0.058		-2.353		0.019		-3.239		0.001	
<i>Order-2</i>	1.306		0.192		-0.257		0.797		0.729		0.466	

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

¹ The null hypothesis is that the instrumental variables are not correlated with the residuals.

² The null hypothesis is that the errors in the first differenced equation display no second order autocorrelation.

Table F.2 Dynamic panel model for ongoing aid from 2005 to 2010

A dynamic panel model using lsum and wsum2 as GMM-instruments for the differenced and level equations.

<i>Ongoing aid</i>	<i>Ongoing aid: y1</i>				<i>Ongoing aid: y2</i>				<i>Ongoing aid: y3</i>			
	<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>	
<i>constant</i>	0.060	0.038	0.110		0.039	0.057	0.493		0.011	0.012	0.375	
<i>y1(i,t-1)</i>	0.948	0.063	0.000	***								
<i>y2(i,t-1)</i>					1.154	0.077	0.000	***				
<i>y3(i,t-1)</i>									1.087	0.028	0.000	***
<i>minister(i,t)</i>	0.051	0.041	0.207		0.038	0.027	0.166		0.006	0.006	0.260	
<i>minister(i,t-1)</i>	-0.043	0.029	0.132		-0.076	0.041	0.067		-0.017	0.011	0.118	
<i>rainfall(i,t)</i>	-0.002	0.002	0.136		-0.002	0.002	0.414		0.000	0.000	0.294	
<i>2005</i>												
<i>2006</i>	-0.035	0.045	0.443		-0.004	0.021	0.842		0.004	0.004	0.303	
<i>2007</i>												
<i>2008</i>	0.002	0.010	0.843		0.025	0.017	0.152		0.002	0.004	0.716	
<i>2009</i>	-0.033	0.018	0.064	*	-0.053	0.019	0.005	***	-0.016	0.004	0.000	***
<i>2010</i>	-0.023	0.013	0.072	*	-0.042	0.015	0.004	***	-0.010	0.004	0.017	**
Observations	278				278				278			
Sargan test ¹	<i>chi2(17)</i>		<i>p-value</i>		<i>chi2(17)</i>		<i>p-value</i>		<i>chi2(17)</i>		<i>p-value</i>	
	0.909		1		5.817		0.994		13.068		0.732	
Arellano and Bond test ²	<i>z</i>		<i>p-value</i>		<i>z</i>		<i>p-value</i>		<i>z</i>		<i>p-value</i>	
<i>Order-1</i>	-1.130		0.259		-2.334		0.020		-3.410		0.001	
<i>Order-2</i>	-1.067		0.286		-0.204		0.838		1.097		0.273	

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

¹ The null hypothesis is that the instrumental variables are not correlated with the residuals.

² The null hypothesis is that the errors in the first differenced equation display no second order autocorrelation.

Appendix G. Fixed effects model in differences

Based on the coefficients on the lagged dependant variables in Table 5.8, where aid is treated as endogenous with *wlsum1* included as an explanatory variable, there is a need for a model in differences. In other words, the coefficient on the lagged dependant variables is close to unity: $\beta \approx 1$. Therefore, a model in differences would eliminate the need for the lagged dependant variable:

$$\Delta lsum_{i,t} = \alpha_i + \varphi \cdot \Delta wlsum1_{i,t} + \vartheta \cdot \Delta x_{i,t}^2 + \omega \cdot \Delta x_{i,t}^3 + \theta \cdot rainfall_{i,t} + \psi_t + \varepsilon_{i,t} \quad (G.1)$$

$$\Delta lsum_{i,t} = \alpha_i + \varphi \cdot \Delta wlsum1_{i,t} + \vartheta \cdot \Delta x_{i,t}^2 + \omega \cdot \Delta x_{i,t}^3 + \tau \cdot \Delta y_{i,t}^2 + \theta \cdot rainfall_{i,t} + \psi_t + \varepsilon_{i,t} \quad (G.2)$$

$$\Delta lsum_{i,t} = \alpha_i + \varphi \cdot \Delta wlsum1_{i,t} + \xi \cdot \Delta x_{i,t}^1 + \delta \cdot \Delta x_{i,t}^4 + \theta \cdot rainfall_{i,t} + \psi_t + \varepsilon_{i,t} \quad (G.3)$$

$$\Delta lsum_{i,t} = \alpha_i + \varphi \cdot \Delta wlsum1_{i,t} + \xi \cdot \Delta x_{i,t}^1 + \delta \cdot \Delta x_{i,t}^4 + \eta \cdot \Delta y_{i,t}^1 + \theta \cdot rainfall_{i,t} + \psi_t + \varepsilon_{i,t} \quad (G.4)$$

where ψ_t is a year fixed effect and ε_t is an error term. A standard fixed effects in differences estimator is used to estimate $lsum_{i,t}$. The explanatory variables that are treated as endogenous in these models are $\Delta wlsum1_{i,t}$ and $\Delta Aid\ Combination_{i,t}$ which are instrumented by $wlsum_{i,t-1}$, each $Aid\ Combination_{i,t-1}$, $minister_{i,t}$, $rainfall_{i,t}$ and $year_t$. Table G.1 shows the significance of $\Delta wlsum1_{i,t}$ at the 1 percent level of significance which indicates a high spatial correlation of changes in the weighted light intensity values of all other night light clusters. However, one must pay attention to the fact that fixed effects are contributing to this fit too. These models show that no differenced aid variable is significant when $\Delta wlsum1_{i,t}$ is used as an explanatory variable. However, this confirms a highly negative spatial correlation in night light intensity between towns or villages. This suggests there is a randomly negative allocation of people or resources over the sample period.

Table G.1 Fixed effects in differences model from 2005 to 2010

Treating the total spatial variable and aid as endogenous. Lags of wlsun1, aid and minister are used as instruments.

<i>Δsum</i>	<i>Aid combination 1</i>				<i>Aid combination 2</i>				<i>Aid combination 3</i>				<i>Aid combination 4</i>			
	<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>		<i>coeff.</i>	<i>s.e.</i>	<i>p-value</i>	
<i>constant</i>	79.582	1.577	0.000	***	79.605	1.553	0.000	***	79.638	1.528	0.000	***	79.624	1.535	0.000	***
<i>Δ wlsun1 (i,t)</i>	-2.219	0.045	0.000	***	-2.219	0.044	0.000	***	-2.222	0.043	0.000	***	-2.221	0.043	0.000	***
<i>Δ x¹ (i,t)</i>									1.245	3.221	0.699		7.147	14.155	0.614	
<i>Δ x² (i,t)</i>	-0.045	0.196	0.819		-0.101	0.253	0.690									
<i>Δ x³ (i,t)</i>	-0.036	0.137	0.794		-0.067	0.157	0.669									
<i>Δ x⁴ (i,t)</i>									0.004	0.007	0.566		0.005	0.008	0.547	
<i>Δ y¹ (i,t)</i>													0.111	0.238	0.640	
<i>Δ y² (i,t)</i>					-0.190	0.541	0.725									
<i>rainfall (i,t)</i>	-0.004	0.003	0.139		-0.005	0.003	0.129		-0.004	0.003	0.115		-0.004	0.003	0.141	
<i>2005</i>																
<i>2006</i>	-44.223	0.880	0.000	***	-44.228	0.868	0.000	***	-44.252	0.852	0.000	***	-44.248	0.856	0.000	***
<i>2007</i>	-93.029	1.855	0.000	***	-93.042	1.824	0.000	***	-93.109	1.790	0.000	***	-93.098	1.798	0.000	***
<i>2008</i>	-30.703	0.604	0.000	***	-30.700	0.599	0.000	***	-30.722	0.586	0.000	***	-30.719	0.589	0.000	***
<i>2009</i>	-111.700	2.232	0.000	***	-111.715	2.189	0.000	***	-111.810	2.147	0.000	***	-111.795	2.156	0.000	***
<i>2010</i>																
Observations	278				278				278				278			
R-squared overall	0.969				0.966				0.970				0.970			
Regression s.e.	0.299				0.299				0.299				0.299			
F-test ¹	<i>F(68,201)</i>		<i>p-value</i>		<i>F(68,200)</i>		<i>p-value</i>		<i>F(68,201)</i>		<i>p-value</i>		<i>F(68,200)</i>		<i>p-value</i>	
	2.320		0.000		2.250		0.000		2.350		0.000		2.320		0.000	

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

¹ The null hypothesis is that all u_i are equal to zero.