Do Differences in Average Happiness Levels Cause Migration? Evidence from Germany.

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Draft Version

Abstract

Models of migration assume that geographical utility differences result in migration flows. Using German panel data from 1992 to 2006 evidence is sought for a causal relationship between Bundesländer level population change and Bundesländer level utility differences. Initial regressions assuming a linear relationship give rise to problems of inappropriate functional form and heteroscedasticity. Instead, a multiple ranks transformation technique is offered as a simple alternative to searching for the correct model specification. A significant bi-directional causality relationship is found to exist between happiness differences and population change in Germany. Happiness is positive and significant in causing population change implying the use of migration as a tool to raise utility. This is better explained by emigration from unhappier Bundesländer rather than immigration to the happiest ones. There is also evidence of reverse causality: Population inflows appear to increase the happiness of Bundesländer. This sits uneasily with hedonic theory whereby population rises should place upward pressure on house prices and downward pressure on wages and consequently decrease happiness. Tests are expanded further by spatially adapting utility differences. However, it is found that this weakens the causality relationship in both cases rather than adding explanatory power.

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INTRODUCTION

The last ten years has seen an unprecedented increase in the use of subjective well-being levels in economics. Their purpose is to allow individuals to self-report their perceived level of well-being on an integer scale rather than assuming it follows traditional economic indicators such as GDP of GDP per capita. Since Easterlin's seminal 1974 paper on the relationship between income and happiness, its study remained on the fringe of economic research. However, recent years has seen a dramatic rise in the interest attached to the potentially powerful information that happiness data may hold. Subjective well-being, happiness and utility are assumed to have the same understanding. Happiness scales provide the researcher with a simple utility scale where the question[2] asked intuitively requires individuals to account for economic and non-economic factors that influence their happiness. This allows a potentially infinite quantity of variables and still fuels the debate as to what makes people happy, or maybe more importantly, what makes them unhappy.

Self-reported happiness scales are an attractive, simple method of enabling researchers to measure an individual's subjective utility. However, they have been a neglected area of economic research despite being employed by psychologists for many years. In the context of migration caused by utility differences, indicators such as wage rates, house prices and unemployment rates have been assumed sufficient. Whilst undoubtedly important, there is still risk in omitting relevant variables. The difference with happiness scales are that they

[2] The following question is asked in the survey used, "How satisfied are you with your life, all things considered?" This is answered on a 0 to 10 integer scale, where 0 means completely dissatisfied and 10 means completely satisfied.

can measure utility itself rather than just what are considered the important contributory elements.

This paper aims to contribute to the current literature on happiness by focusing on the causal relationship that may exist between happiness and migration. Are regional differences in happiness levels causing population change to occur or is a change in population leading to significant changes in happiness? These hypotheses are tested across the 16 Federal States or 'Bundesländer' of Germany using annual average happiness data between 1992 and 2006, obtained from the German Socio-Economic Panel. Happiness differences are calculated by subtracting mean national happiness across the time period from average happiness scores. A spatial element of analysis is also incorporated by differencing average happiness of neighbouring Bundesländer from each Bundesländer's average happiness score. The negative association between migration and distance should make neighbouring Bundesländer relatively more important than using national average happiness differences. These relationships are examined first using linear parametric techniques which are replaced in favour of semi-parametric and non-parametric alternatives; the multiple ranks transformation and contingency tables.

It is believed that migration should occur between Bundesländer corresponding to differences in average happiness levels. However, increased migration to a Bundesländer is in turn also likely to impact on happiness as it exerts pressure on wage rates, house prices and unemployment. To anticipate the results it there is a positive and significant relationship implying happiness differentials cause population change. The source of this is the effort of the least happy to improve their well-being. Bundesländer reporting lower average happiness experience a fall in population, hence net outward migration. However, Bundesländer exhibiting higher average happiness do not receive significantly more migrants. Thus, unhappiness is acting as a motivation for out-migration but migrants are not heading for areas of highest happiness. There appears to be a stronger relationship indicating rises in population have a positive impact on happiness. Bundesländer with greater than average population changes are experiencing higher levels of happiness. This contradicts economic intuition as immigration puts upward pressure on the housing market whilst rises in the supply of labour should push down wages. Both would expect a resultant fall in happiness.

This paper focuses its interest on the German national population. All data on foreign migrants is disregarded, though this reflects a small proportion of the sample size. It is possible that foreign immigrants may consider different motives for happiness compared to domestic migrants due to working ethics, cultural barriers or integration issues. A foreign immigrant from a poorer country may place greater weight on income in their overall reported happiness than a German national. By analysing one specific set of individuals, we hope to minimise any degree of spurious causality that could impact on our results.

The paper is structured as follows. Section 2 reviews the literature, comparing different methods to modelling migration. It introduces happiness scales, the influence it may play in migration and the Granger concept of causality. Section 3 introduces the data sources. Section 4 presents the econometric analysis and derives spatially adjusted differences in happiness. Section 5 describes the econometric procedure followed to derive an optimal regression model specification and the results are analysed. Section 6 concludes.

2. LITERATURE REVIEW

A search of the literature was carried out using the 'EconLit' search tool. Principal searches were carried out in 'Happiness', 'Subjective Well-being', 'Happiness and Migration', 'Subjective Well-being and Migration', 'German Migration', 'Unemployment and Happiness' and 'Happiness and Causality'. Searches were unfiltered with the above keywords to ensure no papers were unduly overlooked. 'Happiness' returned 444 articles compared to 'Subjective Well-being' that offered 147. 'Happiness and Migration' and 'Subjective Well-being' returned 32 and 21 results respectively. Of these only one paper by Knight and Gunatilaka (2007) seemed of any relevance, conducting a study of subjective well-being of rural-urban migrants in China. However, it focuses on the paradox of rural-urban migrants reporting lower average happiness scores than their rural counterparts and the existence of biased expectations. The combined search of 'Happiness and Causality' returned only one article, Frey and Stutzer's 2005 paper on happiness and marriage, again of little relevance in context of migration[3]. Nonetheless, as separate entities, migration and happiness have been widely studied and it is from this that a case is formed for testing the existence of a relationship between the two.

This literature review provides a brief discussion of the important theoretical and empirical models developed to determine what causes migration to occur. Objective models[4] that typically examine the relationship between migration, unemployment rates, wage rates and house prices are discussed. Happiness scales are introduced as a subjective measure of

[3] These searches were undertaken on 15/01/2008.
[4] The use of the word objective has recently been adopted by Happiness Economists as a means to distinguish between more traditional economic measures and subjective well-being measures. For a more in depth discussion see Easterlin and Zimmerman (2006).

utility. They are a direct response from the individual which is equivalent to a self reported level of utility. Research on German migration is reviewed and the theoretical background of Granger Causality is introduced.

2.1 Traditional model

The topic of migration is a highly documented area of Economics. Economic factors, such as unemployment, wage rates and house prices have principally been utilized to determine the factors which create the greatest incentives to migrate. Early research such as Sjaastad (1962) and Greenwood (1975) focus on wage rates and the decision to migrate motivated by an individual's ability to earn more in a different place. An individual will migrate if the benefits of the present value of all future earnings of another region minus the costs associated with the move are greater than their current location. Distance is likely to increase the costs of migration and is a key limiting factor in this model. Greenwood (1975) represents the present value of investment in migration from location 'i' to 'j' as follows:

$$PV_{ij} = \sum_{t=1}^{n} \frac{E_{jt} - E_{it}}{(1+r)^t} - \sum_{t=1}^{n} \frac{C_{jt} - C_{it}}{(1+r)^t}$$

Where E_{it}, E_{jt} are the earnings stream in locations 'i' and 'j' respectively

C_{it}, C_{jt} are the costs associated with living in each location

r is the discount rate and t a time trend.

An individual will only migrate if the present value of location ‘j’ is greater than their current location ‘i’, hence if PV_{ij} is positive.

This early model offers a basic understanding of migration modelling but needs to be expanded in three ways. Firstly, the migration decision is unlikely to consider only their current region of residence and a single location of destination. Location ‘j’ should consist of all other possible migration options with the location offering the highest overall return being the final destination. Secondly, future earning streams can only be based on expectations and so an element of uncertainty must be involved to account for risk. Thirdly, the existence temporary migration implies that in some cases the present value of migration can be very high, or at least the costs associated with it are not high enough to create any significant barriers.

Greenwood et al (1991) discuss the uses of both gross and net migration in empirical research. Gross migration gives an individual migrant’s choice processes and reveals the determinants of migratory behaviour, which may be displayed by factors such as wage rates or environmental attributes. Net migration is gross out-migration minus gross in-migration. More desirable areas should therefore experience net in-migration (i.e. gross out-migration minus gross in-migration is negative). Population change provides collective information on the movement of migrants in and out of each Bundesländer. It therefore reveals whether net in- or out-migration has occurred across the time series. However, it is important to note that migration and population change are not perfectly synonymous since the latter includes a natural increase measure of births and deaths.

2.2 Local Labour and Housing Markets

Migration is a complex area of research, with many possible causes. Understanding local labour markets is essential as factors like wage rates, employment and house prices have major impacts on whether and where one can migrate. Unemployment theory as a motive for migration is a push factor to areas with high employment levels. DaVanzo (1977) accounts for the impact of unemployment by dividing head of households into three groups: unemployed, employed searching for new jobs and employed not searching for jobs. She finds that unemployment rates do affect out-migration rates, but only in the unemployed category. Herzog et al (1993) survey the empirical literature on US unemployment migration and find in almost all cases being unemployed significantly increases the likelihood of migration. High unemployment across Germany makes this a potentially very influential factor. Data available from the German Statistical Office on unemployment rates show large differences between East and West Germany. Between 1992 and 2006 East German unemployment averaged 18.39% compared to 9.96 % in West Germany, almost twice the level.

House prices are intuitively believed to have an opposite effect to wage rates. Higher house prices increase the costs of migration. However, Thomas (1993) finds, for those with jobs who move, house prices have no significant effect. Yet when non-job movers are considered, house prices become highly significant. House prices provide an interesting area of research as regional mobility is likely to be highly dependent on economic conditions and consumer confidence. Cameron et al (2003) find house prices to be significant in the migration decision, that high house prices deter and lower prices attract.

They also consider the existence of the commuter by comparing house prices in neighbouring regions to the average of all regions. Their results suggest a trend that individuals are subject to living in regions with relatively lower house prices and commuting to work in areas with relatively higher house prices with better wage rates.

The hedonic technique reveals preferences for particular amenities and how much an individual is willing to accept lower wages or pay higher house rents to enjoy them, eliminating the net advantages of different location. Rosen (1974) and Roback (1982) are pioneering papers on the development of the hedonic theory, which has become popularized as research into non-marketed amenities expands. Whilst wage rates, unemployment and house prices are key in understanding local markets, the negative impacts of air or noise pollution or the positive impact of national parks of areas or natural beauty, to name but a few, are also elements that need consideration. Smith and Huang (1993) test the hypothesis that air pollution has and negative impact on house prices using data obtained from hedonic studies over the previous 25 years. They find the hedonic technique has been successful in showing that high levels of air pollution puts downward pressure on house prices. This signifies households do reveal a value for environmental amenities in their preferences for housing location.

2.3 Happiness

Happiness in economics has historically, until recently, been the subject of far less empirical research. However, the last ten years has seen an explosion in the use of self-reported happiness scales may hold was realised. Easterlin (1974), widely credited as the pioneer of happiness economics, strived to discover whether there exists an association between income levels and self-reported happiness. He found that intra-country comparisons reveal a strong positive relationship whereas international comparisons and time series data had no clear relationship. Easterlin (1995) strongly rejects the notion rises in income over time lead to rises in happiness. Instead it is that rises in relative income compared to individual's counterparts are more important. Ng (1997) argues that once income levels are adequate enough to care for basic needs then striving for further consumption can actually lead to reductions in our happiness through stress or weight related illness.

The relative income debate, now widely known as the 'Easterlin Paradox', has become the centre of recent happiness research, to try and determine the true impact income has on subjective well-being. Frijters et al (2004) test this theory using time series data in post reunification East Germany. They find that real income does appear to lead to gains in life satisfaction but it is more predominant in the immediate post-reunification years. Clark et al (2008) analyse aggregate time series data and argue it masks the true relationship between income and happiness when compared to specific points in the time period. They assume happiness to be diminishing as income rises, reducing the gradient of the curve in the income-happiness space. At any point in time the richest report greater than average happiness and the poorest less than average but the smoothing effect of the time series aggregate data hides this. The result is that importance of income explaining happiness becomes significantly underestimated. Di Tella and MacCulloch (2008) prefer the explanation that the insignificance of absolute income in determining happiness is not a paradox in itself but simply due to an omission of more important microeconomic measures.

Components of individual preference include proxy's for a work-leisure trade off, environmental quality, crime and health to name a few. Their results suggest that income is not necessarily as important in determining happiness as one might expect.

The sole importance of income as an economic indicator has been questioned as a sufficient measure of happiness. Some research has assessed the possible significance of relative/absolute consumption (Alpizar et al, 2005) and relative wealth and consumption (Headey et al, 2008). The latter use subjective well-being data for five countries to determine if wealth and consumption add explanatory power in life satisfaction compared to income alone (although consumption data is only available for two countries). They find that considering income as a single indicator causes only a fraction of the variance to life satisfaction when wealth and consumption are also included. An OLS regression[5] accounting for objective controls finds wealth to be at least as important as income whereas consumption seems much more country dependent. However, the fact that only two countries (Britain and Hungary) had consumption data available makes a firm conclusion on this impossible. Nevertheless, it provides evidence that perhaps measuring income alone can not fully capture ones happiness.

Happiness data has also been applied to unemployment levels to assess the effect of exogenous economic conditions on subjective well-being. This is to determine whether people may choose to be unemployed in order to receive welfare benefits or if it is actually a source of unhappiness. Clark and Oswald (1994) examine the effect of unemployment on

[5] Headey et al (2008) find their results to be very similar whether using OLS or a more standard ordered probit model, more commonly found in Happiness studies.

happiness. Unemployment is found to be statistically significant and negatively correlated with happiness. Factors such as age and level of education are disaggregated to determine what contributes more to lower subjective well-being. Those unemployed in their thirties and with a higher degree of education are least happy. Di Tella et al (2001) concur by finding lower unemployment and inflation appears to make people happier. A comprehensive study by Blanchflower and Oswald (2004) find similar results and attach dollar values to compensate for varying levels of happiness. To compensate American men exactly for unemployment is calculated to require a rise in income of about $60,000 per annum.

2.4 Why Germany?

Germany offers an attractive setting to test the relationship between happiness and migration. Until 1991 there was a closed frontier between a wealthier, open Western Germany and a poorer, closed Eastern Germany. Reunification has allowed unhindered migration to take place. Migration research in Germany therefore tends to be focused on East-West migration, particularly on wage rate and unemployment level convergence (for example see Burda, 1993; Burda et al; 1998; Parikh and Van Leuvensteijn; 2003, Brücker and Trübswetter; 2007). According to Brücker and Trübswetter (2007), 1.3 million persons migrated from East to West Germany between 1989 and 2001.

Funke and Strulik (2000) study convergence in a reunified East and West Germany using a similar version of the Barro (1990) government spending two-region endogenous growth model. They find East German income levels to be converging relatively rapidly those of

West Germany. It is estimated than East German wages should be 80% of their West German counterparts within 20 – 30 years of reunification. This speed of this implies migration may be playing a large role in wage convergence across Germany.

Easterlin and Zimmerman (2006) provide an in depth account of life satisfaction data for East and West Germany. Using time series data they compare life-satisfaction against household income, unemployment rate and a measure of self-reported satisfaction of income. They find, on the whole that overall life satisfaction tend to follow these economic outcomes. The inclusion of self-reported satisfaction of income represents a 'life domain' approach incorporating subjective economic indicators (see also van Praag et al, 2001). Disaggregating between native population as well as internal and foreign migrants (including Turks and Europeans) demonstrates 'noteworthy differences of various population groups' in terms of life satisfaction and so should be analysed separately.

2.5 An Introduction to Granger Causality and Extensions into Panel Data Analysis.

Granger causality is often employed to determine whether there exists any direct relationship between two variables and in what direction this flows, although it can be extended to include many variables. Granger (1969) offers a simple definition of causality for time series data. For a stationary time series, if X and Y are both stochastic variables, $\overline{X}, \overline{Y}$ their past values and U denotes all other information accumulated in the universe and $\overline{U}$ its past values

$$\text{if } \sigma^2(Y|U) < \sigma^2(Y|\overline{U - X})$$

where $\sigma^2(X|U)$ is the variance of $\varepsilon_t(X|U)$

Then it can be said that X is causing Y, hence when X is removed from the 'all other information' variable the variance rises and makes the estimator less precise. Therefore X should be included.

Roberts and Nord (1985) describe the notion of Granger Causality as follows:

> "…if a variable X 'causes' a variable Y, then Y can be better predicted from the past of X and Y together than from the past of Y alone, other relevant information also being used in the prediction." (p.135)

Therefore if variable X is thought to cause variable Y then a lagged variable of X should be included in a regression estimate for Y. This argues that the variable X will have a future impact on the value of Y.

This, of course, is a very simplistic view and there is no indication to what relevant information should be included in variable U. Therefore the validity of this is dependent on a sufficient model specification. Granger (1969) derives a basic two variable causal model as follows:

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t$$

$$Y_t = \sum_{j=1}^{m} c_j Y_{t-j} + \sum_{j=1}^{m} d_j X_{t-j} + \eta_t$$

Testing the causal relationship of X and Y requires testing the significance of the coefficients b_j and d_j. If, for example, b_j (d_j) is found to be significantly different from zero then Y can be said to be important in causing X (X is important in causing Y).

Granger causality has traditionally been employed in time series analysis. However, more recently it has been used in panel data which have numerous added benefits. This includes dramatically increasing the number of data points and thus the degrees of freedom as well as the ability to ask more complex questions of the data (see Hsiao 1986 for a in depth analysis of panel data).

Granger (2003) reviews the literature and comments on the expansion of self-titled causality into panel data and the assumption that causality is occurring everywhere in the panel. This requires that all cross-sections exhibit a common causal relationship rather than just a proportion of them. If only a sub-section of the panel's cross-sections display a significant causal relationship, it may be masked by other insignificant ones. The assumption of parameter homogeneity is often involved when considering Granger Causality in panel data for simplicity but can lead to misleading results. Testing the existence of causal homogeneity versus the presence of heterogeneous cross-sections has become a priority in understanding Granger Causality in panel data (see, for example Nair-Reichert and Weinhold, 2001; Hood et al, 2006[6] and Hurlin, 2008).

These concerns over the assumption of homogeneous panels makes it a prime importance that the correct model specification is used and that these avenues are sufficiently tested to ensure a true relationship is captured in the econometric analysis.

[6] Hood et al (2006) provide a neat step by step procedure in which the correct type of causality can be ascertained, using a standard fixed effects model. Initially they start by constructing a test statistic for a Homogeneous Non-Causality hypothesis. If this is rejected it indicates there is a causal relationship and therefore this should be checked by constructing a similar test for Homogeneous Causality. A rejection of this hypothesis indicates there must be some parameter heterogeneity and further testing is required. The existence of heterogeneity can be tested under a Heterogeneous Non-Causality hypothesis for each panel member to determine which sub-sections are displaying a significant causality and which are not.

3. DATA SPECIFICATION

Data on 'subjective wellbeing' is acquired from the German Socio-Economic Panel (GSOEP). The GSOEP began in 1984 and is a survey of private households and persons of initially the Federal Republic of Germany (FRG) and then included former East Germany from 1990 onwards after the fall of the Berlin wall and German reunification. Subjective well-being data is utilized from 1992 through to 2006. Over that period the number of individual responses has risen from 13,000 to over 20,000. Happiness is self-reported by individuals taking part in the survey and is measured on an integer scale from 0 to 10, responding to the question 'How satisfied are you with your life, all things considered?'

Data on population was available by Bundesländer across the same time period and obtained from the German Statistical office. Annual population change was calculated for each Bundesländer by subtracting population at time t-1 from population at time t for all years. As a result the 15 population observations from 1992 were lost.

The GSOEP contains an extensive set of data in many different areas. Due to its sample size and interest in subjective well-being questions, it has been the information source for a wide range of previous happiness research[7]. It is possible to make use of further information on the GSOEP respondents in order to ascertain what types of people are most likely to be found migrating to achieve their ultimate goal of happiness. GSOEP data is also obtained on nationality.

[7] For just a small selection see van Praag et al (2001), Frijters et al (2004), Easterlin and Zimmerman (2007), Clark et al (2008) and Rehdanz and Maddison (2008).

Nationality is an important characteristic to disaggregate as foreign workers may exhibit different motivations for being in German Bundesländer to the domestic population. This could be driven by work and the ability to earn a higher wage rate than their home country. Cultural differences may also dictate what is considered the meaning of happiness. Therefore the causes of happiness and influences of migration could be very different for domestic and foreign citizens. This removes a relatively small proportion of the dataset with approximately 90% of the GSOEP sample respondents between 1992 and 2006 being German Nationals. Data on population is correspondingly disaggregated to remove all foreign data ensuring it is only the population changes of German Nationals that are being captured.

Table 1 provides a summary of population changes, mean happiness, mean differences in happiness and spatially adjusted differences in happiness[8] between 1992 and 2006 for each Bundesländer. The lower five Bundesländer represent former East Germany. It can be seen there is a clear jump between mean happiness and spatial happiness over time in West and East Germany. Average combined mean happiness for the West between 1992 and 2006 is approximately 7.21 compared to 6.44 in the East (excluding Berlin). Mean national average happiness is approximately 6.91, making mean differences in happiness positive for all West German Bundesländer, at an average of 0.30 and negative for all of former East Germany, averaging -0.48. These figures represent vast differences in average happiness and highlight utility differentials may be very important in East-West migratory patterns.

[8] See section 4 for a full explanation of the derivation of the spatially adjusted happiness variables.

The spatially adjusted differences in happiness variable offer a similar, but less defined picture. The effect is that happiness differentials only become dependent on the average happiness neighbouring Bundesländer. Thus, for example, Hamburg, despite having an average happiness of 7.30, borders only Schleswig-Holstein and Niedersachsen with comparable happiness levels. The result is a small negative mean spatially adjusted difference in happiness across the time period. The opposite effect is found for Berlin, with a lower mean happiness than the national average but is bordered only by Brandenburg with a much lower average happiness. Consequently, this makes mean spatial happiness differences for Berlin positive.

A unit root test is employed to check for overall stationarity of the data using Eviews 5.1. The 'W- statistic t-bar' test of Im et al (2003 – IPS hereafter) is utilized for this purpose as it performs well for the small number of panels available in this paper. IPS allows for panel heterogeneity, expanding on Levin et al (2002) who allow for individual-specific intercepts and time trends for moderately sized panels. Individual unit root tests for each panel are estimated and then averaged under a null of individual unit root processes in all panels. Both are tested under a null hypothesis of unit roots (non-stationary data). Table 2 contains a summary of the results, alongside four other panel unit root tests. Both Levin et al (2002) and the IPS null hypotheses of unit roots are rejected at the 1% level of confidence for differences in happiness, spatial differences and population change, bar the IPS test for population change which is significant at the 5% level. This indicates the data is satisfactorily stationary across the whole time period. All other unit root tests shown reject the null of unit roots with at least a 5% level of confidence for spatial differences in happiness and population change. Aspatial differences in happiness do not reject the null of no stationarity in two alternative models provided. However, the highly significant IPS test allows us to believe a satisfactory level of stationarity as it is specified for panels with short time periods.

4. ECONOMETRIC ANALYSIS

The econometric foundations of Granger causality have already been addressed in section 2.5. This paper tests for the causal relationship that may exist between happiness and migration.

In the context of happiness and migration, a Granger causality test will establish whether a higher self-reported happiness in German Bundesländer leads to an increase in population (net in-migration). Does a region that exhibits higher happiness today experience future population growth? Testing the reverse causality relationship will reveal any feedback caused by an increase in population may have on these happiness levels. Do population movements have any significant effect on the happiness of those that remain?

The linear form of the parametric causality model can be shown with the following regression:

$$\Delta POP_{j,t} = \alpha_j + \beta_j YEAR_t + \gamma \sum_{i=1}^{i=n} \Delta POP_{\mathrm{j,t\text{-}i}} + \delta \sum_{\mathrm{i=1}}^{i=n} HAPPINESS_{j,t-i} + \varepsilon_{jt}$$

Where j is the Bundesländer, ‘$\mathrm{HAPPINESS}_{j,t-1}$’ represents either differences or spatially adjusted differences in happiness, t is the time period and α_j, β_j, γ, δ are parameters to be estimated. The maximum number of lagged variables is i = n. Testing the hypothesis that the happiness causes a population change involves testing $\delta = 0$. We assume the error terms, ε_{jt}, to be uncorrelated across the time period. The plausibility of this assumption is uncertain as the GSOEP actively attempts to re-survey the same households on an annual basis. Whilst this should capture evolving attitudes and the impacts of economic changes on well-being it risks selection bias and observations being based on responses from previous years.

A correlation between $\Delta POP_{j,t-1}$ and ε_{jt} would render Ordinary Least Squares (OLS) unsuitable. An Instrumental Variables (IV) estimation technique is implemented to reflect the short time period of the panel. Following Anderson and Hsiao (1982), we adopt the use of the twice lagged variables of a change in population and a change in happiness which is assumed correlated with $\Delta POP_{j,t}$ but uncorrelated with the error term. This keeps the γ and δ estimators consistent as the number of Bundesländer are fixed (i.e. N=15). The employment of Instrumental Variables is tested using a Hausman Test to analyse if they are providing any significant differences to an equivalent model without instrumental variables.

Annual average happiness scores for each Bundesländer are spatially adapted in the following way. Firstly a contiguity matrix is constructed for neighbouring Bundesländer and their respective average happiness scores. This is done for each year between 1992 and 2006. The average happiness of neighbouring Bundesländer is then subtracted from the average happiness scores giving a spatially differenced happiness value[9]. This process can be illustrated by use of an example. Taking Bayern as our Bundesländer of interest we can pick out, for example, a 2006 self-reported average happiness of 7.14. Bayern has borders with four other federal states: Hessen, Baden-Württemberg, Thüringen and Sachsen with

[9] An alternative method for spatial adapting differences in happiness was also attempted by subtracting annual average happiness values from the Bundesländer exhibiting the highest happiness score each year. This was to assess if individuals were purely driven to areas of highest happiness. However, the regressions performed poorly and have been omitted for that reason

respective 2006 average happiness scores of 7.07, 7.10, 6.28 and 6.50. Therefore the 2006 spatially differenced happiness value for Bayern will be:

$$7.14 - \frac{7.07 + 7.10 + 6.28 + 6.50}{4} = 0.4025$$

This is carried out across all panels for every Bundesländer. The reasoning for this process is that distance should play a negative role in the migration decision. If a neighbouring Bundesländer exhibits the same average happiness as a Bundesländer on the other side of the country it should not be assumed that an individual should be indifferent between the two locations. It would be considered natural to prefer the closer of the choices. Parikh and Van Leuvensteijn (2002) conduct a panel data analysis of internal migration in Germany against distance as well as other economic indicators. Using a number of regression models including pooled OLS, fixed effects and random effects, distance is found to be having a negatively significant impact on almost all cases.

Testing the linear reverse causality is the hypothesis that a change in population causes a change in happiness can be invoked along similar lines:

$$HAPPINESS_{j,t} = \alpha_j + \beta_j YEAR_t + \gamma \sum_{i=1}^{i=n} HAPPINESS_{\mathrm{j,t\text{-}i}} + \delta \sum_{\mathrm{i=1}}^{i=n} \Delta POP_{j,t-i} + \varepsilon_{jt}$$

Similar to above, testing the reverse causality of whether a change in population has an effect on happiness again involves a test of whether all δ = 0.

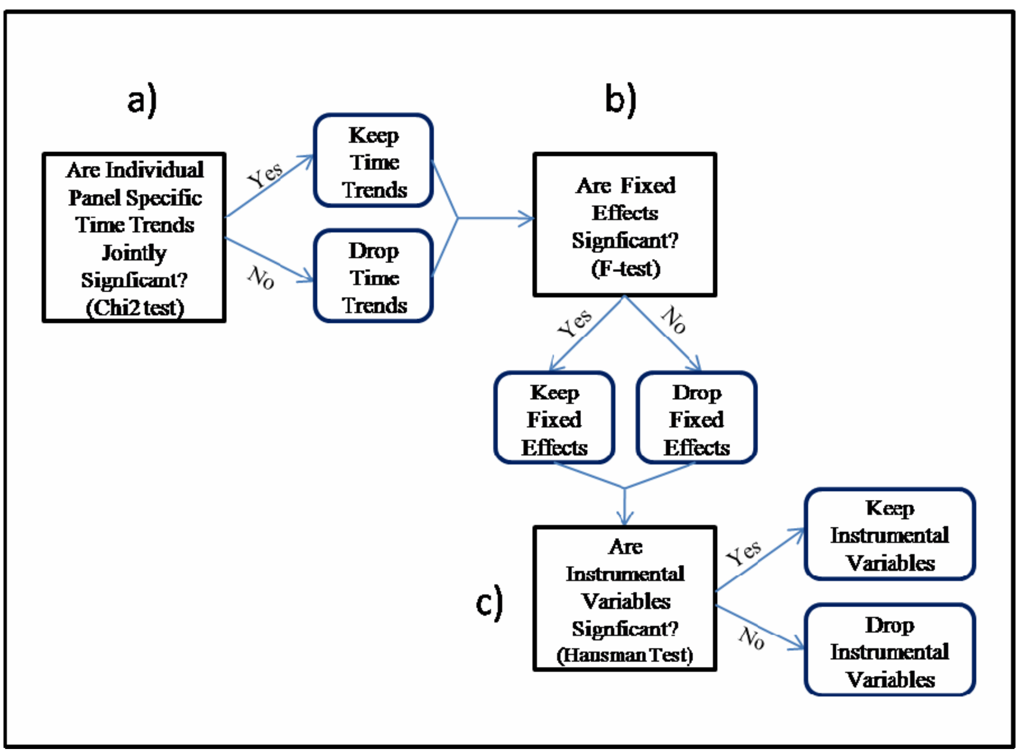
5. ECONOMETRIC SPECIFICATION

The analysis in the previous section provides a starting point from which a formal strategy is adopted. A correct functional form is decisive in the success of the regression and so a number of different forms of population and happiness are considered. Some preliminary regressions suggested that differencing the population over time (ΔPop hereafter) provided a good fit whilst differencing mean happiness from the national average is adopted (Diffhappy hereafter). Furthermore, the spatial differences in happiness described in the previous section are carried out as an extra opportunity of analysis (Spathappy hereafter). Four separate experiments are carried out, named models A, B, C and D to examine the existence of causality and reverse causality respectively. Therefore Model A will test the significance of $Diffhappy_{t-1}$ in influencing the dependent variable ΔPop_t. Model B is the equivalent to Model A but instead uses spatial differences in happiness. Models C and D will test the significance ΔPop_{t-1} has on $Diffhappy_t$ and $Spathappy_t$ respectively.

Initially parametric tests were run to ascertain whether the linear functional form chosen is satisfactory. If functional form is inappropriate and the underlying assumption of homoscedasticity violated then analysis is turned to the Multiple Ranks F-test, a non-parametric procedure. The Multiple Ranks F-test replaces the observations of each variable in rank order from lowest to highest. This makes monotonic transformations of the variables ineffective and so functional form specification no longer matters. Contingency tables are also utilised to provide a more visual evidence of the extent to which Granger causality may exist.

A number of different model specifications were carried out in an attempt to achieve the best possible regression performance. This includes comparison testing the significance of both fixed and random effects, the addition of instrumental variables and the format of time trends to adopt. Regressions were carried out using both panel specific time trends and year specific dummy variables. In both cases this yielded 15 time trends but the for panel specific time trends a common time trend was also included. The inclusion of individual time trends depended on a test of joint significance against the common time trend. Figure 1 illustrates the procedure followed for all regressions, starting with a fixed effects instrumental variables model with panel specific time trends. Dropping both fixed effects and instrumental variables leaves a simple OLS regression.

Figure 1. Flow chart showing order of procedure for each regression



5.1 Parametric Tests

Initially we test the significance of time trends for each Bundesländer. A fixed effects instrumental variables regression, using 15 dummy variables, panel specific time trends ('yearb1 – yearb15' between 1992 and 2006) as well as the inclusion of a common time trend ('year') was implemented. A joint significance chi-squared test, under a null hypothesis of no significance, was carried out to ascertain if the individual time trends have a significantly different impact to including the common time trend alone. The results are provided in Table 3 for all four models.

Models A and B initially return very similar results. Despite the individual significance of some of the panel specific time trends, the overall test of joint significance returns statistically equal to zero with Chi^2 values of 12.63 and 12.16 respectively and they should be dropped for both models. Model A performs better with an overall R^2 of 0.1018 compared to 0.0731 for model B. Model C also finds the panel specific time trends to be jointly insignificant in similar fashion and can be dropped. Model D, on the other hand, borderline rejects the null of no significance at the 5% level and so individual time trends are kept. Model C returns a slightly higher overall R^2 of 0.0838 compared to model D with 0.0545.

Now the optimal format of the time trend is known for both models it is necessary to test their foundations. Firstly, is fixed effects a suitable estimator or can the regression be better explained by OLS? This can be achieved by an F-test to determine whether fixed effects are having any significant effect on the model. A significant F-statistic indicates this is the case and that fixed effects should be kept. Insignificance allows fixed effects to be dropped in favour of OLS. Secondly, the inclusion of instrumental variables is tested, under a null hypothesis of no significance. A Hausman test determines whether the inclusion of instrumental variables adds any explanatory power to the model by comparing it to an equivalent regression which omits instrumental variables. Table 4 provides a summary of these tests for models A, B and C for which the time trends have been dropped. Table 5 gives the results from model D, with the panel specific time trends maintained.

The three columns of Tables 4 and 5 demonstrate the step by step process in which the tests are carried out. The first column tests whether fixed effects are playing any significant role in the regression. Column 2's role is to determine the significance instrumental variables is having. Column 3 provides the results of a simple OLS regression, which is the best fit if both fixed effects and instrumental variables are insignificant and can be dropped.

The top section of Table 4 gives derives the best fit for Model A. Starting with column 1, the regression performs fairly with an R^2 of 0.8014. $\text{Diffhappy}_{(t-1)}$ is insignificant with a z-value of 0.74. The F-test of significance for fixed effects is given at the bottom of column 1. It returns an F-value of 1.31. The null hypothesis of no significance is not rejected and fixed effects are dropped. This is shown in column 2, showing an OLS regression with instrumental variables. The significance of $\text{Diffhappy}_{(t-1)}$ has now risen to 1.70, borderline significant at the 10%. A Hausman test returns a Chi^2 of 0.93 and so also does not reject the null of no significance. Therefore, in the linear parametric form, Model A simplifies to

OLS. R^2 remains steady at 0.7991 and $Diffhappy_{(t-1)}$ remains insignificant with a z-value of 1.45.

Models B and C follow in a very similar fashion. Model B, with $Spathappy_{(t-1)}$ as the explanatory variable, can drop both fixed effects and instrumental variables an F-test and Hausman test return an insignificant F-value of 1.34 and Chi^2 value of 0.42. Thus model B also simplifies to OLS, with an R^2 of 0.7873 and a corresponding insignificant t-value of 0.96 for $Spathappy_{(t-1)}$. Model C, given in the bottom section of Table 4, is slightly different in layout. It can be seen that the F-test finds fixed effects to be borderline significant at the 5% level, with an F-value of 1.75, allowing them to be kept. Thus, the Hausman test is now carried out on exactly the same regression model in column 1 against a fixed effects regression with no instrumental variables, given in column 2. The Chi^2 value is 0.29 and insignificant so instrumental variables are dropped. The final model is therefore a fixed effects regression with no instrumental variables and a common time trend, given in column 2 of model C. The R^2 value is slightly higher than models A and B at 0.8523 and $\Delta Pop_{(t-1)}$ is significant with at the 1% level with a t-value of 3.02. Population change seems to be playing a very important role in positively causing happiness differences. The implications of this result are discussed later.

Table 5 provides the regression results of Model D. Column 1 summarises the F and Hausman tests for fixed effects and instrumental variables. As panel specific time trends were found to be jointly significant these tests are carried out on the initial regression for model D already seen in Table 3. Fixed effects are found to be significant at the 5% level maintaining they should be kept, whilst instrumental variables are once again found to be insignificant and dropped. Thus, the final model is given in column 2. It's R^2 has fallen slightly, to 0.0329 through the loss of instrumental variables. $\Delta Pop_{(t-1)}$ is now weakly significant at the 10% level with a t-value of 1.82 when $Spathappy_t$ is the dependent variable.

Thus far the use of the Spathappy variable has seemed to have a dampening effect on the significance of the results when compared to Diffhappy. This result is somewhat unexpected as one would anticipate individual's to be more sensitive to the actions of neighbouring Bundesländer relative to the country as a whole.

The assumptions of these models are now tested to ensure the linear estimators are most efficient. Using the OLS regressions, given in column 3 of Tables 4 and 5, a test of heteroscedasticity reveals whether the error terms have constant variance and a Ramsey RESET test checks for possible nonlinearity of the functional form of the regression. A Breusch-Pagan / Cook-Weisberg test for heteroscedasticity is implemented under a null of homoscedasticity (constant variance of errors). A RESET F-test with null hypothesis of no omitted variables is run and a significant F-statistic indicates that a more efficient non-linear functional form is available, though not which functional form it should be.

The RESET test has performed relatively well. Model D does not reject the null hypothesis of no omitted variables suggesting it is a suitable functional form. Models A and B are significant at the 5% level with F-values of 2.91 and 2.76 respectively, providing a weak case for switching to a non-linear form. Model C, however, is highly significant at the 1% level with an F-value of 8.38 and is unsuitable to be left in a linear form. The test for heteroscedasticity hasn't performed quite as well. Both models A and B appear have highly heteroscedastic errors, significant at the 1% level, returning Chi^2 values of 26.673 and 20.22. Therefore it is possible that incorrect functional form may be playing a more disruptive role than the RESET test would suggest. Model C is of borderline 10% significance whilst Model D more strongly rejects the null of constant variance of error terms at the 5%.

Appropriate functional form is necessary to ensure the underlying assumption of homoscedasticity. In models A and B in particular, despite the RESET test only being significant at the 5%, the very high probability of heteroscedasticity suggests an alternative functional form could perform better. Therefore, the multiple ranks F-test is undertaken as a precaution to ensure the basic assumptions of OLS are being adhered to.

5.2 The multiple ranks F-Test

There exists no simple method to obtain the correct functional form for parametric tests aside from a trial and error process making parametric testing an arduous procedure. However, it is possible to implement a simple non-parametric test which can examine the existence of a causal relationship without having to make any prior assumptions about the functional form a regression may take.

The multiple ranks F-test ranks both dependent and explanatory variables from lowest to highest (with lowest value ranked one), regardless of time period. It is then possible to apply a simple F-test in the same fashion as the parametric econometric procedure. This is particularly useful with respect to analysing causal relationships as, in the case of two variables, fewer stringent assumptions must be adhered to.

$$R(X_{j,t}) = \alpha_j + \beta_j YEAR_t + \gamma \sum_{i=1}^{i=n} R(X_{\mathrm{j,t\text{-}i}}) + \delta \sum_{\mathrm{i=1}}^{i=n} R(Y_{j,t-i}) + \varepsilon_{jt}$$

Where R denotes the rank of each variable (including the lagged dependent variable). Once all variables have been appropriately ranked, it resembles and is computed in the fashion of the parametric tests.

The ranking of underlying data of each variable of interest is not a new concept. It has been employed by, for example, Iman and Conover (1979), Conover and Iman (1982), Holmes and Hutton (1988) and Holmes and Hutton (1990) as an effective alternative to the often rather strong assumption of correct functional form, underpinned by the requirement of homoscedastic error terms. An initial linear parametric regression suffering heteroscedasticity traditionally may be resolved by subjecting each variable to a monotonic transformation which displays homoscedastic errors. The key advantage in employing multiple ranks is monotonic transformations will make no difference to the order of ranking; functional form is now extraneous. Holmes and Hutton (1990) conduct a causality test of government expenditure and national income using a linear parametric test and the multiple ranks F-test. The linear parametric test concludes an opposite causal relationship (of national income changing government expenditure) to the multiple ranks F-test. The linear parametric test was discovered to violate its assumption of homoscedasticity, having a significant impact on the regression results.

A similar process to the parametric tests above is now used but ΔPop_t, $Diffhappy_t$ and $Spathappy_t$ and their lags are ranked. For example, the lowest Spathappy rating is -0.989 for Mecklenburg-Vorpommern in 1992 and this is ranked first compared to Schleswig-Holstein in 1992 with 0.729 which is ranked lowest at 225[10]. Ranked first Diffhappy is Sachsen in 1992 with -0.867 and last is Bremen in 1996 with 0.853 (at 225). For ΔPop Nordrhein-Westfalen in 1992 is ranked highest with -27,418. The lowest rank (at 210) is Bayern in 2001 with 58,995. Again, the initial starting point is fixed effects instrumental variables with panel specific time trends.

Table 7 tests the joint significance of these panel specific time trends for the multiple ranks models in the same fashion as Table 3 did for the linear parametric models. The results mirror the linear model remarkably closely with Models A, B and C finding the Chi^2 values of the panel specific time trends jointly insignificant, allowing them to be dropped in favour of the common time trend. Model D again finds the time trends jointly significant at the 5% level and so should be kept. The R^2 of all four models have fallen somewhat, but this is not a cause of concern in the initial model. $Diffhappy_{(t-1)}$ is now borderline significant at the 5% in Model A, whilst $\Delta Pop_{(t-1)}$ remains highly significant at the 1% level in Model C, but has jumped to being significant at the 5% in Model D. $Spathappy_{(t-1)}$ remains completely

[10] Note: First-order lagging the variable Spathappy loses the 1992 variables and reduces the number of ranks to 210. The highest rank changes to Mecklenburg-Vorpommern in 1993 with -0.767 whilst lowest rank now becomes Bremen in 1996 with 0.681. The same applies to lagged Diffhappy whose highest rank becomes Brandenburg in 2004 with -0.750 is First order lagging of population change loses 1993 variables but there is no change in the lowest rank as it is in 2001 data for Bayern.

insignificant in Model B, with the only discernable difference being a change in its sign from negative to positive

Now the same procedure as the linear model is followed for the multiple ranks case. Hence, tests of significance are carried out to ascertain whether fixed effects and instrumental variables are playing important roles in the regression. Table 8 provides the regression results for Models A, B and C without panel specific time trends whilst Table 9 has the equivalent results for model D with the time trends. Columns 1,2 and 3 in both tables should be interpreted in the same way as the linear parametric model.

Model A, having dropped panel specific time trends, is subjected to the F-test that all u_i=0, to determine the significance of fixed effects. Returning an F=value of 1.07 it can be seen fixed effects are not adding any explanatory power to the model and can be dropped in favour of OLS. The consequence of this is that $Diffhappy_{(t-1)}$ has become significant at the 5% level and borderline 1%. A Hausman test shows instrumental variables to be highly significant at the 1% with a Chi^2 value of 35.04. This contradicts the linear model where instrumental variables were dropped. The R^2 value has only fallen very slightly to the linear alternative.

A very similar outcome occurs for Model B. An insignificant F test for all $u_i = 0$, with F-value of 1.08, allows the dropping of fixed effects whilst a Hausman test again finds instrumental variables highly significant at the 1% with a Chi^2 value of 16.51. The final regression is provided in column 2 for Model B. R^2 stays fairly high at n0.7819 and $Spathappy_{(t-1)}$ is weakly significant at the 10% level. Therefore, once again, the use of

$Spathappy_{(t-1)}$ seems to be having a dampening effect on the significance of happiness differences across Bundesländer. Nevertheless, using the multiple ranks procedure as opposed to the initial linear parametric model has revealed happiness differences across Germany to playing a much more important role in causing population change.

Once again for Model C, fixed effects is found to significant, this time at the 1% level; a much more convincing rejection of the null hypothesis of no significance. As fixed effects are being dropped, a Hausman Test is also undertaken for the regression in column 1 against the regression of column 2 with no instrumental variables. A Chi^2 value of 0.77 indicates they are insignificant and can be dropped. Therefore the final model is that in column 2 of fixed effects with no instrumental variables and a common time trend. $\Delta Pop_{(t-1)}$ has a z-value of 3.65, highly significant at the 1% level, raising it from the 3.02 found in the linear model.

Model D finds fixed effects significant at the 5% with an F-value of 2.09 and so are kept. Instrumental variables, on the other hand can be dropped. A Chi^2 value of 4.52 is insignificant with the inclusion of the panel specific time trends. Therefore column 2 of Table 9 provides the optimal regression for model D. The R^2 is marginally lower than the linear alternative at 0.0215 compared to 0.0253. $\Delta Pop_{(t-1)}$ is now borderline significant at the 5% level with a z-value of 2.00. This has risen from the equivalent z-value of 1.02 for the linear model

The conclusion of these results indicates that using both the Diffhappy and Spathappy variables offer varying degrees of causal relationship between happiness and differences and population change. Diffhappy provides a more significant relationship with ΔPop. Happiness differences lead to a positive change in population in Bundesländer at the 5% level of significance. The reverse causality set-up is stronger, significant at the 1% level and also displays a positive relationship signifying population change affects happiness. Population rises in Bundesländer increase happiness whilst decreases should have a negative impact. Replacing Diffhappy with Spathappy stipulates the same relationship exists but to a weaker extent. Spatially adjusted differences in happiness also positively causes population change, but only weakly at the 10% level whilst testing reverse causality is significant at the 5%.

A final set of tests for functional form and heteroscedasticity are implemented for the OLS multiple ranks regressions, given in column 3 of Tables 7 and 8, to ensure the transformation of the variables has removed any uncertainty about the underlying assumptions of the model.

Table 10 shows the multiple ranks transformations has deflated the F-value's and Chi^2 values for all four models. Models A, B and D all now satisfy the null hypotheses of no omitted variables and constant variance of error terms as required for the model to be a good fit. The previously very high Chi^2 values in the linear form for Models A and B have fallen drastically to 1.62 and 2.40. This is promising as the RESET test F-values of to 1.31 and 0.24 imply functional forms are no longer having any influence on heteroscedastic errors.

Model C has not performed as well and despite a large fall in the RESET test F-value, it still rejects the null of no omitted variables at the 5%. Surprisingly, probability of heteroscedasticity has risen from the linear model to be significant at the 5% with Chi^2 of 5.70. It is possible this may be causing some disturbances in the results of Model C. There still exists some element of doubt in that these specification tests are not more rigidly rejected with a more than 99% level of confidence. Nevertheless we proceed with due caution for the results for Model C.

The use of the multiple ranks transformation has brought to light some key information in the search for a model that can accurately interpret the causality relationship of happiness differences and causality. Firstly, simply assuming a linear parametric model or any other parametric alternative is likely to result in serious specification errors. This is clear from the RESET and heteroscedasticity tests. Multiple Ranks has, in three of the models, vastly improved their specification by removing the impact monotonic transformations can have on parametric models. This can be seen by the amplification in the significance of the results across all the models when using multiple ranks. Secondly, the spatial configuration of happiness differences seems to dampen the significance of both the causality and reverse causality relationships. The likely reason for this is not econometric but more so the nature of post-reunification. Geographical utility differences in Germany are very much still most striking between former East and West German Bundesländer. It has been 18 years since German reunification in 1990. Whilst some happiness convergence has occurred in this time period, it is clear there is still a long way to go. As all former East German Bundesländer principally border each other, as do the Western ones, the spatial models' interest on neighbouring states may be underestimating the general desire of the Eastern population to migrate to the 'happier West'.

5.3 Panel Homogeneity

One final specification test of Panel homogeneity is carried out on both the linear and multiple ranks models. Homogeneity requires that Granger causality is occurring equally across all panels in the dataset and not just for individual ones. If a null hypothesis of panel homogeneity is rejected and widespread, then further tests are necessary to detect exactly which panels are exhibiting a causal relationship and which are not.

An F-test is undertaken to check homogeneity across individual panels. A fixed effects model with instrumental variables and panel specific time trends is regressed as an unrestricted model against a restricted model of the same nature but only includes a common time trend. The F-test is as follows:

$$F = \frac{(RSS_R - RSS_U)/(n_R - n_U)}{RSS_U/(n_U - k_U)} \sim F_{(n_R - n_U),(n_U - k_U)}$$

Where RSS_R and RSS_U are the residual sum of squares of the restricted and unrestricted models respectively, n_R and n_U their number of parameters . k_U denotes degrees of freedom in the unrestricted model. Table 11 gives the results of the homogeneity F-test.

The results of the homogeneity tests have given some mixed messages. Both the linear causality model and the multiple ranks reverse causality model do not reject the null of homogeneity for both Diffhappy and Spathappy confirming that causality is occurring across every panel in these models. Linear reverse causality is exhibiting panel heterogeneity at the 5% level of significance for Spathappy. This is not a problematic issue as the linear models have already been found to be subject to inappropriate functional form and heteroscedasticity. The multiple ranks causality model is exhibiting heterogeneity for Diffhappy at the 5% level and Spathappy at the borderline 1%. This is of some concern and may be having some impact on the multiple ranks results. However, the general homogeneous nature of the other models indicates that panel heterogeneity can only be occurring to a very limited extent. Therefore, no action is taken against heterogeneity but the possible effect it may be having on the multiple ranks causality model is noted.

5.4 Contingency Tables

The multiple ranks F-test provide a simple method to remove functional form as an underlying assumption to ensure unbiased and efficient estimator. To confirm the credibility to this method another non-parametric test involving contingency tables are utilised to summarise the data in an easy to understand format showing a clear pattern. Initially the mean[11] values of the two variables being tested are calculated. Let these be called μ(X) and μ(Y), where Y reflects the dependent variable and X the once lagged explanatory variable of interest. A contingency table is constructed as follows:

	Greater μ(Y(t))	**Less μ(Y(t))**	**Total**
Greater μ(X(t-1))	a	b	a + b
Less μ(X(t-1))	c	d	c + d
Total	a + c	b + d	a + b + c + d

The total number of data points (a + b + c +d) in this study represents the 15 Bundesländer across all time periods. Therefore the mean of X_{t-1} and Y_t is calculated for each panel. A

[11] The mean is preferred over the median as there are no substantial outliers in the dataset that could distort its central tendency.

contingency table is created for each panel and all are then summed for the whole period to give an overall table.

A contingency table portraying a positively significant Granger causality would expect to see a higher number of results in boxes a and d. This means a greater $\mu(X_{(t-1)})$ cause a greater $\mu(Y_{(t)})$, whereas those with a lower $\mu(X_{(t-1)})$ lead to a lower $\mu(Y_{(t)})$. The significance of a contingency table can be tested using Pearson's chi-squared test for larger samples. The exact function of this test determines whether the proportion of samples with a greater $\mu(X_{(t-1)})$ which have a greater $\mu(Y_{(t)})$ is statistically different to those with a lower $\mu(X_{(t-1)})$. The null hypothesis is independence of the probabilities of each outcome and there is no definitive relationship appearing between X and Y in the data.

The Pearson Chi^2 statistics return significant at the 1% level for Models A, B and C whilst D is significant at the 5% level. The Diffhappy Models A and C are very highly significant with Chi^2 values of 28.59 and 26.33. This equivalent values for the Spathappy Models B and D are 8.14 and 5.37. Therefore there exists a relationship between happiness differences and population change in the contingency tables which is not reflected by chance.

First we consider the impact of $Diffhappy_{(t-1)}$ ($Spathappy_{(t-1)}$) on ΔPop_t given in Model A (Model B) of Table 12. 54.4% (45.6%) of happier than average Bundesländer are reportedly experiencing a greater than average change in population compared to only 17.65% (29.8%). More notably this means 82.35% (70.2%) of less happy Bundesländer are experiencing low positive or negative population changes. $Spathappy_{(t-1)}$ is mirroring $Diffhappy_{(t-1)}$ very closely but to a clearly less significant degree. The positive relationship discovered in both models using the multiple ranks procedure is being caused by individuals migrating away from less happy areas rather than being attracted to Bundesländer with highest self-reported happiness. A logical explanation for this is individuals are motivated by different goals in their ultimate strive for happiness. If Bundesländer are offering significantly different bundles of happiness inducing amenities then individual preference becomes very important, but cannot be monitored in a causality study.

The reverse causality tables for the effect of $\Delta Pop_{(t-1)}$ on $Diffhappy_t$ ($Spathappy_t$) are given for Model C (Model D) in Table 12. 81.8% (61.0%) of Bundesländer with a greater population change are happier than average compared to 44.9% (44.1%) with a lower population change. Consequently only 18.8% (39.0%) of Bundesländer with a greater population change have above average happiness, showing a strong positive relationship. A weaker relationship emanates from lower population changes leading to below average happiness at 55.1% (55.9%)[12]. It appears it is the interaction of both these effects that is leading to the significance of the reverse causality relationship at the 5% level when using the multiple ranks transformation. This result is largely unanticipated as economic intuition would suggest population rises put downward pressure on wages and upward pressure on house prices which negatively impact happiness. A possible explanation is that population changes appear to be relatively low across the time periods analysed, with the highest being under 60,000, and that Bundesländer are sufficiently able to cope with these population

[12] Again, $\Delta Pop_{(t-1)}$ is impacting on $Diffhappy_t$ and $Spathappy_t$ in very similar fashions, though its relationship with Diffhappyt is clearly much stronger.

intakes. The 2001 net inflow of 58,995 in Bayern represents only 0.65% of its total population of over 9 million.

6. CONCLUSIONS

This paper has used panel data to discover the true causal relationship that exists between happiness and migration in Germany by following an econometric procedure that is careful to ensure that an appropriate model has been adhered to. The use of panel data has allowed for this relationship to be tested stringently across a time period of 15 years. Whilst panel data benefits greatly from large time periods, 15 years should be an adequate length to gain an informative understanding of this causal relationship. Comparing the models derived under the linear parametric and the multiple ranks non-parametric alternative show that underlying assumptions functional form and homoscedasticity are key to the successful performance of a regression. Failure to deal with these can have a major impact on the precision of the regression and can ultimately cause misleading results. The multiple ranks transformation has been found to generally satisfy these requirements where the linear parametric alternative has failed.

The overall results from the multiple ranks tests finds a bi-directional causal relationship exists between happiness and migration across German Bundesländer. This relationship is much stronger when aspatial differences in happiness are considered. Contingency tables showed that whilst differences in happiness positively cause population change, it was a motivator to migrate away from unhappy Bundesländer. The exact degree of this relationship is difficult to quantify due to the uncertain effect panel heterogeneity could be having on the multiple ranks causality case, particularly for the spatial happiness model. However, the promising results from the contingency tables indicate that it certainly plays a key role in migratory patterns. Population change, on the other hand, exhibits a stronger positive effect on causing happiness. Whilst this was result was unexpected, the relatively small net migration flows may limit the negative influences on wages, unemployment and the housing market. Again caution must be exercised for the aspatial happiness differences results as the possible functional form and heteroscedasticity of errors may be having a distortionary role on their significance. Nevertheless, the spatial model was found to be free of such misspecification errors and found the relationship to be significant at the 5% level.

Future testing will ascertain the importance these macroeconomic variables are having on happiness and if they can provide further conclusive evidence to the relationship between happiness and migration. Causality tests will be undertaken for happiness against wage rates, unemployment and house prices. This is to test the premise that self-reported happiness scales are a satisfactory measure of utility and that individuals really do incorporate their economic situation and other variables more objective migration models may pass over.

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Table 1: Summary of Data

WEST	1992 Pop.	2006 Pop.	Change Pop.	Mean Hap.	Mean Differences in Happiness	Mean Spatially Adjusted Differences in Happiness
SchleswH	2,120,542	2,219,347	98,805	7.32	0.4252	0.3868
Hamburg	1,260,635	1,282,751	22,116	7.30	0.3016	-0.0626
Nieders	5,871,565	6,137,666	266,101	7.17	0.2525	0.2863
Bremen	519,366	496,338	-23,028	7.32	0.4371	0.1782
NRW	13,161,407	13,354,267	192,860	7.16	0.2465	-0.0214
Hessen	4,349,502	4,496,066	146,564	7.19	0.2974	0.1931
RheinlPfalz*	3,820,325	3,920,444	100,119	7.16	0.2536	0.0013
BadenW	7,310,497	7,773,960	463,463	7.13	0.2122	-0.0671
Bayern	8,801,727	9,326,307	524,580	7.18	0.2731	0.3964
			Average West	**7.21**	**0.30**	**0.14**
Berlin	2,572,002	2,531,488	-40,514	6.63	-0.2982	0.1922
EAST						
MecklenbVP	1,413,392	1,447,945	34,553	6.53	-0.3872	-0.4637
Brandenburg	1,957,018	2,165,621	208,603	6.41	-0.5043	-0.2224
SachsenAnhalt	2,199,371	2,110,452	-88,919	6.41	-0.5041	-0.1907
Thüringen	1,993,388	1,988,513	-4,875	6.34	-0.5785	-0.5568
Sachsen	3,665,379	3,625,923	-39,456	6.50	-0.4269	-0.1036
			Average East	**6.44**	**-0.48**	**-0.31**

Source: SOEP

*GSOEP aggregates the two federal states of Rhineland-Palatinate and Saarland to one region

Table 2: Summary of Unit Root Tests for Stationarity

	Differences in Happiness		Spatially Adjusted Differences in Happiness		Population Change	
Method	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Null: Unit root (assumes common unit root process)						
Levin, Lin & Chu t*	-4.08037	0.0000	-6.60806	0.0000	-4.01695	0.0000
Breitung t-stat	-0.33283	0.3696	-1.69685	0.0449	-3.24	0.0006
Null: Unit root (assumes individual unit root process)						
Im, Pesaran and Shin W-stat	-2.35152	0.0093	-3.3149	0.0005	-2.24522	0.0124
ADF - Fisher Chi-square	44.9608	0.0389	54.6204	0.0039	52.5201	0.0067
PP - Fisher Chi-square	36.6216	0.1884	71.8971	0.0000	76.0030	0.0000

Table 3. Fixed Effects Instrumental Variables with individual time trends

	Model A				Model B				Model C				Model D			
	Dep Var: ΔPop(t)				Dep Var: ΔPop(t)				Dep Var: DiffHappy(t)				Dep Var: SpatHappy(t)			
	Exp Var: DiffHappy(t-1)				Exp Var: SpatHappy(t-1)				Exp Var: ΔPop(t-1)				Exp Var: ΔPop(t-1)			
	Overall R-squared: 0.1018				Overall R-squared: 0.0731				Overall R-squared: 0.0838				Overall R-squared: 0.0545			
	Coef.	S.E	z	Prob>z	Coef.	S.E	z	Prob>z	Coef.	S.E	z	Prob>z	Coef.	S.E	z	Prob>z
Exp.Var.	2724.031	0.2398	0.64	0.519	-2248.639	6320.385	-0.36	0.722	5.13E-06	1.41E-06	3.63	0.000	0.00000161	0.00000111	1.45	0.146
Lagged Dep. Var.	0.3412	660.0539	1.42	0.155	0.3981023	0.2342737	1.7	0.089	0.1355914	0.1844837	0.73	0.462	-0.2611721	0.2574662	-1.01	0.310
year	1175.747	660.0539	1.78	0.075	1229.519	667.5551	1.84	0.066	0.0150942	0.009907	1.52	0.128	0.0348442	0.008741	3.99	0.000
yearb1	-840.6856	819.0999	-1.03	0.305	-1014.627	887.9428	-1.14	0.253	-0.0240511	0.013784	-1.74	0.081	-0.0788785	0.0177654	-4.44	0.000
yearb2	-415.8663	795.0072	-0.52	0.601	-247.1008	801.7296	-0.31	0.758	0.0282665	0.0138945	2.03	0.042	0.035391	0.0133864	2.64	0.008
yearb3	-1373.649	874.9424	-1.57	0.116	-1375.676	874.4064	-1.57	0.116	-0.0078871	0.0129757	-0.61	0.543	-0.0301359	0.0109274	-2.76	0.006
yearb4	-718.7403	824.237	-0.87	0.383	-976.3283	895.0993	-1.09	0.275	-0.0355763	0.0157669	-2.26	0.024	-0.0724243	0.0175243	-4.13	0.000
yearb5	820.3859	1091.075	0.75	0.452	527.7727	1088.017	0.49	0.628	-0.0403365	0.0151456	-2.66	0.008	-0.0364638	0.0122525	-2.98	0.003
yearb6	-1484.958	873.059	-1.7	0.089	-1623.576	900.4687	-1.8	0.071	-0.028496	0.0149294	-1.91	0.056	-0.0594486	0.0149725	-3.97	0.000
yearb7	-1187.1	825.5947	-1.44	0.15	-1272.891	835.0956	-1.52	0.127	-0.0198471	0.013412	-1.48	0.139	-0.0356516	0.0106909	-3.33	0.001
yearb8	-633.2128	914.466	-0.69	0.489	-826.3399	910.3602	-0.91	0.364	-0.0272156	0.0140167	-1.94	0.052	-0.023851	0.0108438	-2.2	0.028
yearb9	-186.517	815.5598	-0.23	0.819	-375.4261	833.9636	-0.45	0.653	-0.0276524	0.0137597	-2.01	0.044	-0.0396847	0.0121069	-3.28	0.001
yearb10	-1866.194	952.3489	-1.96	0.05	-1807.496	944.598	-1.91	0.056	-0.0017713	0.0127326	-0.14	0.889	-0.0108684	0.0099888	-1.09	0.277
yearb11	-2827.29	1070.972	-2.64	0.008	-2835.399	1072.092	-2.64	0.008	-0.0172613	0.0131981	-1.31	0.191	-0.0547382	0.0131824	-4.15	0.000
yearb12	-1878.789	987.9132	-1.9	0.057	-1860.266	983.463	-1.89	0.059	-0.0110448	0.0129038	-0.86	0.392	-0.0337834	0.0108302	-3.12	0.002
yearb13	-1988.437	982.5548	-2.02	0.043	-1963.272	977.1996	-2.01	0.045	-0.0108079	0.0129793	-0.83	0.405	-0.0307058	0.0106006	-2.9	0.004
yearb14	-1882.483	999.3964	-1.88	0.06	-1816.303	989.5342	-1.84	0.066	-0.0061176	0.0127757	-0.48	0.632	-0.0211926	0.0101121	-2.1	0.036
Constant	1175.747	4223.625	-0.037	0.708	-124066.2	399578.3	-0.31	0.756	0.4113755	5.310142	0.08	0.938	-4.043071	3.940329	-1.03	0.305

	Model A	Model B	Model C	Model D
Test of individual time trend joint significance:	Chi2 = 12.63 Prob>Chi2 = 0.6694	Chi2 = 12.16 Prob>Chi2 = 0.6673	Chi2 = 16.39 Prob>Chi2 = 0.3568	Chi2 = 25.41 Prob>Chi2 = 0.0447

Table 4. Deriving an Optimal Linear Regression Configuration for Models A, B and C

	Model A											
	Column 1				Column 2				Column 3			
	Fixed Effects Instrumental Variables, Common Time Trend				OLS with Instrumental Variables and Common Time Trend				OLS, No Instrumental Variables and Common Time Trend			
	Dep Var: ΔPop(t)				Dep Var: ΔPop(t)				Dep Var: ΔPop(t)			
	Exp Var: DiffHappy(t-1)				Exp Var: DiffHappy(t-1)				Exp Var: DiffHappy(t-1)			
	Overall R-squared: 0.8014				Overall R-squared: 0.7923				Overall R-squared: 0.7991			
	Coef.	S.E	z	Prob>z	Coef.	S.E	t	Prob>z	Coef.	S.E	t	Prob>z
Diffhappy(t-1)	2706.816	3681.104	**0.74**	0.462	2606.912	1537.826	**1.70**	0.092	2049.461	1409.015	**1.45**	0.147
ΔPop(t-1)	0.66753	0.89212	**7.48**	0.000	0.9347158	0.429475	**22.28**	0.000	0.88144	0.035379	**24.91**	0
Year	-122.4943	155.8831	**-0.79**	0.432	-286.2526	158.6159	**-1.80**	0.073	-263.2855	141.1978	**-1.86**	0.064
Constant	248525.8	311562.2	**0.80**	0.425	573560.5	317255.4	**1.81**	0.072	528154.6	282342.4	**1.87**	0.063
	F-test that all u_i=0 F(14,162) = 1.31 Prob>F = 0.2053				Hausman test Chi2 = 0.93 Prob>Chi2 = 0.6285							

	Model B											
	Column 1				Column 2				Column 3			
	Fixed Effects Instrumental Variables, Common Time Trend				OLS with Instrumental Variables and Common Time Trend				OLS, No Instrumental Variables and Common Time Trend			
	Dep Var: ΔPop(t)				Dep Var: ΔPop(t)				Dep Var: ΔPop(t)			
	Exp Var: SpatHappy(t-1)				Exp Var: SpatHappy(t-1)				Exp Var: SpatHappy(t-1)			
	Overall R-squared: 0.7926				Overall R-squared: 0.7963				Overall R-squared: 0.7873			
	Coef.	S.E	z	Prob>z	Coef.	S.E	t	Prob>z	Coef.	S.E	t	Prob>z
Spathappy(t-1)	1228.778	4565.183	**0.27**	0.788	2289.359	2076.078	**1.10**	0.243	1807.567	1891.196	**0.96**	0.34
ΔPop(t-1)	0.6776	0.0908	**7.46**	0	9.46E-01	0.0414	**22.85**	0	0.8885	0.035	**25.35**	0
Year	-113.4924	115.6083	**-0.73**	0.466	-2.81E+02	159.7403	**-1.76**	0.081	-258.2553	141.6804	**-1.82**	0.07
Constant	230441.5	310994.7	**0.74**	0.459	562109.3	319500.9	**1.76**	0.08	1634.669	609.4945	**1.83**	0.0069
	F-test that all u_i=0 F(14,162) = 1.34 Prob>F = 0.1888				Hausman test Chi2 = 0.42 Prob>Chi2 = 0.8121							

	Model C											
	Column 1				Column 2				Column 3			
	Fixed Effects Instrumental Variables, Common Time Trend				Fixed Effects, No Instrumental Variables and Common Time Trend				OLS, No Instrumental Variables and Common Time Trend			
	Dep Var: ΔPop(t)				Dep Var: ΔPop(t)				Dep Var: ΔPop(t)			
	Exp Var: DiffHappy(t-1)				Exp Var: DiffHappy(t-1)				Exp Var: DiffHappy(t-1)			
	Overall R-squared: 0.8699				Overall R-squared: 0.8523				Overall R-squared: 0.8523			
	Coef.	S.E	z	Prob>z	Coef.	S.E	z	Prob>z	Coef.	S.E	t	Prob>z
ΔPop(t-1)	2.85E-06	9.64E-07	2.95	0.003	2.89E-06	9.58E-07	3.02	0.003	1.24E-06	6.70E-07	1.85	0.065
DiffHappy(t-1)	0.5072337	0.1121369	4.52	0.000	0.4570676	0.0614441	7.44	0	-2.46E-03	2.67E-03	-0.92	0.359
Year	-0.0010455	0.0025413	-0.41	0.681	-0.0007335	0.002469	-0.3	0.767	0.8893924	0.0266765	33.34	0
Constant	2.070298	5.080386	0.41	0.684	1.4461	4.935431	0.29	0.77	4.91104	5.345506	0.92	0.359
	F-test that all u_i=0 F(14,162) = 1.75 Prob>F = 0.0492											
	Hausman test Chi2 = 0.29 Prob>Chi2 = 0.8668											

Table 5. Deriving an Optimal Linear Regression Configuration for Model D

Model D									
Column 1		Column 2				Column 3			
Fixed Effects Instrumental Variables With Time Trends		Fixed Effects, No Instrumental Variables With Time Trends				OLS, No Instrumental variables With Time Trends			
		Dep Var: Spathappy(t), Exp Var: ΔPop(t-1)				Dep Var: Spathappy(t), Exp Var: ΔPop(t-1)			
F-test that all u_i=0 F(14,163) = 1.81 Prob>F = 0.0412		Overall R-squared: 0.0329				Overall R-squared: 0.8855			
		Coef.	S.E	z	Prob>z	Coef.	S.E	z	Prob>z
	ΔPop(t-1)	9.82E-07	9.61E-07	1.02	0.308	1.10E-06	7.77E-07	1.42	0.157
Keep Fixed Effects	SpatHappy(t-1)	0.1372776	0.0752333	1.82	0.070	0.5477299	0.0590529	9.28	0.000
	year	0.0268939	0.0067025	4.01	0.000	0.0007662	0.0019651	0.39	0.697
Hausman test Chi2 = 2.62 Prob>Chi2 = 0.9999	yearb1	-0.056005	0.0100769	-5.56	0.000	8.05E-06	0.0000202	0.4	0.691
	yearb2	0.0213083	0.0094502	2.25	0.025	-0.0000356	0.0000206	-1.73	0.085
	yearb3	-0.0231918	0.0092961	-2.49	0.014	-4.32E-06	0.0000213	-0.2	0.839
Drop IV	yearb4	-0.0499793	0.0100256	-4.99	0.000	-0.0000102	0.0000192	-0.53	0.598
	yearb5	-0.0268523	0.009923	-2.71	0.008	-0.000065	0.0000215	-3.02	0.003
	yearb6	-0.0420796	0.0097236	-4.33	0.000	-0.0000252	0.00002	-1.26	0.210
	yearb7	-0.0293782	0.009214	-3.19	0.002	-0.0000459	0.0000205	-2.24	0.026
	yearb8	-0.0178401	0.0094203	-1.89	0.060	-0.000082	0.0000256	-3.2	0.002
	yearb9	-0.0288936	0.0093662	-3.08	0.002	0.0000143	0.000025	0.57	0.568
	yearb10	-0.0122025	0.0091955	-1.33	0.186	-0.0001248	0.0000266	-4.69	0.000
	yearb11	-0.0415506	0.0096181	-4.32	0.000	-0.0001166	0.0000244	-4.78	0.000
	yearb12	-0.0275245	0.0093549	-2.94	0.004	-0.0000834	0.000022	-3.79	0.000
	yearb13	-0.0254317	0.009325	-2.73	0.007	-0.0001702	0.000029	-5.86	0.000
	yearb14	-0.0188022	0.0092418	-2.03	0.044	-0.0000593	0.0000208	-2.85	0.005
	Constant	-3.337638	3.617614	-0.92	0.358	-1.432205	3.930663	-0.36	0.716

Table 6 Ramsey RESET test and Breusch-Pagan/ Cook-Weisberg Test for Linear Parametric Models

		Model A	Model B	Model C	Model D
Ramsey RESET test	H_0: Model fitted has no omitted variables H1: Model can benefit from nonlinear functional form	F(3,188) = 2.91 Prob>F = 0.0360	F(3,188) = 2.76 Prob>F = 0.0474	F(3,188) = 8.38 Prob>F = 0.000	F(3,188) = 1.20 Prob>F = 0.3105
Breusch-Pagan / Cook-Weisberg test for heteroscedasticity	H0: Constant variance of error terms H1: Errors are Heteroscedastic	Chi2 = 26.73 Prob>Chi2 = 0.000	Chi2 = 20.22 Prob>Chi2 = 0.000	Chi2 = 2.87 Prob>Chi2 = 0.0905	Chi2 = 4.10 Prob>Chi2 = 0.0430

Table 7. Multiple Ranks Fixed Effects Instrumental Variables with Individual Time Trends

	Model A				Model B				Model C				Model D			
	Dep Var: r_ΔPop(t)				Dep Var: r_ΔPop(t)				Dep Var: r_Diffhappy(t)				Dep Var: r_Spathappy(t)			
	Exp Var: r_Diffhappy(t-1)				Exp Var: r_Spathappy(t-1)				Exp Var: r_ΔPop(t-1)				Exp Var: r_ΔPop(t-1)			
	Overall R-squared: 0.0370				Overall R-squared: 0.0253				Overall R-squared: 0.0783				Overall R-squared: 0.0300			
	Coef.	S.E	z	Prob>z	Coef.	S.E	z	Prob>z	Coef.	S.E	z	Prob>z	Coef.	S.E	z	Prob>z
Exp. Var.	0.1613	0.0815	**1.98**	0.048	0.0241	0.1110	**0.22**	0.828	0.3212	0.0817	**3.93**	0.000	0.1416	0.0663	**2.14**	0.033
Lagged Dep. Var.	0.0490	3103549.0	**0.16**	0.875	0.2192	0.2947	**0.74**	0.457	0.0040	0.1901	**0.02**	0.983	-0.3366	0.2636	**-1.28**	0.202
year	8.3640	3.1177	**2.68**	0.007	7.4462	3.1050	**2.40**	0.016	1.2293	2.0644	**0.60**	0.552	8.2737	2.0916	**3.96**	0.000
yearb1	-3.1879	3.0986	**-1.03**	0.304	-3.1511	3.3446	**-0.94**	0.346	-4.6664	2.9046	**-1.61**	0.108	-17.2711	3.6341	**-4.75**	0.000
yearb2	-1.0636	3.0397	**-0.35**	0.726	0.0769	3.0198	**0.03**	0.980	8.5087	3.1994	**2.66**	0.008	9.2965	3.1240	**2.98**	0.003
yearb3	-6.9912	3.5177	**-1.99**	0.047	-5.9259	3.4685	**-1.71**	0.088	0.2074	2.8019	**0.07**	0.941	-7.2533	2.5868	**-2.80**	0.005
yearb4	-4.7021	3.2579	**-1.44**	0.149	-4.9689	3.5553	**-1.40**	0.162	-6.0443	3.1462	**-1.92**	0.055	-17.0650	4.0077	**-4.26**	0.000
yearb5	4.7953	4.1397	**1.16**	0.247	3.0574	4.0526	**0.75**	0.451	-6.2957	3.0060	**-2.09**	0.036	-8.7353	2.6706	**-3.27**	0.001
yearb6	-11.7371	4.2426	**-2.77**	0.006	-10.9290	4.2864	**-2.55**	0.011	-5.1827	3.1422	**-1.65**	0.099	-13.5390	3.4317	**-3.95**	0.000
yearb7	-7.8842	3.2752	**-2.41**	0.016	-7.5271	3.3064	**-2.28**	0.023	-2.9581	2.8370	**-1.04**	0.297	-8.6066	2.5053	**-3.44**	0.001
yearb8	-5.7760	2.9667	**-1.95**	0.052	-5.8183	2.9398	**-1.98**	0.048	-1.8670	2.8068	**-0.67**	0.506	-3.6957	2.3421	**-1.58**	0.115
yearb9	-6.8265	3.3228	**-2.05**	0.040	-6.2304	3.3404	**-1.87**	0.062	-1.8967	2.8150	**-0.67**	0.500	-8.7884	2.7099	**-3.24**	0.001
yearb10	-15.8885	4.9982	**-3.18**	0.001	-13.6854	4.8297	**-2.83**	0.005	2.1456	2.8652	**0.75**	0.454	-5.2821	2.4923	**-2.12**	0.034
yearb11	-15.5413	4.7279	**-3.29**	0.001	-13.8402	4.6724	**-2.96**	0.003	-1.7100	2.8452	**-0.60**	0.548	-12.1465	3.0216	**-4.02**	0.000
yearb12	-13.5151	4.8538	**-2.78**	0.005	-11.6034	4.7373	**-2.45**	0.014	0.1122	2.8697	**0.04**	0.969	-8.4022	2.6540	**-3.17**	0.002
yearb13	-15.0952	5.1845	**-2.91**	0.004	-12.9669	5.0329	**-2.58**	0.010	0.5024	2.8936	**0.17**	0.862	-7.4653	2.6479	**-2.82**	0.005
yearb14	-15.2292	5.2054	**-2.93**	0.003	-12.9700	5.0247	**-2.58**	0.010	1.4084	2.8769	**0.49**	0.624	-5.0108	2.4337	**-2.06**	0.040
Constant	-821.9593	1453.16	**-0.57**	0.572	-610.36	1430.1710	**-0.43**	0.670	-12.9209	1097.4780	**-0.01**	0.991	-1217.1370	909.0032	**-1.34**	0.181
Test of individual time trend joint significance:	Chi2 = 19.12				Chi2 = 17.32				Chi2 = 18.477				Chi2 = 21.92			
	Prob>Chi2 = 0.2083				Prob>Chi2 = 0.3000				Prob>Chi2 = 0.2242				Prob>Chi2 = 0.0155			

Table 8. Deriving an Optimal Multiple Ranks Regression Configuration for Models A, B and C

	Model A											
	Column 1				Column 2				Column 3			
	Fixed Effects Instrumental Variables, Common Time Trend				OLS with Instrumental Variables and Commmon Time Trend				OLS, No Instrumental Variables and Common Time Trend			
	Dep Var: r_ΔPop(t)				Dep Var: r_ΔPop(t)				Dep Var: r_ΔPop(t)			
	Exp Var: r_Diffhappy(t-1)				Exp Var: r_Diffhappy(t-1)				Exp Var: r_Diffhappy(t-1)			
	Overall R-squared: 0.7869				Overall R-squared: 0.7875				Overall R-squared: 0.7674			
	Coef.	S.E	z	Prob>z	Coef.	S.E	t	Prob>z	Coef.	S.E	t	Prob>z
r_Diffhappy(t-1)	0.1469	0.0755	**1.95**	0.052	0.1023	0.0397	**2.57**	0.011	0.0690	0.0379	**1.82**	0.070
r_ΔPop(t-1)	0.7337	0.1078	**6.80**	0.000	0.9816	0.0465	**21.13**	0.000	0.9191	0.0397	**23.13**	0.000
year	-0.6682	0.6040	**-1.11**	0.269	-1.0280	0.6149	**-1.67**	0.096	-0.9201	0.5669	**-1.62**	0.106
_cons	1356.942	1204.94	**1.13**	0.260	2056.497	1229.587	**1.67**	0.096	1850.45	1133.127	**1.63**	0.104
	F-test that all u_i=0 F(14,162) = 1.07 Prob>F = 0.3859				Hausman test Chi2 = 35.04 Prob>Chi2 = 0.0000							

	Model B											
	Column 1				Column 2				Column 3			
	Fixed Effects Instrumental Variables, Common Time Trend				OLS with Instrumental Variables and Commmon Time Trend				OLS, No Instrumental Variables and Common Time Trend			
	Dep Var: r_ΔPop(t)				Dep Var: r_ΔPop(t)				Dep Var: r_ΔPop(t)			
	Exp Var: r_Spathappy(t-1)				Exp Var: r_Spathappy(t-1)				Exp Var: r_Spathappy(t-1)			
	Overall R-squared: 0.7836				Overall R-squared: 0.7819				Overall R-squared: 0.7674			
	Coef.	S.E	z	Prob>z	Coef.	S.E	t	Prob>z	Coef.	S.E	t	Prob>z
r_Spathappy(t-1)	0.0999	0.0874	**1.14**	0.253	0.0673	0.0393	**1.71**	0.088	0.0598	0.0374	**1.6**	0.112
r_ΔPop(t-1)	0.7581	0.1115	**6.8**	0	0.9955	0.0471	**21.14**	0	0.9216	0.0399	**23.12**	0
Year	-0.5953	0.6084	**-0.98**	0.328	-0.9709	0.6227	**-1.56**	0.121	-0.8877	0.5679	**-1.56**	0.12
Constant	1213.538	1214.11	**1**	0.318	1944.575	1245.143	**1.56**	0.12	1786.428	1135.373	**1.57**	0.117
	F-test that all u_i=0 F(14,162) = 1.08 Prob>F = 0.3812				Hausman test Chi2 = 16.51 Prob>Chi2 = 0.0009							

	Model C											
	Column 1				Column 2				Column 3			
	Fixed Effects Instrumental Variables, Common Time Trend				Fixed Effects, No Instrumental Variables and Common Time Trend				OLS, No Instrumental Variables and Common Time Trend			
	Dep Var: r_Diffhappy(t)				Dep Var: r_Diffhappy(t)				Dep Var: r_Diffhappy(t)			
	Exp Var: r_ΔPop(t-1)				Exp Var: r_ΔPop(t-1)				Exp Var: r_ΔPop(t-1)			
	Overall R-squared: 0.7310				Overall R-squared: 0.7551				Overall R-squared: 0.7986			
	Coef.	S.E	z	Prob>z	Coef.	S.E	z	Prob>z	Coef.	S.E	t	Prob>z
r_ΔPop(t-1)	0.2128	0.0572	**3.72**	0.000	0.2054	0.0563	**3.65**	0.000	0.0772	0.0375	**2.06**	0.041
r_Diffhappy(t-1)	0.4344	0.1157	**3.75**	0.000	0.5186	0.0648	**8.00**	0.000	0.9072	0.0358	**25.33**	0.000
year	-0.1503	0.5042	**-0.30**	0.766	-0.2196	0.4957	**-0.44**	0.658	-0.3296	0.5356	**-0.62**	0.539
_cons	346.7694	1005.016	**0.35**	0.730	477.3039	989.3101	**0.48**	0.630	669.0975	1070.692	**0.62**	0.533
	F-test that all u_i=0 F(14,177) = 2.53 Prob>F = 0.0026											
	Hausman test Chi2 = 0.77 Prob>Chi2 = 0.8562											

Table 9. Deriving an Optimal Multiple Ranks Regression Configuration for Model D

Fixed Effects Instrumental Variables With Time Trends		Fixed Effects, No Instrumental Variables With Time Trends				OLS, No Instrumental Variables With Time Trends			
		1)				r_ΔPop(t-1)			
		Overall R-squared: 0.0215				Overall R-squared: 0.8894			
		Coef.	S.E	z	Prob>z	Coef.	S.E	t	Prob>z
F-test that all u_i=0 F(14,163) = 2.07 Prob>F = 0.0157	r_ΔPop(t-1)	0.1158	0.0579	2.00	0.047	0.1263	0.0496	2.55	0.012
Keep Fixed Effects	r_SpatHappy(t-1)	0.1968	0.0808	2.44	0.016	0.6085	0.0636	9.56	0.000
	year	5.7531	1.5408	3.73	0.000	0.2102	0.4311	0.49	0.626
Hausman test Chi2 = 4.52 Prob>Chi2 = 0.9988	yearb1	-11.5830	2.2206	-5.22	0.000	-0.0008	0.0046	-0.18	0.855
	yearb2	5.0118	2.1415	2.34	0.020	-0.0093	0.0047	-1.99	0.048
	yearb3	-4.9820	2.0988	-2.37	0.019	-0.0053	0.0050	-1.07	0.287
Drop IV	yearb4	-10.4319	2.2822	-4.57	0.000	-0.0039	0.0043	-0.92	0.360
	yearb5	-6.3600	2.1611	-2.94	0.004	-0.0185	0.0050	-3.72	0.000
	yearb6	-8.5029	2.2336	-3.81	0.000	-0.0089	0.0047	-1.88	0.062
	yearb7	-6.7096	2.0837	-3.22	0.002	-0.0134	0.0048	-2.78	0.006
	yearb8	-2.7920	2.0469	-1.36	0.174	-0.0232	0.0057	-4.08	0.000
	yearb9	-5.9218	2.0977	-2.82	0.005	-0.0001	0.0054	-0.01	0.991
	yearb10	-3.7179	2.1181	-1.76	0.081	-0.0303	0.0060	-5.07	0.000
	yearb11	-8.3161	2.1713	-3.83	0.000	-0.0316	0.0060	-5.29	0.000
	yearb12	-6.0571	2.1506	-2.82	0.005	-0.0210	0.0051	-4.11	0.000
	yearb13	-5.2319	2.1648	-2.42	0.017	-0.0340	0.0062	-5.52	0.000
	yearb14	-4.0512	2.1254	-1.91	0.058	-0.0157	0.0048	-3.29	0.001
	Constant	-805.6361	789.4808	-1.02	0.309	-354.9265	861.2614	-0.41	0.681

Table 10: Ramsey RESET test and Breusch-Pagan/ Cook-Weisberg Test for Multiple Ranks Models

		Model A	Model B	Model C	Model D
Ramsey RESET test	H_0: Model fitted has no omitted variables H1: Model can benefit from nonlinear functional form	F(3,188) = 1.31 Prob>F = 0.2717	F(3,174) = 1.22 Prob>F = 0.3043	F(3,188) = 3.52 Prob>F = 0.0162	F(3,174) = 0.23 Prob>F = 0.8779
Breusch-Pagan / Cook-Weisberg test for heteroscedasticity	H0: Constant variance of error terms H1: Errors are Heteroscedastic	Chi2 = 1.62 Prob>Chi2 = 0.2031	Chi2 = 1.89 Prob>Chi2 = 0.1687	Chi2 = 5.70 Prob>Chi2 = 0.0170	Chi2 = 2.40 Prob>Chi2 = 0.1210

Table 11. Panel Homogeneity F-tests

Regression Model	Happiness Variable	F-Value	Conclusion
Linear Causality	Diffhappy	1.61	Do Not Reject Null of Homogeneity
	Spathappy	1.69	Do Not Reject Null of Homogeneity
Multiple Ranks Causality	Diffhappy	2.54	Reject Null of Homogeneity at 5%
	Spathappy	3.16	Reject Null of Homogeneity at 1%
Linear Reverse Causality	Diffhappy	1.45	Do Not Reject Null of Homogeneity
	Spathappy	2.36	Reject Null of Homogeneity at 5%
Multiple Ranks Reverse Causality	Diffhappy	1.55	Do Not Reject Null of Homogeneity
	Spathappy	0.86	Do Not Reject Null of Homogeneity

Note: Critical Values are P(F>1.39) = 0.25, P(F>1.83) = 0.1, P(F>2.17) = 0.05 and P(F>3.08) = 0.01

Table 12. Contingency Tables

	Model A		
	Greater ΔPop(t)	**Lower Δpop(t)**	Total
Happier(t-1)	68	57	125
Less Happy(t-1)	15	70	85
Total	83	127	210

Pearson chi2(1) = 28.5924 Pr = 0.000

	Model B		
	Greater ΔPop(t)	**Lower Δpop(t)**	**Total**
Happier(t-1)	52	54	106
Less Happy(t-1)	31	73	104
Total	83	127	210

Pearson chi2(1) = 8.1375 Pr = 0.004

	Model C		
	Happier(t)	**Lower Happy(t)**	**Total**
Greater ΔPop(t-1)	63	14	77
Less Δpop(t-1)	53	65	118
Total	116	79	195

Pearson chi2(1) = 26.3296 Pr = 0.000

	Model D		
	Happier(t)	**Lower Happy(t)**	**Total**
Greater ΔPop(t-1)	47	30	77
Less Δpop(t-1)	52	66	118
Total	99	96	195*

Pearson chi2(1) = 5.3694 Pr = 0.020

*15 observations lost for Δpop as created from 1992-2006 population data. This has effectively removed the 1992 panel.

Note for Contingency Tables: Greater and less $\Delta Pop_{(t-1)}$ are relative to $\mu(\Delta Pop_{(t-1)})$ and do not represent in-migration and out-migration.