DEMOGRAPHIC RESEARCH

A peer-reviewed, open-access journal of population sciences

DEMOGRAPHIC RESEARCH

VOLUME 30, ARTICLE 36, PAGES 1035–1074
PUBLISHED 3 APRIL 2014
http://www.demographic-research.org/Volumes/Vol30/36/
DOI: 10.4054/DemRes.2014.30.36

Research Article

A Bayesian analysis of the spatial concentration of individual wealth in the US North during the nineteenth century

Alice Bee Kasakoff

Andrew B. Lawson

Emily M. Van Meter

Table of Contents

Demographic Research: Volume 30, Article 36
Research Article

A Bayesian analysis of the spatial concentration of individual wealth in the US North during the nineteenth century

Alice Bee Kasakoff[1]

Andrew B. Lawson[2]

Emily M. Van Meter[3]

Abstract

BACKGROUND
Kin effects can be difficult to distinguish from those of spatial proximity, since kin tend to live close to each other. Thus, past research showing correlations between the wealth of relatives may be showing the effects of proximity and shared locations, not the effects of kin.

OBJECTIVE
What are the effects of kin and of spatial proximity upon wealth? This is studied both for fathers and sons and for brothers.

METHODS
Data comes from a genealogical sample that has been linked to the US census of 1860. The genealogies allow us to identify fathers, sons, and brothers, information that is not available from the census itself. A Bayesian hierarchical approach can model family and spatial effects at the same time, thereby distinguishing them from each other.

RESULTS
Data on fathers and sons is difficult to interpret from a single time. Many of the fathers in the census had died, so the sample size was small. A man's wealth was positively associated with his brothers' average wealth, even after their father had died. Therefore, there was evidence for lasting family effects; however, proximity to the other brothers was not related to an individual's wealth.

[1] Department of Anthropology, University of South Carolina, Columbia, SC, U.S.A.
[2] Department of Public Health Sciences, Medical University of South Carolina, Charleston, SC, U.S.A.
[3] Corresponding author. Division of Cancer Biostatistics, Markey Cancer Center, University of Kentucky, Lexington, KY, U.S.A. E-Mail: emily.vanmeter@uky.edu.

CONCLUSIONS
The family effects were stronger than the spatial effects at this time, even though this sample was highly mobile. Thus, there was evidence for family effects apart from spatial effects.

COMMENTS
This study shows how Bayesian spatial analysis can be used to disentangle the effects of family from the effects of spatial location. The method was capable of distinguishing spatial from family effects.

1. Introduction

There is evidence for a growing role of families in creating inequality in income today, especially in the US (Solon 1999; Corak 2004; Bowles, Gintis, and Groves 2008). Inequality in income is also a byproduct of uneven spatial development (Lobao and Hooks 2007). It is difficult to study both the spatially differentiated economic environment and the family environment at the same time, as clustering from each of these sources may be difficult to distinguish. Family members tend to live close to each other, whether due to inertia, economic benefits from family members, chain or family migration, or obligations to provide support for each other. If “family effects” are really the result of the locations where people grew up or lived, researchers who do not separate these from each other underestimate the roles of location and past migration in creating income inequality, and overestimate family effects.

Parents may influence the income or wealth of their children through many channels. They may pass on actual capital, human capital, or social capital. They may also influence their children through genetics, which could operate in many different ways. Bowles et al conclude that “little intergenerational inequality is due to parents passing superior IQ on to their children, and much is due to parents passing their material wealth to their children, at least for those at the top of the income distribution” (2008). They do not rule out a genetic aspect, however. Another channel through which parents can affect their children is through “spatial capital” (Kesztenbaum 2008). Parents also have connections outside the immediate local area that can be used by children if they decide to leave that area. Spatial clustering of family members can continue even after people have left their birthplaces.

Economists have estimated a family effect upon income by estimating correlations between the income of siblings and, in some cases, fathers and their children (Solon et al. 1991; Solon 1992, 1999, 2002). But this effect includes everything an individual shares with these relatives. Attempts to estimate the proportion of effects due to "neighborhoods" rather than families generally conclude that neighborhoods were not as important as families (Corak 2004). If families sort themselves by location so that similar families are to be found in the same "cluster", then some of the neighborhood effect is, in fact, a family effect, further reducing the role of location. One way to assess the effect of proximity upon family effects is to compare siblings' incomes with incomes of people raised nearby (Page and Solon 2003). Such "neighborhood" effects were found to decrease over time in Norway, and researchers hypothesized that this was due to a decrease in spatial differences in school quality, a policy consciously pursued by the government, but the methods used did not allow this to be studied directly (Raaum, Salvanes, and Sørensen 2006). Other methods that distinguish location effects from family effects are needed in order to understand exactly how families contribute to income inequality.

We conceive of a "family effect" on wealth as composed of many separate, sometimes interconnected, effects. We are specifically concerned with separating effects of spatial location (in our case the county where a person lived) from other effects. We examine the wealth distribution amongst family members during the census year 1860 in the northeastern US. Our analysis is based on a unique source of data: genealogies linked with the 1860 US census. This allows us to examine "deep" effects upon wealth by comparing the wealth of branches in earlier and later generations. We examine the effect of family membership and spatial clustering along with complicating factors via the use of Bayesian hierarchical models. The models are structured to allow for fixed family effects and additive random spatial effects (which can be correlated spatially or not). The inclusion of these additive effects makes considerable allowance for complicating factors, which are always present in population level studies. Appendix A describes in detail the general model employed. Variants and sub-classes of this model in particular applications are described in more detail in the methods and measurement section.

Incorporating spatial effects for individual social mobility by including regions, or classifying data as urban versus rural as a variable does not systematically indicate spatial effects (Irwin 2007). Recently new methods in the frequentist tradition have been used to study incomes, poverty, and the degree of inequality at the county level in the US (Irwin 2007; Curtis, Voss, and Long 2012; Peters 2012). This is part of a move to study "subnational" units (Lobao and Hooks 2007) These have not been employed to model individual level wealth. Recent work on social mobility in the US has described large spatial differences between regions and cities today, but these differences have not been modeled systematically or included in analyses along with the other variables studied. Bayesian hierarchical modeling has several advantages over spatial variables in a regression model. First, even when spatial variables are included in the model, there might be other spatial effects that were not included. We provide estimates of two different spatial effects (random and correlated) and estimates of how much they improve model fit. Second, the methods provide maps of these effects. These show where the model fits well, and where it underestimates or overestimates individual wealth. These may suggest further spatial variables. Third, incorporating spatial variables into a model without taking into account the clustering of observations and the hierarchical structure of the data can lead to misleading estimates. The models used here do not have this problem. These methods offer the potential of being able to distinguish between several of the different underlying effects that might lead to inheritance of wealth in families. We analyze effects on several different temporal and spatial scales and attempt to model them explicitly in order to distinguish several different ways wealth could be inherited within families.

The use of a historical genealogical sample allows us to explore deep effects of families that go beyond two generations; effects that, as Mare (2011) has pointed out, often go unstudied due to lack of data, but which are potentially quite important. Even historical samples can rarely go beyond three generations, however, in this paper we explore the effects from 5 generations back, examining the effect of having a common ancestor in the 2nd generation upon men in the 7th. While we could go backwards from a dataset collected from living individuals, there is also merit in going forwards from a founding ancestor, as our data does. By going forward from a founder, we are able to study all descendants, not just those who have living offspring today. Of necessity, a historical sample capable of exploring effects going this far back will be looking at quite a different economic system; in our case, one in which about half the men were farmers and the major form of capital was land. By studying a different economic context, we are able to contribute to a broader theoretical framework for studying how families affect social mobility. We can shed light on what factors facilitate mobility in changing economic environments. Differences in human capital were not as great then as they are today, and this may mean that there is more opportunity to observe family effects. But since a father’s income is becoming more important in predicting the income of children today than it has been in the past, it can be argued that in the future, wealth in the form of capital may become even more important. Again, we can compare this to the situation we are describing here, in which the death of the father is an important predictor of wealth.

2. The genealogical sample

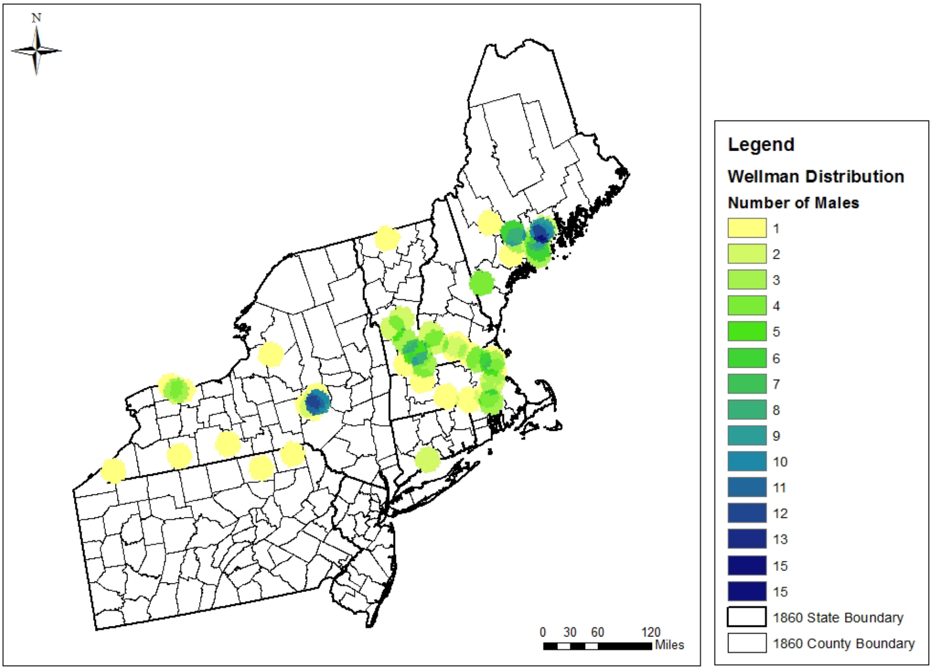
Our data come from the US Population Census of 1860. We extracted the wealth data of men only in a genealogical database tracing the male descendants of 9 ancestors with different surnames who had come to Massachusetts from England before 1650. The census provides information on individual wealth, location, household composition, and occupation, while the genealogy provides information about exactly how the individuals are related.

Each genealogy reflected a similar pattern of colonization as the families moved northwards out of Massachusetts in the eighteenth century, and then westward to New York and the Middle West. The population increased rapidly. In the early years each couple had, on average, 6 children who survived to have children themselves. High fertility in towns that were settled early in their history left its traces in large clusters of relatives, as can be seen in Figure 1 (Castro and Kasakoff 2007) which shows the spatial location of the Wellmans, one of our nine genealogy families. The first member of this family settled around Lynn, Massachusetts, before 1640. In 1860 we found 95 descendants, through the male line, ages 20 or older on the census. There was still a cluster in the area where they had first settled more than 200 years before. At first the family moved locally into Southern New Hampshire. But several men moved into land that had opened up after the Revolutionary War (1775–1783), founding two branches in Maine in 1784 and 1805. The cluster in New York illustrates the pioneering of this generation. The founder had been born in Massachusetts, took up land in Southern Vermont after the Revolutionary War, where there was still a cluster remaining in 1860, but then moved into New York in 1805. Spatial clustering and genealogical distance were related in these data; the fewer the individuals in a particular location, the more closely they were related.

Because the women changed their names at marriage, it was more difficult for the genealogists to follow them throughout their lives. Therefore, we used only men descended though the male line born into the 9 families who were alive in 1860. We study the 1,009 men, aged 20 or older, found on the census of 1860 and were living in New England, New York, and the northern tier of Pennsylvania, which had been settled from New York. This is a large area – 345,138 square kilometers.

Income or earnings have been more frequently studied than wealth in contemporary populations because that information is more readily available. Historically, information about wealth was more available because census-takers frequently collected information about it at an individual level. We use this measure. In 1860, census takers listed all the individuals in each dwelling and family by name, and recorded the wealth of each of them: both real property and personal property, as measured in US 1860 dollars. We add them together and use that as our dependent variable. Others using historical census data from the US have found that inequality of wealth was greater than inequality of income. It was also more stable from year to year, and family effects upon wealth were greater than those upon income (Kearl and Pope 1984, 1986a, 1986b). Real estate was 70% of total wealth and contributed importantly to growing inequality (Steckel and Moehling 2001).

Figure 1: Kin density in 1860 counties of Northeast US: Wellman Family



2.1 Economic context and sample characteristics

The northeastern US was undergoing a transformation in 1860 from dependence on farming to manufacturing and commercial enterprises. This affected different parts of the study area differently. In southern New England, less land was being farmed, especially in areas distant from cities. People found work in the growing manufacturing sector, which was located in western Connecticut and southern New Hampshire, along rivers that could provide water power. Those who left farming experienced a decline in wealth, as shown in Table 1. However, farms close to urban centers continued to do well by supplying the cities with bulky or perishable products, such as milk, butter, and cheese. In New York, farming continued to be very important, despite the fact that grain was supplied from outside the region at this time. New York also specialized in dairy products and other farm products that could be shipped via the major waterways: the Erie Canal, and the Hudson-Champlain waterway.

Table 1: Characteristics of men 20 and older in genealogical sample found on the census in New England and New York in 1860

	Non Farmers (1)	Farmers (1)	All
% living in birthplace	29 %	41%	36%
Median distance moved between birth and 1860 for those who had moved (2)	24.8 miles	30.2 miles	29.2 miles
Mean age	39	47	43
% of individuals with zero total property	36 %	22 %	29 %
Median total property for property holders	$1283	$2400	$2050
Proportion total property which was real	48 %	68 %	59 %
N	460	532	1009

Notes: (1) This is the census occupation, but if that was missing, we were able to add information on occupation for 7% of the sample using information from other sources. If noted as a farmer at any time during his life, he was considered a farmer even if he had worked at non-farm occupations. As a result only 2% of the sample did not have an occupation.
(2) Distance in a direct line between birth-place and place of residence at the time of 1860 census.

Table 1 displays characteristics of men ages 20 and older in our sample who were found in the 1860 census. Of the 1,309 men found in the 1860 census, 1,009 (77%) lived within the region we are studying. The rest lived largely in the Middle West. The population was becoming divided between the long-settled New England area, where migration was primarily to towns, cities, and areas further west, where people continued to pioneer. When farmers moved, they went farther than non-farmers to settle new areas. In the group we are studying, fathers had moved to New York from Northern New England taking their families with them. The sons cleared land, and after the father died, the farm was often divided among the sons. At marriage, the father might give his son a piece of the property or money to buy a farm elsewhere. The ideal was equal inheritance among all the sons. Non-farmers often went to neighboring towns. 54% of sample subjects were farmers, and generally younger than the non-farmers, as would be expected in a population where young men took up non-farm work instead of farming as their fathers had. The non-farmers were less apt to hold property, and when they did, they had less than the farmers; possibly due to their youth as well as their occupation. These farms were family farms, and there were few tenants. Giving up farming proved to be important in wealth transmission in another nineteenth century study: correlation in brothers' occupations accounted for much of the family effect (Kearl and Pope 1986a). Fathers seemed to play an important role, however, in their children's choice of occupation (Kearl and Pope 1986b).

Our sample is biased towards men living with or near their family in what was a highly mobile population. In our sample, 90% of the fathers of men whose fathers were known to be alive at the date of the census were found in the census. However, we were more apt to find the fathers if they were living with their sons. For 15% of the sample, we did not know the death date of the father, and the last date on the father's record was before the census date of 1860. Some of these men were probably also still alive and their sons needed to be counted among the group whose fathers were alive and not found on the census. In analyses of brothers' wealth and distances between brothers, we included only the brothers found in the census, which was more likely when they lived in the same household, and only those brothers found within the study area. Still, even among those who had remained in the study area, 64% had left the towns where they had been born.

179 men were living in the same household as their fathers. It was usually the father who had the wealth in the household, while the son had no property (65% of the cases). In only 15% of cases did the son have property and the father have none (in 4% neither had property, and in 16% they both had some, but in 75% of those cases, the father had more than the son).

2.2 Representativeness of the sample

We assess representativeness of the genealogical sample compared to the general population at the time, by examining households with individuals in our sample that were also found in the 1850 census with a comparable sample from the public use sample (IPUMS). We used the households in that sample in which at least one person was born in the state where the people in the genealogical sample was born (New England area, New York, Pennsylvania, and the Middle West). 16% of the IPUMS sample included households with US-born adult children of more recent immigrants, while the genealogical sample had none. Only in 1870 did the census contain a question about the birthplaces of parents, so there was no way to distinguish people descended from the earliest migrants, the people in our dataset, from those descended from more recent migrants to the US.

The men in the genealogical sample were only slightly more likely to have been farmers than were those in the IPUMS extract. Those in our sample were only wealthier: median wealth of those with real property was $1,500 while for those in the IPUMS extract it was $1,000. However, a greater proportion of the IPUMS extract had no real property. The genealogical sample included more established residents. It is surprising that they were so close economically to the general population born in the same states, because a longer history in a place could be an economic advantage. This comparison used 1850 census data, not 1860 data. However, the genealogical sample would be the same in both, simply 10 years older.

The North American continent was colonized along latitudes, i.e. from east to west, with very little north to south migration. This was due at least in part to the sensitivity of crops to number of frost-free days. Varieties of corn available then grew specifically in certain latitudes. Also, the major rivers used for transportation ran from east to west. Our sample followed the same patterns of other families descended from early settlers who came to New England, so similarity to the census could not have come from selection due to out-migration.

The sample we use comes from an early stage of our census research, and was collected prior to the availability of online search tools; we estimate that it includes 71% of the men 20 or older in the genealogies who were living in the study region at the time. To assess whether the 29% we had not found were different from those we had found, we used the group that had been found on the 1850 census, which is complete. We divided the men found in the study area on the 1850 census who were thought by the genealogists to be alive in 1860 and still living in the study area into two groups: those we had found in 1860 (used in our analyses to follow) and those who had not yet been located in the census. The two were almost identical in age and in wealth. Although some of the 9 genealogies were better represented than others, they did not differ greatly in number (ranging from 63 to 80% of each genealogy identified).

The sample is biased towards farmers who lived in rural areas that had been settled for a while. We found 75% of the farmers in 1850 that we thought were still in the study area, but only 64% of the non-farmers. We found fewer men in the states that were most urban: Massachusetts and Rhode Island. Thus, the sample is slightly biased towards large family clusters in rural areas, where finding one person allowed us to find others on the same census page, which our transcribers were directed to collect.

3. Methods and measurement

3.1 Bayesian hierarchical spatial modeling

Bayesian hierarchical models offer a direct way to examine the roles of family and spatial variables, and take into account the clustering that has to be specially dealt with in multilevel models. These models also allow the inclusion of random effects within models for familial wealth, and can allow for a variety of sources of extra variation. All parameters have prior distributions specified; estimation is obtained by sampling of the posterior distribution of the parameters, given the data. Such posterior sampling is often achieved via Markov chain Monte Carlo (MCMC) methods. The package WinBUGS (Lunn et al. 2009) has been designed to allow such sampling for a range of complex models. For spatial modeling, the package GeoBUGS can also be used to provide additional GIS capability and to map output from models (Lawson 2009). It is possible to flexibly include different spatial variables within linear hierarchical models, for example; spatial unit level effects (e.g. county or town) can be employed, while distance-based effects can also be included. Random effects can be scale-dependent and at multiple aggregation levels.

Hierarchical multilevel modeling is now commonly used in social science and related disciplines (Leyland and Goldstein 2001; King, Rosen, and Tanner 2004; Gelman and Hill 2007; Goldstein 2011) to model hierarchical spatial effects. The advantages of hierarchical modeling are that variation within the data can be considered within a hierarchy, and conditioning can be allowed for within that hierarchy. In our example, subsets of family structures allow conditional inference. For instance, the relation between individual wealth and average brothers' wealth may be different when either the father is alive (and in the dataset) or is not alive. Conditioning on the subset of "father alive" could lead to a different inference than when considering the whole dataset. This conditional inference is handled in a multilevel hierarchical context. Bayesian hierarchical modeling allows the incorporation of spatial effects with non-diffuse prior distributions (spatial CAR models) and allows complex hierarchies of effects (such as towns within counties or brothers within families) (Lawson, Browne, and Vidal Rodeiro 2003).

3.2 Measures of spatial and family effects

We consider family effects in our data, as well as two spatial effects: distance based and residual spatial random effects. The distance-based effects are inter-personal distances measured as Euclidian distance between towns; the residual effects are unobserved county level effects. We analyze the data on the county level while at the same time accounting for distances between brothers, based upon their town locations.

We first consider "family effect" variables. As we do not have family interactional data (Snijders and Kenny 1999) we cannot include bidirectional relations. Instead we must consider either generational factors or direct measures of paternal or fraternal influence. Examples of the former take the form of locating an individual within the patrilineal family tree by assigning a unique number corresponding to a family branch in the paternal line to a subject. A common ancestor in a particular generation might affect the wealth of his descendants through the ancestor's own wealth, or through something he did that could have raised or lowered the wealth of his descendants, such as migrating to a particular area where descendants might be found later on. If the ancestor gave up farming, the wealth of his descendants might have been lowered, as it would be rare for his descendants to return to farming. Individuals belonging to the same branch of the family had more ancestors in common and were more closely related to each other than were members of other branches. Their wealth could reflect the common experiences of their ancestors. Many generations could be considered, because the majority of individuals alive in 1860 were seven and eight generations from the founder of the family in the US. We have focused on two that provide important markers for this census. Branching in the second generation after the arrival of the founder provides a measure of deep family effects – generally members of the second generation lived between 1630 and 1700 – while the fifth generation measures more recent effects, usually two or three generations removed from the men in our 1860 sample, ancestors who would have lived from about 1755 to 1835. The effects of more recent ancestors should be picked up by the wealth of the fathers and brothers, which we measure directly.

The inclusion of either the second or the fifth generation effect improved overall model goodness of fit as judged by the Deviance Information Criteria (DIC) (Spiegelhalter et al. 2002); however, neither were ever well estimated (as defined in further detail in section 3.4). When comparing which generation effect most improved model fit, the second-generation factor was preferable to the fifth-generation factor, or a combination of the two. It is not clear why branching so far back in time should have affected wealth so many years later, when the more recent measure, the fifth generation, did not. These variables are hierarchically related: each branch at the second generation is subdivided into several branches in the fifth generation. If there were effects in the fifth generation, they would have to be over and above those in the second. The second-generation branches with extreme values of wealth in 1860 were considerably smaller than the others, suggesting some random variation. Few if any members of these extreme branches lived in New York State or Pennsylvania, the areas that had been settled most recently. These small branches, then, did not reflect the wealth of the entire sample, because members were concentrated in the longest-settled areas. Wealth, therefore, varied the most in the areas that had been settled the longest, just as species have the most diversity in the area where they originated. The family branches that did not leave the oldest areas were in more specialized niches and did not reflect the broader opportunities available through migration. This produces the counter-intuitive result that earlier branching affected wealth more than later branching.

Besides generational markers, we have modeled paternal effects (father alive, father lives in same household, and father's wealth) as well as sibling effects (average brothers' wealth and inter-brother distance in terms of minimum and median values of distance to any brother). The census of 1860 contains the names and the wealth of each individual in two spatial units: the dwelling was defined as a structure with a common roof which could include more than one family, which was defined as a group using the same entrance. Wealth and incomes are usually examined at the household level.

However, we examined the wealth of individuals: all the men 20 years of age or older we were able to locate on the census of 1860, which is our source of information for wealth. We were able to model household effects directly by including variables describing whether the relatives were living in the same household (dwelling).

A man's wealth was highly dependent on whether his father was alive or dead, therefore we have included this variable in our analyses. Although there were certainly *inter vivos* transfers, the difference in wealth between men whose fathers were alive and dead suggests that more property was distributed after the father died. Thus it is a stronger test of the influence of the family upon wealth to divide the sample into men whose fathers had died and those whose fathers were still alive. This also sheds light upon mechanisms of transmission. A living father might have affected his children's wealth though professional contacts (social capital), aid in actual labor or in securing the labor of brothers or other relatives, provision of equipment, and even human capital, for example. But these effects would not so easily persist after his death.

Fathers and sons are necessarily observed at different ages. The effect of the fathers' wealth on that of his sons will be underestimated because some of the sons caught early in their careers will become wealthy but others will not (Grawe 2006; Haider and Solon 2006). Wealth peaked later in life than earnings (as was found in nineteenth century Utah where wealth peaked at age 58, while income peaked at age 42) and the issue of comparable ages is more important for wealth than it is for earnings (Kearl and Pope 1986a). Sons were, on average, 31 years old, and their fathers 64 years old, much closer than their sons to the age when wealth peaked.

In contrast to today, high fertility meant there were many men who had several brothers who were found on the census. In half the cases, only one brother had been found, but in 20% of cases three or more brothers (the maximum was five) had been found. Our models also included the number of brothers who survived to the age of 20. The number of brothers would be important in determining wealth, because the inheritence would be divided between them. In terms of spatial effects, the distance between brothers is measured in two variables: the minimum distance between brothers and the median distance between brothers. The minimum distance describes the distance to the closest brother, while the median gives a measure of the dispersion of the brothers overall. The distance used the latitudes and longitudes of the locations where the individuals were found on the census (usually towns or townships which comprised the county). The amount of dispersion increased with the number found.

Besides inter-brother distance, we have considered both an uncorrelated county effect and a spatial conditional autoregressive (CAR) random effect component for spatial correlation (Lawson 2009). These effects are included as contextual effects at the county level. This allows an individual to be assigned the county effect for the county they reside in.

3.3 Bayesian model fitting to the familial data

The dependent variable is individual wealth (total of real and personal property logged; if none was reported, we assigned $2 so it could be logged) of men over age 19 found in the 1860 census. Various individual and familial variables are added as regression variables in a Bayesian linear model framework. In the most general model (see Appendix A), individual frailty, and both uncorrelated and correlated county level effects are assumed in the model:

$$y_i = f_i^T \boldsymbol{\alpha} + g_i^T \boldsymbol{\beta} + R_i + e_i$$
$$R_i = \tau_i + w_i + v_i$$

where $f_i^T \boldsymbol{\alpha} + g_i^T \boldsymbol{\beta}$ are the linear predictors including the personal and family covariates, and τ_i is an individual frailty effect (describing individual extra-variation in wealth accumulation), w_i is a county level spatial correlation effect and v_i is the uncorrelated county effect. These effects are given prior distributions within the Bayesian approach. The individual effect represents a variance component, which allows there to be differential wealth response at the individual level (above/below the average effect). We assume here that this effect has a zero mean Gaussian distribution with precision $1/\sigma_\tau^2$. The w_i effect is assumed to have a conditional autoregressive (CAR) prior distribution which models the spatial correlation in the outcome, while the v_i effect is assumed to have a zero mean Gaussian prior distribution. The precisions of these the effects ($1/\sigma_\tau^2$, $1/\sigma_w^2$, $1/\sigma_v^2$) are assumed to have their distributions defined by non-informative uniform distributions on the standard deviation, i.e. $\sigma_* \sim U(0, c_*)$, where c_* is a fixed constant. (Gelman 2006). All regression parameters are assumed to have zero mean Gaussian prior distributions with SD uniform hyperpriors for precisions. Appendix A gives the details of this general specification.

3.4 Posterior sampling

Bayesian models are based on the construction of posterior distribution for the parameters of interest. These distributions are often difficult to evaluate directly and it is now common to resort to Monte Carlo sampling of posterior distributions. Specifically, a set of methods called Markov chain Monte Carlo (MCMC) has been established that allow sampling of parameter values from posterior distributions. These methods have been incorporated within the package WinBUGS. Usually, when reporting MCMC results for Bayesian models it is common to provide mean estimates from the resulting sample of parameter values. Hence we report posterior mean estimates for parameters from each model, and provide their sample-based standard deviation and 95% credible interval. The sample size for these estimates is usually at least 1000 (post-convergence) thus obtaining reasonable accuracy.

Overall model adequacy is examined with goodness-of-fit measures. The primary measure used is the deviance information criterion (Spiegelhalter et al. 2002). This relative measure is used to compare models. Models yielding a reduction in DIC values (of 3–5 units) are regarded as improved models, therefore assessing the contribution of various effects within our analysis. In particular, we are interested in the effect of adding spatial effects (correlated or uncorrelated) to our analysis. If these effects reduce the DIC by at least 3 units, then we regard them as providing a better model fit. Note that DIC is scale-dependent, and dependent on sample size. If sub-samples are taken, they can't directly be compared via DIC to a full sample; the scaling is completely different. DIC comparison is only valid for the same response data but with different model ingredients (covariates or REs). Any differences in DIC will vary if the sample size varies.

In what follows we use the term 'well estimated' when there is strong evidence for a posterior mean parameter estimate. For regression parameters, if the interval does not cross zero then the parameter is 'well estimated'. More generally, and approximately, if the absolute value of the parameter estimate divided by its SD is greater than 2 then the parameter is declared 'well estimated'. Different combinations of spatial, family, and individual effects were included to provide a range of models for each dataset examined, so that we could see how the DIC was affected by adding different variables.

3.5 Mapping and spatial random effects

Our models include random effects that are spatial, and hence can be mapped. The mapping of these effects can provide important information concerning the localized variation in model fit as well as global information. Two basic components are usually considered (see Appendix A: $\{v_i, w_i\}$). As a diagnostic, the uncorrelated effect should be seen as yielding information about adequacy of fit. The mapped posterior mean of the uncorrelated effect (v_i) can be interpreted as 'salt and pepper' noise where random set of highs and low counties are scattered across the map. There should be little or no clustering in the map, if the model fits well. If it doesn't fit well, then this effect could be contaminated with artifacts that have not been modeled well. For example, if correlated noise is not included, then some clustering could appear in the uncorrelated effect. The correlated term (w_i) is meant to absorb the clustering of the data, and shows peak areas where elevated or lower responses are found together. Sometimes these are easily identifiable areas, such as cities, or along transportation routes, and thus the maps of correlated effects provide information about groups of spatial units connected to each other where effects are either underestimated or overestimated by the model. This information can sometimes be used to add variables to the model that will improve the model fit.

Model 1:

$$y_1 = f_i^T \boldsymbol{\alpha} + g_i^T \boldsymbol{\beta} + e_i$$
$$g_i = \{g_{1i}, g_{2i}, g_{3i}, g_{4i}\}^T$$
where
g_{1i}: age
g_{2i}: age^2
g_{3i}: farm occupation (binary factor)
g_{4i}: marital status (binary factor)
$$f_i = \{f_{1i}, f_{2i}, f_{3i}\}^T$$
where
f_{1i}: father alive (binary factor)
f_{2i}: number of brothers
f_{3i}: second generation effect

We included only individual covariates (age, age squared, farm occupation and marital status in 1860, and for appropriate subsets, father's and brother's characteristics) as primary variables. For the analysis of the complete dataset, we examined a variety of basic models but found that the best-fitting models always included the seven covariates listed above. In later analyses we examined subsets to examine specific hypotheses that could be tested only when we had information about the wealth of fathers or brothers, and therefore could use only cases where those relatives were found on the census. For models based on subsets of the full dataset, we examined some models with smaller sets of covariates. Then we examined a sequence of models with different combinations of random effects.

4. Analyses

4.1 The full dataset

First we examined the full dataset with individual wealth regarded as the dependent variable, and included a combination of individual covariates known to affect wealth that have been described in Model 1. This allowed us to study factors that we would have to include in our more specific analyses of how the wealth of brothers and fathers affected an individual's wealth. Because the model did not include the wealth of relatives, we were able to estimate this for the entire dataset, a larger sample than is available for our analyses of fathers' and brothers' wealth. For the full census the final model combinations had a linear model of the form

$$y_i \sim N(\mu_i, \sigma_y^2)$$
with a linear predictor of the form:
$$\mu_i = f_i^T \boldsymbol{\alpha} + g_i^T \boldsymbol{\beta} + R_i$$
where
$$R_i = \tau_i + v_i$$

The covariates only model had DIC = 4819.380. Adding the individual frailty term reduced the model DIC considerably to 4477.350. The addition of uncorrelated spatial context effects also lowered the DIC, and produced the lowest DIC value of 4411.150. The inclusion of a spatially correlated effect increased the DIC considerably, so this was not a competitive model. It is clear from these results that family effects, as well as frailty and context at the county level, are important in modeling the full data set. It should be noted that even though the DIC was lowered by the inclusion of the number of brothers and second generation family effects, these parameters never appeared significant in terms of zero crossing of their 95% credible intervals. Hence for the full dataset we have both family and spatial effects making significant improvements in explanation of wealth. The sample size for this analysis was n = 992, and the parameter estimates are given in Table 2.

Table 2: Parameter estimates for the best model controlled for number of brothers, second generation family effect, uncorrelated heterogeneity, and an individual frailty term using the full dataset, n = 992. DIC for this model is equal to 4411.150

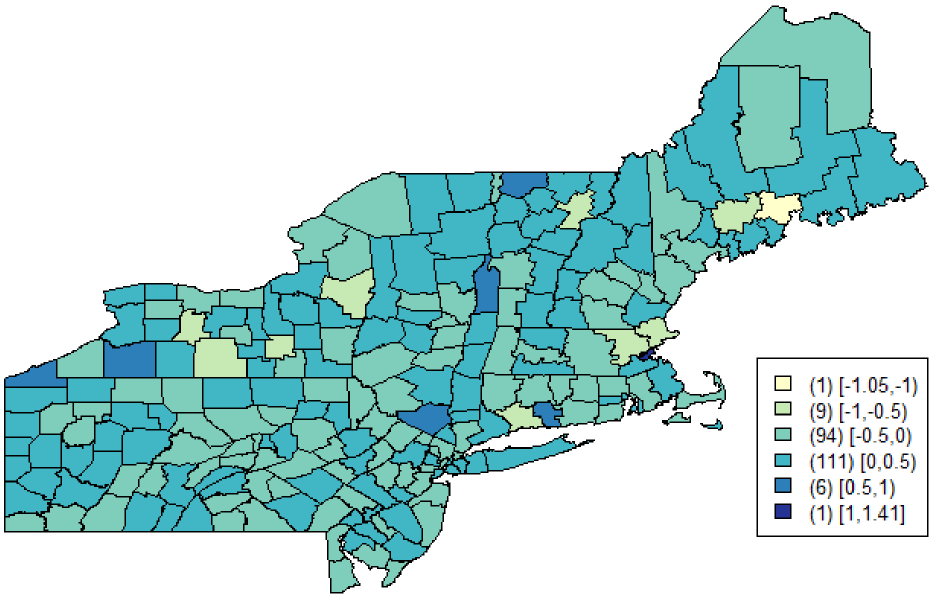
Variable	Mean	Std Dev	2.5% quantile	97.5% quantile
*Intercept	-5.849	0.706	-7.250	-4.475
*Age	0.434	0.031	0.373	0.496
*Age Squared	-0.004	0.0003	-0.005	-0.004
*Occupation = Farmer	0.848	0.178	0.496	1.195
*Married by 1860	1.843	0.223	1.403	2.281
Father is still alive in 1860	-0.384	0.201	-0.777	0.013

Note: *Parameters, for which the quantile-based 95% credible intervals do not cover zero

Note that the intercept, farmer occupation, marital status, age, and age2 are all significant. Squaring age captures the decline in wealth in old age. All covariates except whether the father was alive in 1860 have positive effects. If the father was alive at the time of the census, the son's wealth was lower, but this effect was not statistically significant. The number of brothers family factor, which can have up to 9 levels (0–8 brothers surviving to age 20) displayed no effects; neither did the generational effect. Farmers were wealthier than non-farmers because they owned more real property: their farms.

The link between age, marital status and occupation and increased wealth is not surprising. However, it is interesting that the generational effect and the brother effect are not significant, although they provide some reduction in DIC. It is surprising that large numbers of brothers surviving to adulthood did not reduce individual wealth. However sons provided labor for the family and, with cheap land available, they could eventually buy their own farms. Thus having several sons might well increase wealth. Finally, individual random variation (frailty) had a major effect, as did the spatial contextual effects, which suggests that there may be considerable unobserved confounding in this full dataset. Figure 2 displays the posterior expected estimates for the spatial county-level contextual effects for the best model for the full census dataset. As can be seen the v_i map is relatively random and this suggests that the model has captured effects well.

Figure 2: Map of 1860 counties in the North East US: posterior mean V_i estimates for a model using the full dataset, n = 992



Note: There is small variability in the effect estimates not shown on map.

4.2 Testing for the effect of family members' wealth

To test hypotheses about how an individual's wealth was affected by the wealth and proximity of family members, it was necessary to use subsets of the data so that we could include only cases in which the relatives in question were found on the census, the source of information on their wealth.

4.2.1 Father's wealth

Hypothesis: Father's wealth is positively related to an individual's wealth.

To assess the role of the father's wealth, we analyzed a subset whose fathers were also found on the 1860 census. The sample size for this analysis was n=348.

The initial model was

$$y_i \sim N(\mu_i, \sigma_y^2)$$
with a linear predictor of the form
$$\mu_i = f_i^T \boldsymbol{\alpha} + g_i^T \boldsymbol{\beta} + R_i$$
where
$$R_i = \tau_i + v_i + w_i$$
and
$$f: \{f_2, f_3, f_4, f_5\}$$
$$g: \{g_1, g_2, g_3, g_4\}$$

The initial model included age (g_1), age squared (g_2), whether the person was a farmer or not (g_3), marital status (g_4), the father's wealth (f_4), and whether the father and son were in the same household (f_5). The basic family effects of number of brothers (f_2) and second-generation effect (f_3) were added and further frailty and contextual effects also. As in the analysis of the full data set, the lowest DIC model did not include the spatial w_i effect, but did include the frailty and v_i contextual effect (DIC = 1480.03). In this case, also, a spatial correlation term did not improve the overall goodness-of-fit.

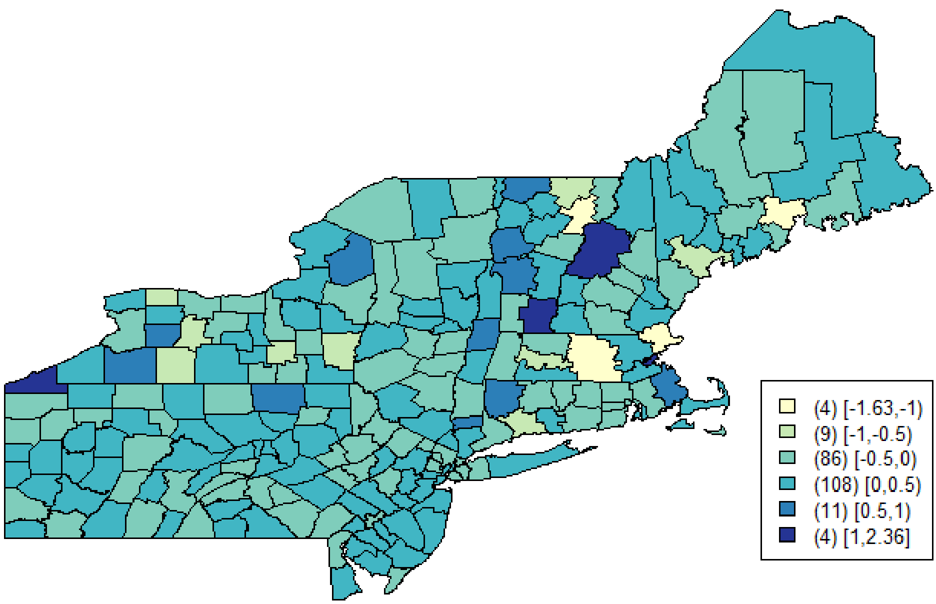
Table 3 displays the parameter estimates, standard errors, and goodness of fit (DIC) for this model with frailty effect and contextual effect added. Figure 3 displays the posterior estimated uncorrelated effects for these data. The results suggest that age is again a significant predictor, but neither occupation as a farmer nor marital status were found significant. A negative effect was found for father living in same household, and this might be expected when a father has not passed on his wealth. The relationship changed depending on whether the son lived in the same household as his father: father's wealth was negatively related to sons' wealth if the sons lived in his household, but the relationship was positive when they were in different households. The men in this subset were on average 32 years old, younger overall than the men in the full dataset, because their fathers were still alive. These results show the importance of the father during young adulthood. If a son lived with his father he was not as wealthy as sons who did not and sons who had married were wealthier than those who had not. Nearly all established their own households when they married; generally when sons married, their fathers gave them land, if they were to continue to be farmers. Each son would inherit an ideal equally.

Table 3: Parameter estimates for the model using a subset of individuals where the father is recorded located in the dataset and controlling for number of brothers, second generation family effect, V_i, and an individual frailty term, n = 348. DIC for this model is equal to 1480.030

Variable	Mean	Std Dev	2.5% quantile	97.5% quantile
*Intercept	-6.244	1.915	-10.100	-2.513
*Age	0.542	0.106	0.336	0.752
*Age Squared	-0.005	0.001	-0.008	-0.003
Occupation = Farmer	0.535	0.295	-0.058	1.113
Married by 1860	0.374	0.360	-0.335	1.069
*Father lives in the same household	-1.101	0.335	-2.049	-0.743
*Father's Wealth	-0.110	0.048	-0.195	-0.006

Note: *Parameters, for which the quantile-based 95% credible intervals do not cover zero.

Figure 3: Map of 1860 counties in the North East US: posterior mean V_i estimates for a model using the subset of individuals where the father is recorded in the dataset, n = 348



Note: There is small variability in the effect estimates not shown on map.

4.2.2 Brother's wealth

Hypothesis: A brother's wealth is positively related to an individual's wealth.

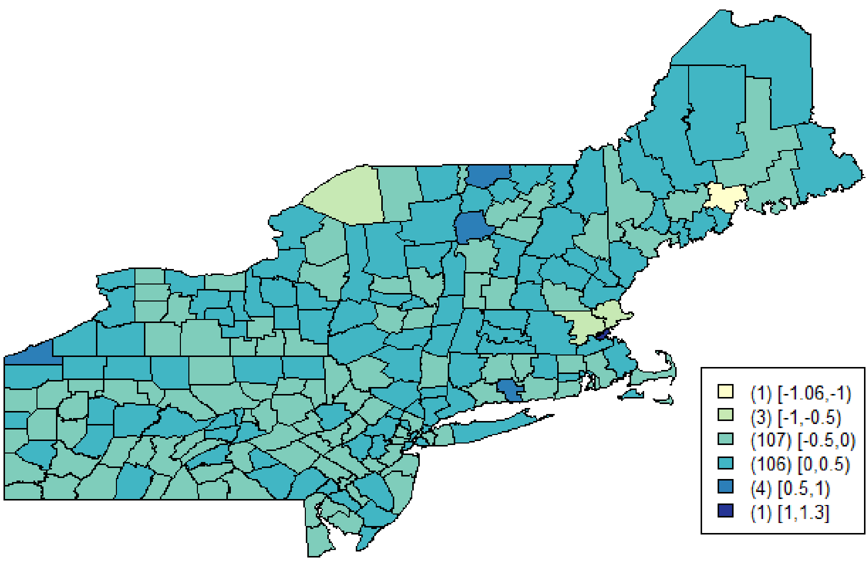
We were also interested in the relationship between the wealth of a man and his brothers, which Solon considers a broader measure of family effects than the relationship between a father's wealth and his son's wealth. If the wealth of brothers were related, especially after the father had died, this would be evidence that wealth transmission was a self-sustaining process within families. In this case we analyzed a subset of the data in which at least one brother appears in the dataset (n = 600). Since men could have more than one brother, we averaged the wealth of his brothers. In a model containing average brother's wealth, occupation, age, and age squared, brother's wealth was significant, thus confirming Solon's ideas (Kearl and Pope 1986b). The best model included a frailty effect and an uncorrelated county level effect (DIC = 2569.60). Table 4 displays the estimated parameters and standard errors as well as credible intervals for this model. For this analysis, besides the inclusion of the basic personal and family covariates ($f_2, f_3, f_4, f_5, g_1, g_2, g_3, g_4$), we also added average brother's wealth (f_6) and distance measures to brothers (distance to closest brother: f_7 and median distance to all other brothers : f_8). In this case, age, having an occupation as a farmer, being married by 1860, and average brother's wealth have a positive relation with individual wealth. The brothers used in this analysis were only those who were found on the census within the study area. Although a father still alive in 1860, and distance to the closest brother, and median distance to all other brothers were not significant, if the father was still alive an individual's wealth was reduced as would be expected. Figure 4 displays the mapped posterior expected v_i effect for these data. In this case a random patterning is apparent and this suggests little correlated confounding remains. Whether the father was alive or not was included in the model, thus, the correlation between the wealth of brothers cannot be due to the fact that men with living fathers were poorer because their fathers had not yet distributed their wealth. This subset is older than the previous subset, and this may be why the occupation affected wealth while it had no significant effect in the previous analysis, which included younger men whose fathers were alive.

Table 4: Parameter estimates for the model using a subset of individuals where at least one brother is recorded in the dataset and controlling for number of brothers, second generation family effect, V_i and an individual frailty term, n = 600. DIC for this model is equal to 2569.60

Variable	Mean	Std Dev	2.5% quantile	97.5% quantile
*Intercept	-5.861	0.931	-7.679	-4.035
*Age	0.384	0.044	0.297	0.471
*Age Squared	-0.004	0.0004	-0.005	-0.003
*Occupation = Farmer	0.697	0.218	0.271	1.125
*Married by 1860	1.504	0.287	0.946	2.072
Father is still alive in 1860	-0.041	0.241	-0.511	0.424
*Average Brothers' log Wealth	0.251	0.041	0.169	0.330
Minimum distance to brothers	0.002	0.003	-0.003	0.007
Median distance to brothers	-0.002	0.002	-0.006	0.003

Note: *Parameters, for which the quantile-based 95% credible intervals do not cover zero

Figure 4: Map of 1860 counties in the North East US: posterior mean V_i estimates for a model using the subset of individuals where at least one brother is recorded in the dataset, n = 600



Note: There is small variability in the effect estimates not shown on map

Hypothesis: The positive relation between brothers wealth would lessen if the father were dead.

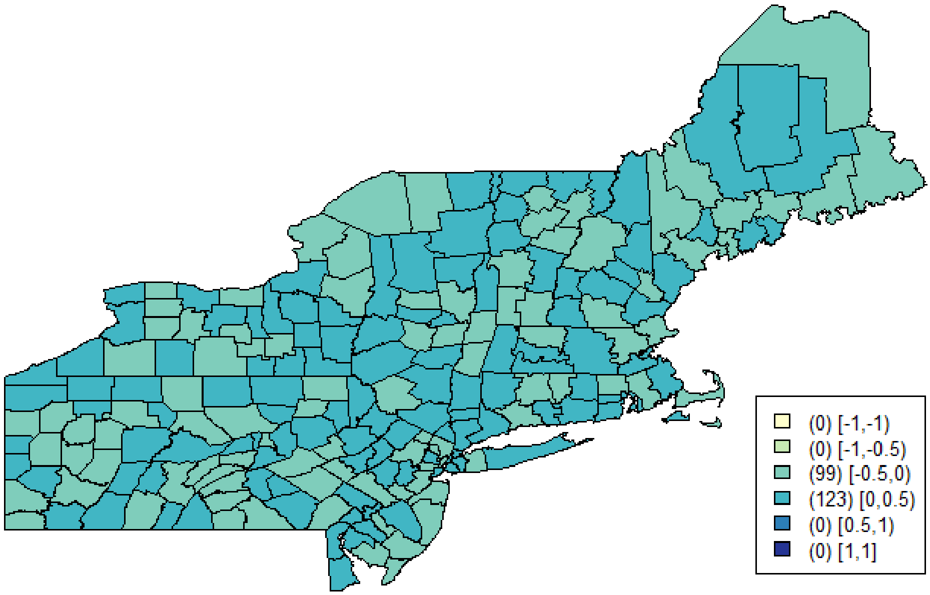
Did the family effect last after the death of the father? We also modeled a man's wealth as a function of his average brothers' wealth when the father was dead. In this subset, we have a sample size of n = 374. The average age of these men was 51, close to the age at which wealth peaked in this group. Again the best DIC model was the one with frailty effect and v_i county level effect (DIC = 1573.800). There was a significant positive relationship between an individual's wealth and average brothers' wealth, age, age squared, farming occupation and marital status. Table 5 displays the estimated parameters and standard errors. Figure 5 displays the posterior expected v_i random effects. Once again these display a random patterning which suggests that little spatial correlation remains in the wealth data. That a man's wealth was related to that of his brothers even after their father had died suggests important and lasting family effects, effects which might be explained by the property sons had inherited, but also could be due to the father moving his family to areas where farms were valuable (or not doing so) or, if both father and son were out of farming, teaching sons a trade.

Table 5: Parameter estimates for the model controlling for number of brothers, second generation family effect, V_i and an individual frailty term using a subset of individuals where the father has died and at least one brother is located in the dataset, n = 374. DIC for this model is equal to 1573.800

Variable	Mean	Std Dev	2.5% quantile	97.5% quantile
*Intercept	-5.071	1.230	-7.449	-2.647
*Age	0.341	0.056	0.229	0.451
*Age Squared	-0.003	-0.0005	-0.004	-0.002
*Occupation = Farmer	0.727	0.262	0.212	1.233
*Married by 1860	2.125	0.382	1.379	2.868
*Average Brothers' log Wealth	0.213	0.054	0.103	0.316

Note: *Parameters, for which the quantile-based 95% credible intervals do not cover zero.

Figure 5: Map of 1860 counties in the North East US: posterior mean V_i estimates for a model using the subset of individuals where both the father has died and at least one brother is recorded in the dataset, n = 374



Note: There is small variability in the effect estimates not shown on map.

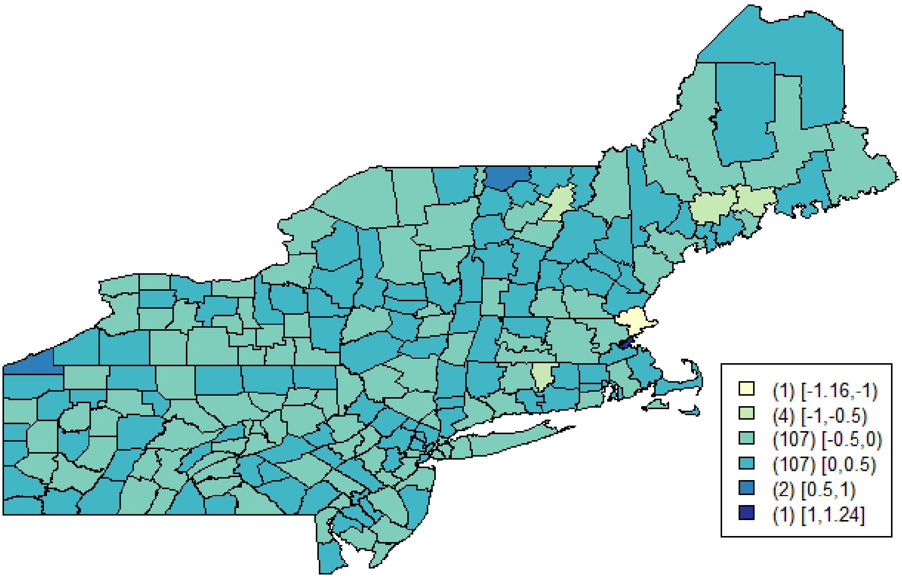
We also examined the situation when the father was alive and brothers appeared in the dataset. There were n = 226 in this subset. For the models considered the best (lowest) DIC model by a large margin was that with frailty effect and uncorrelated v_i county level effect (DIC = 991.370). Table 6 displays the parameters estimates and credible intervals. In this case, average brothers' wealth had a larger posterior average parameter estimate (0.289) than for the case where the father was dead (0.213), however the farming occupation factor is no longer significant. This suggests that the father effect is more dominant than the occupation effect in this subset. Men whose fathers were alive were on average 32 years old, 18 years younger than those whose fathers were dead. Occupational differences in wealth were less pronounced than they were at later ages, when the amount of property held by farmers was almost twice that of non-farmers. The fathers who were still alive had not yet distributed their wealth to many of their sons. Thus, it is reasonable to expect that occupational effects would not have been as strong in this younger subset. Figure 6 displays the uncorrelated spatial effect (v_i) for this subset of individuals. Although the effect of the wealth of the brothers lessened after their father had died, it was still significant, suggesting that the inheritance of forms of capital that lasted after the father's death, such as skills or land, was an important factor.

Table 6: Parameter estimates for the model controlling for number of brothers, second generation family effect, V_i and individual frailty using a subset of individuals where the father is alive and at least one brother is located in the dataset, n = 226. DIC for this model is equal to 991.370

Variable	Mean	Std Dev	2.5% quantile	97.5% quantile
*Intercept	-8.647	2.297	-13.170	-4.143
*Age	0.544	0.133	0.281	0.803
*Age Squared	-0.006	0.002	-0.009	-0.002
Occupation = Farmer	0.632	0.372	-0.100	1.359
*Married by 1860	0.873	0.431	0.031	1.719
*Average Brothers' log Wealth	0.289	0.071	0.150	0.431
Median distance to brothers	0.0005	0.002	-0.003	0.004

Note: *Parameters, for which the quantile-based 95% credible intervals do not cover zero

Figure 6: Map of 1860 counties in the North East US: posterior mean V_i estimates for a model using the subset of individuals where both the father is alive and at least one brother is recorded in the dataset, n = 226



Note: There is small variability in the effect estimates not shown on map.

Hypothesis: The farther apart brothers lived the smaller the association in their wealth.

To find out whether the familial effect was due to brothers remaining in close proximity, we added a variety of terms describing the relationship between wealth of brothers and the distance between them. These included the median distance (f_8) between brothers and the minimum distance (f_7) between them. In addition, we examined combinations of f_8 and f_7 on their own with average brothers wealth (f_6) and other variables in the models. The addition of these inter-brother distance effects were not significant in any model discussed above. However, including them improved the fit of the models in two of the three analyses that included the average wealth of brothers. In the analysis of the subset where there was at least one brother in the dataset (Table 4) the best model included both f_8 and f_7. This was also the case when the father was alive (Table 6), In this case the DIC was nearly identical when either f_7 (DIC = 991.6) or f_8 (DIC = 991.4) was in the model. The closeness of the two results may reflect the overlap of f_8 and f_7 when the father was alive and a large number of men were still living close to their fathers and brothers. These measures of spatial clustering did not improve the model fit when the father had died. Therefore at older ages when the father had died and brothers were more apt to have lived apart, the effect that the wealth of a brother had was not due to their proximity. This is evidence of a strong family effect that was not due to the spatial locations of the brothers.

5. Results

Family effects were more important than spatial effects. As one would expect in a population such as this, some results are: wealth increasing with age and declining at older ages. Many findings supported the idea that actual capital was more important than human capital at this time. For example, farmers had more wealth than non-farmers, which is not surprising in a population where farmers owned their own farms. Men whose fathers were dead were wealthier than those with living fathers, showing that wealth was transmitted, at least in part, through direct inheritance from fathers. When the father was alive, a son's wealth was negatively related to his father's wealth, because most sons were living with their fathers and their fathers had not yet distributed their property. Occupation was not as important as whether a son lived with his father at the younger stages of adulthood when their fathers were still alive. Men who had left their fathers' households were wealthier than those who had not. Presumably they had accumulated enough wealth to live on their own, which was a basic feature of the European family pattern, which had been transplanted in America.

We have also been able to test for several family effects upon wealth that are less often studied.

Even after the father died, there was still a relationship between a man's wealth and that of his brothers.

This relationship was not due to spatial proximity within the study area.

Family branching at the second generation affected wealth many generations later, but more recent branching, at the fifth generation, did not.

In each model there were important uncorrelated spatial effects, but the family effects noted above were still significant or improved the model fit.

6. Discussion

We have confirmed that family effects were more important than spatial effects, as others have noted. This is important because our methods take both spatial effects and clustering of family members into account. Family effects might be expected to be greater upon wealth than upon income, the usual measure in contemporary studies, since wealth is more stable than income over time. Wealth is also more affected by direct inheritance, as the importance of the death of parents clearly shows. To be sure, in all of the analyses the best fitting model included an uncorrelated spatial effect, but these appear to be highly random. They do not reflect the known differences in wealth within the study area, even though such differences existed at the time. For example, farms in Maine were worth quite a bit less than farms in New York, which were on better soil and along a major transportation route, the Erie Canal. In their model of the risk of migrating, Bonneuil, Bringé, and Rosental also found that variables such as region, or smaller units, were not significant while certain family factors were (Bonneuil, Bringé, and Rosental 2008). In their study, the only spatial variable that led to an increased risk of migration was urban residence. They note that the family effects may mask the other geographic effects. In our case, being a farmer, which was much more common outside of southern New England, might also have masked such regional effects.

Our results point to the importance of the inheritance of actual capital over social, human, or even spatial capital. A large proportion of total wealth was in real property, particularly for farmers, who were half of our sample. Thus spatial factors, on a micro scale, such as the quality of soil or proximity to transportation, could well have led to the effect of average brothers' wealth on the wealth of an individual. This might have been true while the father was alive. But we included the distance between brothers in the model, and after the death of the father, the wealth of brothers was associated regardless of how far apart they lived. Thus a family effect went beyond the immediate area where the brothers had been raised. Social capital was probably not involved, because social networks would be more important when brothers were in the immediate vicinity. Also, pooling of labor does not seem to be important, another effect that would manifest itself at shorter distances. There may, of course, have been other sorts of inheritance from fathers that led to the effect of brothers' wealth we have found in the form of human capital, such as specific farming techniques or skills outside of farming that would affect wealth. However, these would have had to be transferrable over distance. The explanation for why the wealth of brothers continued to be related after the father had died needs to be examined more fully. A further important effect that we did not include in our analyses is the occupation o,f the brothers. Many men in southern New England were giving up farming at this time and presumably this was at least in part due to the profitability of the farms. If more or most brothers stopped farming due to the inability to make a living in certain areas, they would be less wealthy, and this might account for the relationship between brothers' wealth after their fathers had died. But there were many sibling sets in which some brothers were farmers and others were not. Brothers who gave up farming may have been able to translate their share of the farm into wealth outside of farming. Or, if they were all poor, it may mean that men who left farming could not, at least in one generation, overcome the poverty of their farm background. To fully understand this, a more thorough analysis of their occupations and wealth would be needed.

We found that very early family branching was reflected in outcomes several generations later, thus confirming that "deep" family effects, those that had their origins in earlier generations, deserve more attention than they have been given so far (Mare 2011). The deeper effect improved the model fit and most recent effects (father's wealth and brother's wealth) also affected wealth, but the fifth generation effect did not. DeLong (2003) has argued that the 19th century was a turning point in America, when bequests became far less important as determinants of wealth, and Menchik (1980) provided evidence from the 1930's and 1940's that equal inheritance was indeed the norm at that time. But as early as the late 18th century, Ditz showed that the practice was to divide property equally between the children in the Northern US (Ditz 1986). Kasakoff found that in 1850, using the genealogical sample discussed here, it was usually the youngest, not the oldest, sibling who lived closest to their elderly parents, but after controlling for age and size of sibling group, the patterns were quite variable (Kasakoff 2010). This is in accord with the decline of primogeniture DeLong discusses as the result of economic growth, in this case colonization in an area where land was available as well as opportunities outside of farming. Why, then, was there any affect of the father at all? We show that some attribute was shared by siblings that influenced their wealth and which survived the father's death, but are unable to specify what that attribute is. More research will be needed to assess the importance of real estate as opposed to other forms of capital or a combination of different attributes. There might have been genetic effects but, as Vetta and Courgeau have shown, environmental and genetic effects cannot be distinguished quantitatively (Courgeau and Vetta 2003).

When one goes back to the second generation, the family branches vary greatly in size, more so than the branches at the fifth generation. The outliers in wealth in the second generation were the smallest family branches, and were also more spatially clustered. The larger family branches, which predominated in the sample, were to be found over a wide area, and thus would have been expected to replicate the variation found in the entire sample. Smaller family branches could, and did, achieve extreme values in wealth. Those that were poor were clustered in Southern New England, suggesting that they had been left behind and were unable to benefit from pioneering.

This is a very interesting, if unexpected, finding. Although the outlier second-generation branches were small, they all consisted of several sets of brothers. Since branching at the second (and fifth generation) was included in the analysis of the relationship between the wealth of brothers once the father had died, that enduring effect among brothers is not be due to the small branches at the second generation. This kind of effect should be studied more in the future, with a focus on what determines the different sizes of family branches. Our finding underscores Mare's emphasis on the size of family branches as an important factor in social mobility (Mare 2011). Branches at the fifth generation were similar in size and spatial distribution, and thus it was more difficult to find significant differences between them.

However, there are some caveats: the sample size is small, and the absence of spatial effects was due in part to the scale of analysis. The area we are studying is quite large. Our unit of analysis for the study of random and correlated spatial effects was the county, which was relatively large, ranging from 55 square kilometers to 17,688 square kilometers (median was 1853 square kilometers). However, we included a measure of proximity at a smaller scale, by incorporating distances between fathers and sons and between brothers in our analyses. Proximity at a smaller scale was more important while the father was alive, but had no effect after he had died.

Solon has criticized studies of twins and other homogenous populations because of the high ratio of noise to effects (Solon 1999). Our data is from a more homogenous population than a national survey or administrative data and thus may contain a lot of "noise" which makes it even more remarkable that we found the effects that we did. The group being studied was only one segment of an increasingly complex US, which contained descendants of many different ethnic groups by 1860. Conclusions from the Yankee ethnic group, descendants of the first wave of settlers, would not apply to the others.

Unlike other "linked" census samples (Ferrie 1996), we used information about other members of the household to link an individual from the census to the genealogy and only included men who could be linked to the genealogy. We were more apt to link an individual if he had been found on the census living with known family members, and thus we have more cases where both father and son were living together than existed in the general population. But in these cases, the wealth of father and son were not correlated, because in most of them the father held the property of the household. Still, if we were able to include more sons living away from their fathers, our results might have been different. Our measures of brothers' wealth and distance between brothers were only for brothers who stayed within the study area, and thus it is possible that the importance of brothers' wealth was not as important for those who pioneered outside the study area as it was for those who remained behind. Yet the fact that we have found effects of the brothers' wealth even after the father had died suggests that these results are not simply an artifact of our linkage methods.

The US was a colonizing society. Individuals who moved to new areas were able to increase their wealth (Stewart 2006). 20% of the men ages 40 to 60 that had been born in the study area had left by 1860. Those who left were wealthier in 1860 than those who had stayed in the areas where they had been born. This was especially true for farmers who pioneered outside the region. The literature on pioneering emphasizes that a farmer had to have a certain amount of capital in order to homestead. While the land was relatively inexpensive, the implements, building materials and livestock were costly. The process of clearing the land could take from 5 to 10 years, and was usually accomplished through family labor: a family that had to be fed. There would be little money left to send back to relatives in the study area (Atack, Bateman, and Parker 2000). For those men not farming who moved West, the situation might have been different, as wages at the frontier were initially much higher than they were in the areas that had been settled longer (Margo 2000). Yet there is no evidence that those men who were not farming who left the study area sent part of their wages back to their relatives in the study area.

This context of greater opportunity may account for why the number of brothers did not result in a decrease in wealth. At the time there was an ideology of equal inheritance. Sons inherited land (some was transferred at marriage and some when the father died) and daughters got moveable property when they married. In the context of the population we are studying, men who pioneered in new areas had the most children, and the combined labor of the brothers clearing land could have added to the family's wealth, since non-family labor was quite expensive at the frontier (Margo 2000). Thus we find that the characteristics of the immediate family, brothers and fathers, did affect wealth in 1860 in the US. Bonneuil, Bringé, and Rosental (2008) found that the propensity to move was not related to the number of children in the family but, instead, there were complex patterns associated with sibling order and inheritance. Using the same set of families as we discuss in this paper, (Kasakoff 2010) found that which son remained close to their parents in old age depended very much on the number of brothers. In small families, the last son did so, while in large families it was the first son. Again, the effect of family size on migration and outcomes was complex.

7. Conclusion

We have shown that fathers were able to give sons a legacy that had an important impact upon their wealth even after the fathers had died. This result is important, because spatial effects can masquerade as family effects if the two are not modeled explicitly. We used methods that are capable of testing for both; methods that can distinguish these two sorts of effects, which are often comingled. Of course, the use of these methods requires information on location - in our case, the county of residence - which may not always be available.

Family processes were clearly in evidence in the difference the death of the father made. Yet family effects lasted beyond the death of the father. The family effect was not a result of proximity of family members, and was presumably related to either wealth they had inherited or to skills that could be transferred across locations. The correlated spatial components did not improve the fit of any of our models. This suggests that there is little residual spatial correlation in the data. If there were any, it must exist at a scale below the county level, the level we used in our models. However, when we introduced variables at a smaller scale – distances between relatives – these were important only while the father was alive.

The importance of family factors changed over the life course. When the father was alive, the distance between fathers and sons was not significant, although it did improve the model fit. This was also true in models of brothers' wealth, whether the father was alive or dead, and in such models when he was alive. Distances between brothers were not important, however, after the father had died. It was more likely that sons would remain in an area after their father had died, if the land there was good for farming, while those whose fathers had settled in areas with poorer farms were more likely to have scattered after his death, or sought work outside of farming in the newly developing industrial and commercial sectors. Since the effect of brothers' wealth after the father had died was not related to proximity, brothers who moved or stopped farming were set on a track established by their fathers or, perhaps, another experience the brothers shared.

Because we are observing fathers, sons, and brothers, whose wealth was measured at different ages, the family effects are probably even stronger than we have found. Our sample, which is more homogeneous than the US as a whole and catches fathers near their peak wealth, while sons were much younger, must underestimate the relationship between fathers' and sons' wealth and also that of brothers widely separated in age.

We have demonstrated a lasting family effect that cannot be attributed to the spatial clustering of relatives. The importance of land among farmers in this sample may make our conclusions less applicable to modern populations, in which human capital is more important and, at least in some countries, much more equally distributed than wealth or land. In those societies, inheritance from parents in the form of wealth may make less of a difference than it did in the past (Long and Ferrie 2007; Bourdieu, Ferrie, and Kesztenbaum 2009).

8. Acknowledgements

We would like to acknowledge two grants from the Demographic and Behavioral Sciences Branch of the National Institute of Child Health and Human Development, National Institutes of Health which have supported this research: “Modeling Spatial and Family Factors in the Transmission of Wealth” (Grant #R21HD060111-02), our current grant and an earlier grant “Migration and Intergenerational Processes” (with John W. Adams). We began compiling the data during a fellowship from the National Endowment for the Humanities awarded by the Newberry Library. An EPSCOR grant and grants from the National Science Foundation (Geography Regional Sciences Program) and the Anthropology Program, a Newberry Library Fellowship (Spring 1987), and a research award from the College of Liberal Arts, University of South Carolina all contributed to the development of these data. We would like to thank Jun Long Wu for his work on the statistical models and Stephen Feetham for help with analysis.

References

Atack, J., Bateman, F., and Parker, W.N. (2000). The Farm, The Farmer, and The Market. In: Engerman, S.L. and Gallman, R.E. (eds.). *The Long Nineteenth Century*. Cambridge: Cambridge University Press: 245–284. doi:10.1017/CHOL9780521553070.

Bonneuil, N., Bringé, A., and Rosental, P.A. (2008). Familial components of first migrations after marriage in nineteenth-century France. *Social History* 33(1): 36–59. doi:10.1080/03071020701833325.

Bourdieu, J., Ferrie, J.P., and Kesztenbaum, L. (2009). Vive la difference? Intergenerational mobility in France and the United States during the Nineteenth and Twentieth Centuries. *Journal of Interdisciplinary History* 39(4): 523–557. doi:10.1162/jinh.2009.39.4.523.

Bowles, S., Gintis, H., and Groves, M.O. (2008). *Introduction to Unequal Chances: Family Background and Economic Success*. New York: Princeton University Press.

Castro, M. and Kasakoff, A.B. (2007). *Spatial concentration of wealth in the American North in 1860*. Paper Presented at Annual Meeting of the Social Science History Association, Chicago, IL, November 15–18, 2007.

Corak, M. (2004). *Generational Income Mobility in North America and Europe*. Cambridge: Cambridge University Press. doi:10.1017/CBO9780511492549.

Courgeau, D. and Vetta, A. (2003). Demographic Behaviour and Behaviour Genetics. *Population* 58(4–5): 401–428.

Curtis, K.J., Voss, P.R., and Long, D.D. (2012). Spatial variation in poverty-generating processes: Child poverty in the United States. *Social Science Research* 41(1): 146–159. doi:10.1016/j.ssresearch.2011.07.007.

DeLong, J.B. (2003). Bequests: An Historical Perspective. In: Munnell, A. and Sunden, A. (eds.). *Death and Dollars: The Role and Impact of Gifts and Estates.* Washington, DC: Smithsonian Institution Press: 33–63.

Ditz, T. (1986). *Property and Kinship: Inheritance in Early Connecticut, 1750–1820*. Princeton, New Jersey: Princeton University Press.

Ferrie, J.P. (1996). A New Sample of Males Linked from the Public-Use-Microdata-Sample of the 1850 US Federal Census of Population to the 1860 US Federal Census Manuscript Schedules. *Historical Methods* 29: 141–156. doi:10.1080/01615440.1996.10112735.

Gelman, A. (2006). Prior distributions for variance parameters in hierarchical models. *Bayesian Analysis* 1: 515–533. doi:10.1214/06-BA117A.

Gelman, A. and Hill, J. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. New York: Cambridge University Press.

Goldstein, H. (2011). *Multilevel Statistical Models*: London/New York: John Wiley & Sons.

Grawe, N.D. (2006). Lifecycle bias in estimates of intergenerational earnings persistence. *Labour Economics* 13(5): 551–570. doi:10.1016/j.labeco.2005.04.002.

Haider, S. and Solon, G. (2006). Life-cycle variation in the association between current and lifetime earnings. *The American Economic Review* 96: 1308–1320. doi:10.1257/aer.96.4.1308.

Irwin, M.D. (2007). Territories of Inequality: An Essay on the Measurement and Analysis of Inequality in Grounded Place Settings In: Lobao, L.M., Hooks, G., and Tickamyer, A.R. (eds.). *The Sociology of Spatial Inequality*. Albany: State University of New York Press: 85–109.

Kasakoff, A.B. (2010). Which Sons Lived Closest to their Elderly Fathers? Sibling Differences Among Native Born Families in the US North in 1850. In: Arrizabalaga, M.P., Bolovan, I., Eppel, M., et al. (eds.). *Many Paths to Happiness? Studies in Population and Family History: A Festschrift for Antionette Fauve-Chamoux*. Amsterdam: Aksant Academic Publishers: 119–140.

Kearl, J.R. and Pope, C.L. (1984). Mobility and Distribution. *The Review of Economics and Statistics* 66: 192–199. doi:10.2307/1925819.

Kearl, J.R. and Pope, C.L. (1986a). Choices, rents and luck: economic mobility of nineteenth-century Utah households. In: Engerman, S. and Gallman, R. (eds.). *Long-Term Factors in American Economic Growth*. Chicago: University of Chicago Press: 215–260.

Kearl, J.R. and Pope, C.L. (1986b). Unobservable family and individual contributions to the distributions of income and wealth. *Journal of Labor Economics* 4: S48–S79. doi:10.1086/298120.

Kesztenbaum, L. (2008). Places of Life Events as bequestable wealth. Family territory and migration in France, 19th and 20th centuries. In: Bengtsson, T. and Mineau, G.P. (eds.). *Kinship and Demographic Behavior in the Past.* Dordrecht: Springer: 155–184.

King, G., Rosen, O., and Tanner, M. (2004). *Ecological Inference: New Methodological Strategies*. New York: Cambridge University Press. doi:10.1017/CBO9780511510595.

Lawson, A.B. (2009). *Bayesian Disease Mapping: Hierarchical Models in Spatial Epidemiology*. New York: CRC Press.

Lawson, A.B., Browne, W.J., and Vidal Rodeiro, C.L. (2003). *Disease Mapping with WinBUGS and MLwiN*. New York: Wiley. doi:10.1002/0470856068.

Leyland, A. and Goldstein, H. (2001). *Multilevel Modeling of Health Statistics*. New York: Wiley.

Lobao, L.M. and Hooks, G. (2007). Advancing the Sociology of Spatial Inequality: Spaces, Places, and the Subnational Scale. In: Lobao, L.M., Hooks, G., and Tickamyer, A.R. (eds.). *The Sociology of Spatial Inequality*. Albany: State University of New York Press: 29–62.

Long, J. and Ferrie, J.P. (2007). The path to convergence: intergenerational occupational mobility in Britain and the US in three eras. *The Economic Journal* 117: C61–C71. doi:10.1111/j.1468-0297.2007.02035.x.

Lunn, D., Spiegelhalter, D., Thomas, A., and Best, N. (2009). The BUGS project: Evolution, critique and future directions. *Stat Med* 28(25): 3049–3067. doi:10.1002/sim.3680.

Mare, R.D. (2011). A multigenerational view of inequality. *Demography* 48(1): 1–23. doi:10.1007/s13524-011-0014-7.

Margo, R.A. (2000). *Wages and labor markets in the United States, 1820–1860*. Chicago: University of Chicago Press.

Menchik, P.L. (1980). Primogeniture, Equal Sharing, and the U.S. Distribution of Wealth. *Quarterly Journal of Economics* 95: 299–316. doi:10.2307/1884542.

Page, M.E. and Solon, G. (2003). Correlations between brothers and neighboring boys in their adult earnings: the importance of being urban. *Journal of Labor Economics* 21(4): 831–856. doi:10.1086/377021.

Peters, D.J. (2012). Income Inequality across Micro and Meso Geographic Scales in the Midwestern United States, 1979–2009. *Rural Sociology* 77(2): 171–202. doi:10.1111/j.1549-0831.2012.00077.x.

Raaum, O., Salvanes, K.G., and Sørensen, E.Ø. (2006). The neighbourhood is not what it used to be. *The Economic Journal* 116: 220–222. doi:10.1111/j.1468-0297.2006.01053.x.

Snijders, T.A.B. and Kenny, D.A. (1999). The social relations model for family data: A multilevel approach. *Personal Relationships* 6(4): 471–486. doi:10.1111/j.1475-6811.1999.tb00204.x.

Solon, G. (1992). Integrational income mobility in the United States. *American Economic Review* 82: 393–408.

Solon, G. (1999). Intergenerational mobility in the labor market. In: Ashenfelter, O.C. and Card, D. (eds.). *Handbook of Labor Economics*. Amsterdam: North Holland: 1761–1800.

Solon, G. (2002). Cross-country differences in intergenerational earnings mobility. *Journal of Economic Perspectives* 16: 59–66. doi:10.1257/089533002760278712.

Solon, G., Corcoran, M., Gordon, R., and Laren, D. (1991). A longitudinal analysis of sibling correlations in economic status. *The Journal of Human Resources* 26(3): 509–534. doi:10.2307/146023.

Spiegelhalter, J., Best, N.G., Carlin, B.G., and van der Linde, A. (2002). Bayesian deviance, the effective number of parameters and the comparison of arbitrarily complex models. *Journal of the Royal Statistical Society B* 64: 583–640. doi:10.1111/1467-9868.00353.

Steckel, R.H. and Moehling, C.M. (2001). Rising inequality: trends in the distribution of wealth in industrializing New England. *Journal of Economic History* 61: 160–183. doi:10.1017/S0022050701025086.

Stewart, J.I. (2006). Migration to the agricultural frontier and wealth accumulation, 1860–1870. *Explorations in Economic History* 43: 547–577. doi:10.1016/j.eeh.2005.08.002.

Appendix A

Define the ith individual's wealth logged within the 1860 census sample as $y_i, i = 1, \dots, m$, where m is the sample size. Wealth is defined as total real and personal property for men found in the 1860 census. Further we assume that the log of wealth will be randomly distributed around a mean level μ_i. We assume a Gaussian distribution for the outcome:

$y_i \sim N(\mu_i, \sigma_y^2)$ with variance σ_y^2. The general specification for the mean level in our application can be defined as follows. Consider, first, family effects which are measured for each individual. These could be brother and/or father measures (such as presence in dataset, distance, alive or dead). We denote these as a vector of predictors: f_i of length p_f The associated parameter vector is $\boldsymbol{\alpha}$. Second, we consider spatial effects in the form of random components which are added linearly into the model. First, individuals have county assignments and so we assume contextual county effects (Lawson 2009). Denote two such effects as v_1 and w_1. We assume that v_1 is an uncorrelated county effect and w_1 is a spatially correlated county effect. In effect each individual inherits the county effect from the county they live in i.e. $v_i = v_j, i \in j, w_i = w_j, i \in j$ if the ith individual lives in the jth county. Second, individuals could have random variation in wealth themselves and so we include a 'frailty' term (τ_i) allowing for this. Fixed effects are also present at the individual level (such as age or marital status) and the vector of these is denoted g_i. The associated parameter vector is $\boldsymbol{\beta}$ of length p_g

Our general linear mixed model is:

$$\mu_i = f_i^T \boldsymbol{\alpha} + g_i^T \boldsymbol{\beta} + R_i \ ,$$

where $R_i = \{\tau_i + v_i + w_i\}$. As we assume a Bayesian hierarchical model all parameters are assumed to have prior distributions. The prior distributions assumed are non-informative in that they do not restrict the parameter space. For the fixed (predictor) effects we make the common assumption of a zero mean Gaussian distributions:

$$\alpha_j \sim N\left(0, \sigma_{\alpha_j}^2\right) \quad \forall j$$
$$\beta_j \sim N\left(0, \sigma_{\beta_j}^2\right) \quad \forall j.$$

For the individual frailty effect we assume a zero mean Gaussian distribution:

$$\tau_i \sim N(0, \sigma_\tau^2)$$

This assumption is reasonable given we do not have prior information about how far or in what direction the individual deviation from the average will arise (positive or negative). We also assume a non-informative prior specification for the precision of the effect and so this allows considerable latitude in the estimation of any individual's effect. This also allows for skewness in frailty due to the non-informativeness of the prior distribution.

For the uncorrelated random effects we assume:

$$v_j \sim N(0, \sigma_v^2).$$

This is also a non-informative specification. Finally, we also specify a spatially correlated effect (w_j). This effect is employed to address the spatial clustering of the wealth at the county level. For this effect we assume an intrinsic conditional autoregressive prior distribution:

$$w_j | \{w_k\}_{k \neq j} \sim N\left(\overline{w}_{\delta_j}, \sigma_w^2 / n_{\delta_j}\right)$$

where δ_j is a neighborhood if the jth county, n_{δ_j} is the number of neighbors, and $\overline{w}_{\delta_j}$ is the average in the neighborhood.

For the variances $\left\{\sigma_{\alpha_j}^2, \sigma_{\beta_j}^2, \sigma_z^2, \sigma_v^2, \sigma_w^2\right\}$ we assume $\sigma_* \sim U(0, C_*)$ which is a uniform distribution on a fixed, but large, range. We usually assume C_* = 10.

Appendix B

Example of WinBUGS code for Model Used on Full Dataset:

```
Full dataset➔
model➔{
for (i in 1:n){
y[i]~dnorm(mu[i],tauy)
bro1[i]<-broalive[i]+1
mu[i]<-al0+al1*age[i]+al2*agesq[i]+al3*farm[i]+
al4*married[i]+al5*fatheralive[i]
+bro[bro1[i]]+gen2[Ngen2[i]]+v[cores[i]]+v1[i]
v1[i]~dnorm(0,tauv1)
}
for (j in 1: regions){
v[j]~dnorm(0,tauv)}
for (j in 1:10)      {
bro[j]~dnorm(0,taubro)}
for (j in 1:18)      {
gen2[j]~dnorm(0,taugen2)}
sdvgen2~dunif(0,2)
taugen2<-1/(sdvgen2*sdvgen2)
tauv1<-pow(sdv1,-2)
sdv1~dunif(0,2)
sdvv~dunif(0,2)
tauv<-1/(sdvv*sdvv)
invv<-1/tauv
sigy~dunif(0,2)
sdvbro~dunif(0,2)
tauy<-1/(sigy*sigy)
taubro<-1/(sdvbro*sdvbro)
al0~dnorm(0,0.001)
al1~dnorm(0,0.001)
al2~dnorm(0,0.001)
al3~dnorm(0,0.001)
al4~dnorm(0,0.001)
al5~dnorm(0,0.001)}🡐
data⇨⇦
🡐
```