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The Economics of Hatred:
Evidence from Sweden

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Abstract: This study investigates if *there is an association between economic conditions and hate crime incidence.* By combining existing models on hate crimes in economics (Gale et al., 2002; Medoff, 1999 & Glaeser, 2005) a model that connects hate crime motivation with economic conditions is developed based on Gary Becker's framework on time allocation (Becker 1965; 1968). The predictions of the model are then tested using aggregated panel data from twenty Swedish counties, from 2008 to 2013. The results do not support the hypothesis that there is a correlation between hate crime incidence and economic conditions. However, we are reluctant to draw definite conclusions due to possible weaknesses in our method and data. We highlight that the findings of our study coincide with similar studies at lower levels of aggregation, e.g. county, while studies that find a correlation do so at higher levels of aggregation, e.g. state or national level. This should be investigated further in future multi-level studies.

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" I was not sympathetic to the assumption that criminals had radically different motivations from everyone else. I explored instead the theoretical and empirical implications of the assumption that criminal behavior is rational."

Becker (1992)

1. Introduction

Hate crimes are any "crimes committed against persons or property that are motivated by the perpetrator's hatred or prejudice against the racial, ethnic, religious, or sexual identity of the victim" (Boyd et al., 1996, p.819). The concurrent advent of demographic changes, the increase in the incidence of hate crimes and the turbulent economic conditions in Europe have brought the issue of hate crimes to the fore of the public debate. Starting in the early 1990s, freedom of movement within the European Union (EU) coupled with the socioeconomic and political situation outside has engendered a significant demographic change. Today, migration across national borders, both within the EU and from outside the EU, is the dominant factor affecting the demography of Europe, the size of the population, its rate of change and its composition (Coleman, 2008; Kerr & Kerr, 2011).

The heightened ethnic fractionalization in Europe accompanied by the increase in the incidence of hate crimes has sparked a public debate about possible policy responses, chiefly legislative ones (Dancygier & Laitin, 2014). This has also been the case in Sweden, which was recently reprimanded by the UN due to an increase in hate crimes towards ethnic minorities (UN Human Rights Council, 2014; UN Association of Sweden, 2014). In recent years, specifically after the financial crisis and economic downturn in Europe during the late 2000s, the cause of the increase in xenophobic hate crime across Europe has been attributed to the state of the economy (European Union Agency for Fundamental Human Rights, 2014). Implicitly, the scapegoating of ethnic minorities and immigrants for the economic misfortunes experienced by the majority is what links cause, economic downturn, and effect, the increased incidence of hate crimes. Looking at European history, it is not surprising that such an intuitive explanation might easily be accepted.

The empirical support for such an explanation, however, is tenuous to say the least. Evidence of a correlation between economic conditions and hate crime incidence is inconclusive, making it all the more difficult to make causal inferences. Unfortunately, the ambivalence in the literature and the academic debate often juxtaposes the treatment of the topic in the media and by extension the public debate where a causal link can sometimes be taken for granted. Without an empirically verified theory, intuitively appealing explanations are not helpful, and can lead to incorrect policy recommendations. The aim of this study is to address this ambiguity, by investigating the research question:

Is there an association between economic conditions and hate crime incidence?

A literature review reveals that a majority of previous studies that investigate this relationship do so within the field of sociology. A sociological approach has many benefits, as we will show, and it has driven this research field forward. However, we argue that a sociological approach on its own does not suffice to specify mechanisms that are related to economic variables; rather a complementary economic approach is necessary. In sociological theories, economic hardship is theorized to cause hate crimes, however, this is not amenable to specific theorization within the sociological framework. What we mean by that is that it is hard to specifically pinpoint how economic hardship is best measured in practice. Partially as a result of this, in empirical studies, sociologists have operationalized economic hardship in different ways, using a variety of economic variables such as unemployment, income, GDP growth, and percentage of population in poverty. Consequently, studies are hard to compare and results difficult to reconcile. Furthermore, there is a lack of general theory of hate crime motivation; rather the focus has been on specific forms of hate crime motivation, for example racially motivated hate crimes. This is understandable as what motivates hate crimes against sexual minorities is not necessarily the same as what motivates crimes against ethnic minorities. However, the lack of a general theory has led to a lack of an understanding of motivations that are difficult to study empirically, for example crimes against sexual minorities. In short, there is a lack of standardization, generality and comparability.

We argue therefore for a neoclassical economic approach as a complement to sociology, as it suitably addresses the weaknesses. Ostensibly, a hate crime is difficult to reconcile with the idea of a rational individual. However, hate can be viewed as a rational phenomenon best defined as envy, that is deriving utility from the decreased well-being of a third party (Becker 1981; Gale et al., 2002). Indeed, hate is at the heart of an emerging research field in economics, thus beyond the policy implications, scholarship on hate crimes contributes to the academic literature in this research fields and related ones. Hate crimes are argued to be related to other superficially irrational, and exceedingly heinous phenomena such as terrorism (Krueger & Malečková, 2003) and genocide (Glaeser, 2005).

A review of empirical studies in economics shows, however, some of the same weaknesses sociological studies do, especially when it comes to a standardized empirical approach. We identify several issues that we hope to address, namely a lack of a complete theory of hate crime in economics, that synthesizes existing scholarship, flaws in the methods of previous studies and a limited geographic scope of the research field. We do so by combining existing economic models to develop a general model of all crimes motivated by hatred. The model relates the incidence of hate crimes to a number of economic variables, and yields six empirically testable hypotheses. We test these hypotheses using an econometric model, taking a conservative and rigorous approach to model specification. The data used is Swedish panel data at the county level from 2008 to 2013 for our main regression, and from 2010 to 2013 for our secondary regression. Performing this study in a country not previously covered in the literature, we widen the geographic scope of this research field.

The results from our study indicate that there does not appear to be a correlation between economic conditions and the incidence of hate crimes. We argue that if a true but weak relationship exists, weaknesses related to our theory, method and data might have a confounding effect leading to an incorrect conclusion. Among these, we highlight the low number of observations available at the time of the study and the low level of aggregation; we call for further studies investigating the association between economic conditions and the hate crime incidence.

The paper is organized as follows – section 2 reviews previous research. Section 3 develops a theoretical framework from which we derive six hypotheses. In section 4, we present and discuss our empirical method. Section 5 follows with a description of the dataset used to test the hypotheses. Section 6 presents the results of our regression analyses that are then discussed in section 7. Section 8 concludes, section 9 summarizes.

2. Previous Research

In this section we present previous studies that investigate the same, or similar, research question as ours: *Is there an association between economic conditions and the incidence of hate crimes?* In the first part, we present a review of sociological studies. The rationale for this is twofold. First, a majority of the studies of this type, and indeed the most famous ones, are within the sociological framework. Second, we aim to highlight weaknesses in the framework, both theoretical and related to the method, that are suitably addressed from the complementary approach of neoclassical economics. We finish the first section by highlighting the weaknesses. In the second section we show how empirical studies within economics have addressed some of the identified weaknesses. However, we note that there is room for further improvements in the economic approach, both in theory and method. In the final section, we synthesize the main findings of previous research and identify a research gap that we attempt to bridge with our study.

Hate Crimes in Sociology: Theories and Empirical studies

In this section, we present the most important empirical studies in sociology. What these studies have in common is that they all test sociological, as opposed to economic, theories of hate crime motivation. These theories fall into one of two broad categories, the frustration thesis of hate crime motivation and the globalization thesis (a form of the broad modernization theory of hate crime motivation) (Green, McFall & Smith, 2001, henceforth Green et al., 2001).

The frustration theory posits that scarce resources are the main cause of hate. Shortly, frustration, due to economic hardship, causes aggression toward scapegoated minorities. In the first study of this kind, Hovland and Sears (1940), using time-series analysis, find a negative correlation between the price of cotton and the incidence of lynching in the Southern states of the US between 1883 and 1930. Subsequently, these findings have been confirmed using more precise data and more sophisticated econometric methods (Tolnay & Beck, 1995; Hepworth & West 1988). Conversely, Green, Glaser and Rich (1998) dispute these findings; extending the period of analysis beyond 1930, they find that the correlation is no longer statistically significant.

In more recent studies, Ryan and Leeson (2011), using panel data from US states between 2001 and 2008, find that the evidence supports that economic hardship, unemployment primarily (although they test a great number of variables), is correlated with the incidence of hate crimes. Conversely, Adamczyk et al. (2014) find that the evidence did not support that economic deprivation has any association with hate crime incidence using county-level panel data in the US. Adamczyk et al. suggest that the level of aggregation might play a role; noting that the effect might exist only in larger units of analysis, for example state level.

While empirical studies have tended to focus on the US, a number of similar studies have been conducted in Germany also. These have tested the globalization theory of hate crime motivation (Green et al., 2001). The globalization theory predicts unskilled workers who are economically and socially marginalized by globalization scapegoat immigrants. McLaren (1999) undertakes a time-series analysis, regressing incidence of anti-immigrant crime on a number of economic variables. McLaren finds that the national unemployment rate, in interaction with an increase in the immigrant population, correlates with the incidence of antiforeigner crime in Germany, between the years 1971 and 1995. The results of the study are confirmed by similar studies looking at right-wing extremist crime and unemployment

(Falk & Zweimüller, 2011). Unfortunately, we cannot find any such studies in Sweden or any other European countries.

From this short review, we would like to highlight two issues that are characteristic of the sociological approach. First, there is no all-encompassing theory of hate crime motivation; rather anti-foreigner, racially motivated and homophobic crimes are theorized to have different causes. This has led to an underdevelopment of theories and empirical studies of certain types of hate crimes that are difficult to study empirically. Secondly, empirical studies within sociology do not explicitly discuss the motivation for their measure of economic conditions, and tend to include many economic explanatory variables in their empirical models. We expand on these topics below, but first we turn to a theory of hate crime motivation which predicts that economic conditions have no effect on hate crime incidence.

The Defended-Neighborhood Model

There are theories that connect the incidence of hate crime to subjective interpretation, i.e. individual motivation, and other theories that do the same for objective conditions, e.g. theoretical models on how the unemployment rate, mean income and other factors affect the incidence of hate crimes (Green et al., 2001). Green et al. find, however, that there are few theories that combine both subjective interpretation and objective conditions, i.e. a complete mechanism from cause to effect. Green, Strolovitch & Wong, (1998, henceforth Green et al., 1998) develop one of the few complete models that can help explain "day-to-day" hate crimes, what they call the defended-neighborhood model.

The defended-neighborhood model is based on insights from sociology and supported by strong empirical evidence. Green et al. (1998) postulate that the main cause of interracial violence is demographic change. When a new ethnic group moves into a previously ethnically homogenous area, members of the majority group will undertake actions to defend the established group, under the belief that their well being, status or way of life is threatened by the minority group. Over time, the model predicts that as more of the minority group move into the area, familiarity will decrease the animosity between the two groups, and the group will redefine its identity. Violence will give way to acceptance and indifference. The most salient aspect, at least for our purposes, is that it predicts that there is no association whatsoever between economic variables and the incidence of hate crimes.

Green et al. (1998) use panel data from 1987 to 1995 at the community district level from the Bias Crime Unit of the NYPD to perform an empirical test of their model. They find that the evidence supports the predictions of their model. Further, they find no correlation between hate crime incidence at the community district level and macroeconomic conditions. This study stands out from the other surveyed studies due to the granularity of the collected data.

Weaknesses in Theory and Method: The Purpose of A General Economic Theory

We identify some flaws in the method of sociological studies. Generally, we argue that the underlying cause is a mismatch of using the sociological framework when dealing with what are economic variables. We identify two broad such weaknesses in method, which we believe are best addressed by applying a complementary neoclassical economic approach.

First, sociologists tend to over specify empirical models and each author seems to have her own preference. This is understandable because it is hard to specify a complete and detailed mechanism within the sociological framework. The frustration thesis cannot within the sociological framework specify whether it is rising unemployment, falling income or stagnant growth that is the most appropriate measure of the relevant economic conditions. Thus, an economic approach is complementary as tools are available that enable the theorization of detailed mechanism from cause, worsening economic conditions, to effect, increased hate crime incidence.

Second, empirical studies in sociology tend to focus on specific forms of hate crime motivation, for example racially motivated, at the expense of a general theory. The preference for specific models can be attributed to their explanatory power, and from a sociological perspective, a lack of a believable general model. In the case where each specific hate crime motivation can be empirically studied independently, it is desirable to develop models with high explanatory power, which are then tested individually. These studies taken together would then in practice be equivalent to a study of general hate crime motivation.

However, whenever it is difficult to test a specific theory empirically, some forms of bias-motivate crimes have tended to be overlooked in the literature. For example, among the studies of specific types of hate crime motivation we find a dearth of empirical studies on factors, economic or otherwise, that influence the incidence of hate crimes against sexual minorities. This has been due to the difficulty in controlling for sexual identity, and thus the difficulty in determining whether the lack of hate crimes towards sexual minorities is due to the absence of the target group or the influence of other factors; Green, Strolovitch, Wong and Bailey (2001) comment on this issue and identify possible solutions. In this case, a focus on the specific can, and has, led to an underdeveloped scholarship, especially from an empirical perspective, of certain types of hate crime motivation.

In such cases, we argue that general theories of hate crime motivation are an important complement to specific theories. General theories help us understand the theoretical underpinnings of types of hate crimes that are difficult to study on their own, for example homophobic hate crimes. We believe that a general theory of hate crime motivation, with sufficient explanatory power, can be developed and that a neoclassical approach is best suited for such a task.

Hate Crime in Economics: Empirical Studies

Empirical research on this topic in economics is rather recent and has been conducted with a theoretical framework that is under development. This has led to some of the same mistakes made by sociologists. Although each variable is explicitly motivated based on theory, we see a tendency to over specify empirical models. Looking at the two studies we have found, they suffer from a lack of standard theoretical approach, even though both are based on utility maximization, the choice of explanatory variables differs, making comparisons difficult.

Conceptualizing hate crimes as a good that is time-intensive in consumption and production, Medoff (1999) hypothesized that the incidence of hate crimes should increase as the value of time falls and consumption and production of hate crimes is made more or less difficult by certain factors. Medoff uses aggregated measures, based on a time-allocation model in Becker (1965), to measure the value of time and environmental factors that affect the time opportunity cost of committing a hate crime. These measures are then regressed on the incidence of hate crimes in US states in 1995. Medoff finds that unemployment, percentage of youth and average wages have a statistically significant correlation with hate crimes. Other variables included, such, as education and religion, are not statistically significant. Although the theoretical approach is sound, we argue that there is a weakness in the empirical approach. The use of cross-section data does not seem appropriate in an observational study where the researcher cannot control for fixed effects in each US State. Being unable to control for the myriad of such factors that can influence the empirical model, leaving results open to significant confounding effects, means caution must be taken. To us, the use of time-series data seems to be more appropriate. Panel data allows to better isolate the effects of variables we are interested in, by comparing both over time and across units of analysis, while also allowing for fixed effects to impact differently between units (Wooldridge, 2013).

In another study, Gale et al. (2002) use panel data on US states between 1992 and 1995. They posit that hate crime is motivated by envy, defined in Becker (1981) as negative altruism, and predict that envy is increased by economic deprivation and low social mobility. They find a statistically significant positive correlation between the incidence of hate crimes in the US at the state level and the corresponding unemployment rate and decreasing income disparity between blacks and whites. Other tested variables, however, such as annual income are not found to be statistically significant. We find an important flaw in the estimation model. They estimate a random effects (RE) model, we argue that it is more appropriate to use fixed effects (FE), considering that the units are geographical in nature. This is a serious flaw compounded by the fact that the statistical significance on the tested variables is only present in the RE, and not the FE, specification. We therefore have serious misgivings about the conclusions of the study due to the error in econometric method. We discuss this in greater depth in section 4, where we discuss and motivate our own choice of model.

The economic approach improves on the sociological in some aspects; economists tend to explicitly motivate the inclusion of explanatory variables in their econometric models based on theories and focus on hate crimes in general. While theories tend to be underdeveloped they are based on some valuable insights. Indeed, it is the combination of the theories presented in these two studies that forms the core of the theoretical framework of our study, as we discuss in section 3.

Research Gap

The findings of previous studies, economic and sociological, are mixed and limited in geographic scope. A number of studies find that evidence supports that economic conditions correlate with the incidence of hate crimes, while others find that they are independent of each other. Generally, authors who hypothesize an association between the incidence of hate crimes and economic conditions find one, while those who test the opposing hypothesis tend to find evidence that supports theirs. This might be an effect of publication bias. It is difficult to reconcile the contradicting results as studies differ in significant ways, in the choice of explanatory variables, in the econometric specification or even the type of data, i.e. panel, time-series or cross-section. No two studies are alike. Finally, the lack of similar research outside of the US and Germany also highlights the importance of broadening the geographic scope of this research field.

We attribute the lack of standardization in the studies based on the economic framework to a lack of a general economic theory of hate crime motivation. Rather there are a number of existing complementary models. We address the deficiencies by combining these models. We then test the hypotheses we derive from this theory using data in a new geographic context, Sweden, thereby addressing the lack of geographic breadth in the literature. In doing so we also adopt a more rigorous stance in our model specification and estimation process as we discuss in section 4.

3. Time Allocation and Hate: A General Economic Model

In this section we present the economic theories on hate crimes, some of which we briefly touched upon in the previous section, which we combine to construct a complete general model. As we note throughout this section, our approach builds in large part on Becker's (1965; 1968) seminal works applying the neoclassical framework to studying crime, the so-called time allocation model. We take inspiration from Green et al. (1998), the defended-neighborhood model, by building the model to have both a subjective interpretation component and an objective conditions component.

The model is made of three parts. First, the subjective interpretation component, based on the model in Gale et al. (2002), captures the individual's motivation to commit a crime in economic terms. The second component is a model that describes the mechanism by which the incidence of hate crimes depends on economic conditions, namely the opportunity cost of time, based on Medoff (1999). The final component of the model captures how the subjective interpretation might be influenced by factors external to the individual, here presented as political messages, based on Glaeser (2005). Taken separately, the three constituent models have explanatory power, but are incomplete. As they are complementary, by integrating them a complete model can be developed that can relate the incidence of hate crimes to economic conditions.

Medoff's model constitutes the nucleus of our model, however, its lack of subjective interpretation renders it incomplete. The model is based on an observation that hate crimes have a greater opportunity cost relative other crimes. The risk of getting caught is higher as perpetrators tend to attack unknown victims and must go out of their way to unfamiliar locations to commit the crime (Flannery, 1997). Furthermore, there is rarely monetary gain for the perpetrator, as hate crimes rarely involve robberies (Berk, 1990). If we assume a rational agent, the perpetrator must conceivably receive a non-monetary benefit that mitigates this increased opportunity cost. Medoff's model does not address what this benefit might be, where it might come from or why it exists. Instead, he takes the empirically verified observation that individuals are willing to bear higher opportunity costs as ex-post justification for the existence of such a benefit. This incompleteness is the main weakness of the model.

To understand individual motivation we turn instead to the model in Gale et al. (2002). They use the concept of envy, as presented in Becker (1981). Envy is the opposite of altruism; whereas altruism implies that a person's utility function depends positively on the wellbeing of another person's or a group of people, the utility function of an envious person depends negatively on the utility function of another person or a group of people (Gale et al. 2002; Becker, 1981). An envious person commits a hate crime because she derives utility, from decreasing the well being of her victim, which exceeds the associated costs, which are relatively high.

Conceptualizing the individual motivation component, envy, allows us to endogenize the change in the level of envy in society, at least partially. To do so we must establish what might cause envy in the first place, to which Glaeser (2005) makes the most meaningful contribution in economics. According to him, the clearest example of hate is the behavior of participants in ultimatum games, "this behavior is known as reciprocity, reciprocal altruism, fairness, or spite, but in substance (if not degree) negative reciprocity looks like hate" (Glaeser, 2005, p. 51). Interestingly, this definition is very similar to the one adopted by Gale et al. (2002) of hate as envy, which is to say the inverse of altruism, showing an implicit consensus in substance, though not in terminology, of the description of hate in economic terms.

As opposed to Gale et al. (2002), Glaeser argues that messages spread by politicians, and authorities in general, are the root cause of hate in society. In this, his model coincides with Karapin (1996). He refers to the spreading of hateful, true or false (but often false), messages as the supply side of hate. On the other hand, the demand is determined by willingness of individuals to accept this message at face value, "[h]atred will not spread among groups who have private incentives to learn the truth about a minority" (Glaeser, 2005, p. 48). Thus, according to Glaeser, hate will increase as politicians use hateful messages to further their aim, this might lead to an increase in the incidence of hate crimes or, in the worst case, as Glaeser argues, to catastrophic events such as genocides. Conversely, increased integration and greater contact between groups should lower the costs of individuals to learn the true nature of the minority group leading to a decrease in the level of hate and thereby its manifestation in hate crimes, which shares an affinity with Green et al. (1998).

Utility Maximization and Time Allocation

We now present our general economic model of hate crimes by integrating the subjective interpretation component, from Gale et al. (2002), with the objective condition component in Medoff (1999), while at the same time adding a final component based on Glaeser (2005). In doing so we derive six hypotheses that we test empirically in the coming sections. The heart of our model is the model in Medoff's paper that uses the time-allocation framework, as presented by Becker (1965), to describe a mechanism through which economic conditions affect the incidence of hate crimes. The exposition below is to a large extent a reproduction of the derivation of the model as presented in the original text, with two significant departures. First, we integrate envy into the model. Second, we endogenize envy based on insights from Glaeser (2005). Otherwise, the exposition is true to the original text. Consequently, we note these changes and any additions of our own explicitly:

Assume utility-maximizing individuals, who are forward-looking agents with stable preferences. Furthermore, assume an individual's utility (U) depends on the consumption of two goods: antisocial hateful behavior (H) and all other commodities combined in an aggregate good (Z). An individual's action is constrained by income, time, other limited resources, and market opportunities. The utility function is given by:

$$U = U(H, Z)$$

Goods H and Z are not perfect substitutes for each other. For the reasons given before, H is more time-intensive in consumption and production relative Z. Additionally, H cannot be purchased as Z can, but must be produced using goods and services from the market and one's own time. Both H and Z are produced using a vector of market goods x_i and a vector of its own time t_i within a context of environmental variables E in which production takes place:

$$H = h(x_h, t_h, E)\ , \quad Z = z(x_z, t_z, E)$$

In the model, the environmental variable, E, captures any factors in the environment that might affect the time opportunity cost of producing H, Z, or both.

The total available time to an individual, T, is the sum of the time spent working, t_w, and the time spent producing H, t_h, and the time spent producing Z, t_z, given by the constraint:

$$T = t_w + t_h + t_z.$$

The income constraint, for an individual, is given by the equation

$$wt_h + wt_z + p_h x_h + p_z x_z = M.$$

Where w is the market wage rate, p_i, are the prices of the respective market-good inputs used in producing H and Z, and M is the individual's potential full income. We now maximize the utility function, subject to the production function and the income constraint:

$$\max_{H,Z} U(H,Z)$$

$$s.t. \qquad H = h(x_h, t_h, E)\ , \quad Z = z(x_z, t_z, E);\ \text{and}$$

$$wt_h + wt_z + p_h x_h + p_z x_z = M.$$

Solving using the method of Lagrange, gives us the following first order conditions (FOCs):

$$\frac{\partial L}{\partial H} = \frac{\partial U}{\partial H} - \lambda\left(w\frac{\partial t_h}{\partial H} + p_h\frac{\partial x_h}{\partial H}\right) = 0$$

$$\frac{\partial L}{\partial Z} = \frac{\partial U}{\partial Z} - \lambda\left(w\frac{\partial t_z}{\partial Z} + p_z\frac{\partial x_z}{\partial Z}\right) = 0$$

Hence,

$$\frac{\partial U}{\partial H} = \lambda\left(w\frac{\partial t_h}{\partial H} + p_h\frac{\partial x_h}{\partial H}\right)$$

$$\frac{\partial U}{\partial Z} = \lambda\left(w\frac{\partial t_z}{\partial Z} + p_z\frac{\partial x_z}{\partial Z}\right)$$

Dividing the first FOC by the second we get the following expression,

$$\frac{\frac{\partial U}{\partial H}}{\frac{\partial U}{\partial Z}} = \frac{w\frac{\partial t_h}{\partial H} + p_h\frac{\partial x_h}{\partial H}}{w\frac{\partial t_z}{\partial Z} + p_z\frac{\partial x_z}{\partial Z}} \equiv \frac{MC_H}{MC_Z}$$

The numerator of the right hand side represents the marginal cost (MC) of commodity H. $MC_H\ is$ given by the sum of the opportunity cost of time $\left(w\frac{dt_h}{dH}\right)$ and the cost of producing a unit of commodity H $\left(p_h\frac{dx_h}{dH}\right)$. Similarly, the denominator represents the MC of commodity Z. An increase in the value of an individual's time (w) would increase the marginal cost of both H and Z, but especially H, which is relatively more time-intensive in consumption, leading to a decrease in its consumption. Thus, an increase in an individual's market wage will lead to a decrease in hateful activity.

Hypothesis 1: The incidence of hate crimes is negatively related to the market wage level.

As a corollary to this, there are a number of individuals with no market wage, that is the unemployed. The increase in the rate of unemployment will lead to a decline in the value of time. Thus, a decrease in the value of an individual's time due to unemployment should lead to a decrease in the marginal cost of both H and $Z,$ but especially H, which is relatively more time-intensive, leading to an increase in its consumption.

Hypothesis 2: The incidence of hate crimes is positively related to the unemployment rate.

An individual's market wage, that is value of time (w), varies over a person's life cycle. As such, at an early stage in the life cycle, the value of an individual's time is relatively low and the value of goods high. This suggests that the relative consumption of goods that are more time-intensive in consumption, such as H, will be higher when individuals are young.[1]

Hypothesis 3: The incidence of hate crimes is positively related to the youth share of the population.

A change in E, the environmental variable, changes the amounts of time and goods, but not the price of goods, required in producing a given amount of either H or Z. The effect of a change in E on MC_H is given by deriving the first order condition relating to commodity H with respect to E.

$$\frac{\partial \mathrm{MC}}{\partial E} = \frac{\partial t_h}{\partial H}\frac{\partial w}{\partial E} + w\frac{\partial^2 t_h}{\partial E \partial H} + \frac{\partial p_h}{\partial E}\frac{\partial x_h}{\partial H} + p_h\frac{\partial^2 x_h}{\partial E \partial H}$$

However, as a change in E does not, by construction, affect the price of the goods, this simplifies to:

$$\frac{\partial \mathrm{MC}}{\partial E} = \frac{\partial t_h}{\partial H}\frac{\partial w}{\partial E} + w\frac{\partial^2 t_h}{\partial E \partial H} + p_h\frac{\partial^2 x_h}{\partial E \partial H}$$

There are many examples of possible factors influencing *E*, therefore it is impossible to measure all of them. We include the environmental variables that we believe have the most significant impact. One significant environmental variable is law enforcement activity, an increase in law enforcement activity will raise the amount of time or goods required to produce a given amount of hateful activity $\left(\frac{\partial^2 t_h}{\partial E \partial H} > 0, \frac{\partial^2 x_h}{\partial E \partial H} > 0\right)$. This increases the marginal cost of hateful activity $\left(\frac{\partial \mathrm{MC}}{\partial E} > 0\right)$ discouraging its consumption.

Hypothesis 4: The incidence of hate crimes is negatively related to law enforcement activity.

Another potentially significant environmental variable is population density. It would result in more hateful activity if it lowered the amount of time or goods required to produce hateful activity $\left(\frac{\partial^2 t_h}{\partial E \partial H} < 0, \frac{\partial^2 x_h}{\partial E \partial H} < 0\right)$ by reducing the search costs or reducing the probability of being apprehended by law enforcement.

Hypothesis 5: The incidence of hate crimes is positively related to the degree of population density.

Finally, we add that the spread of hateful political messages should also influence the incidence of hateful activity by increasing the level of envy. Glaeser (2005) develops a

[1] The attentive reader will note that such an argument could be expanded to include pensioners as well as small children.

mathematical model for how politicians, and authority figures, spread hateful messages, that can be true or false, in order to further their own goals, and thereby incite hate crimes and violence towards out-groups. The inclination to hate depends on the costs individuals face in order to obtain information about the out-group, and Glaeser argues that this depends primarily on the physical distance between in-group and out-group. Thus, greater integration should lower hate crime incidence, while rising segregation should lead to an increase. We do not present an exposition of the model here, as it would take up too much space, instead we refer the interested reader to the original text. Fortunately, even tough the model itself is highly technical the conclusions are quite simple and it is feasible to test empirically.

Hypothesis 6: The incidence of hate crimes is positively related to the spread of hateful political messages and the degree of segregation.

Our model yields six testable hypotheses. Five of these hypotheses are virtually identical to those in Medoff (1999), as his model is at the heart of our model. These same five hypotheses, with the exception of hypothesis three, are also found in Gale et al. (2002), although in a different guise.[2] Gale et al. hypothesize certain variables as proxies for causes for envy, for example black/white income differences. We disfavor this approach, as the theoretical underpinnings are underdeveloped: the choice of black/white income differences seems quite arbitrary. We prefer instead an approach based on Glaeser (2005), and indeed it is from Glaeser's work that the sixth hypothesis comes from.

Therefore, it would be justified to state that our study is a replication of Medoff (1999) and Gale et al. (2002). However, while it is similar in the hypotheses we test and the research design, we note several differences. First and foremost, both previous studies included more explanatory variables than we do. We choose not to include some of these, as we were not convinced by the arguments made for their inclusion. Second, we improve on the statistical method as we discuss in sections below.

Arguably, the list of determinants is not exhaustive and a variety of other economic factors could influence the incidence of hate crimes. Nonetheless, we believe that our limited list is the most appropriate in this case. The lack of a consensus on whether hate crime incidence has any economic determinants at all makes us hesitant to include more determinants than those that have already been tested. Indeed, only hypothesis six has yet to be tested empirically. We are conservative with our choice of explanatory variables, as it seems unwise to test all possible correlates without first ascertaining that a relationship exists at the most basic level. It also facilitates comparison, which as we argued previously is a problem with previous studies.

The model contradicts some of the theories and empirical findings that we discuss previously in that it predicts that economic conditions are determinants of hate crime incidence. A number of our hypotheses, the first four and to a certain extent the fifth, contradict the defended-neighborhood model, the most complete sociological model of the determinants of hate crime incidence, and the empirical findings that support it. Hypothesis six, on the other hand, much like the defended neighborhood model predicts a decrease in the incidence of hate crimes with increased integration. However, an external factor, namely the power of hateful messages communicated by politicians, is posited to be the main determinant of hate

[2] For example,in accordance with Medoff (1999), we use wage, while Gale et al. use total income.

crime incidence. Thus, the empirical test of our model should help shed light on which of the two models is applicable in the Swedish context.

The most important aspect of the model is that it does not apply only to a certain type of hate crime motivation but to all hate crimes. It is equally adept at explaining racially motivated, xenophobic and homophobic crime. Envy as the subjective interpretation component is general in its conception, in that it is sufficiently broad to analyze all hate crimes without excluding any biased motivated crimes regardless of the perpetrator or victim's social group association. This strength cannot be understated, as other theories of hate crime motivation often degenerate to theoretical explanations of hate crimes in only one direction, i.e. majority to minority, or of only one type, as we discussed previously. This has significant consequences, as the ignored types of hate crimes are not negligible. It is also most appropriate in our case as the definition of hate crimes in the data, as we discuss in section 4, is broad and it is important that our model is consistent with the definition of hate crimes in our data, which is collected by a third party.

As we argue previously, general theories will almost always have lower explanatory power than specific ones. Thus, the role of general theories is to complement these specific theories. Although unlikely that the motivation for homophobic and xenophobic crime are the same, a general theory helps us to understand the commonalities and it facilitates the empirical study of types of hate crime motivation that would otherwise be neglected, as we have touched upon previously.

Assumptions and Limitations

The theoretical approach that we adopt is based to a large extent on the work of Becker and the neoclassical approach to crime he pioneered in his seminal works. Thus, we take as a given the assumptions that underpin the neoclassical paradigm, individuals with rational preferences who maximize utility and act independently on the basis of full and relevant information (Weintraub, 1993). It is not hard to formulate valid arguments against the reasonableness of any of these assumptions, especially when it comes to analyzing criminal behavior. On this we side with Becker's stance as conveyed in the quote on the first page of this study, and his extensive work on this topic that has shown the value of such an approach.[3]

A major weakness is that our model does not specify a cause for envy in general. For the purposes of our study, envy is exogenous. The final component of our model, based on Glaeser (2005), specifies how politicians might heighten the existing level of hate in society by creating stories that either heighten existing hostilities or can create stories directing hate towards a given group. While we consider this a good explanation of how hate, or envy, might increase in a society, that is how it might grow endogenously, it still must assume an exogenously given stock of envy, this is hard to specify accurately and exhaustively. There are many theories that can explain how and why envy might arise in other disciplines. For example, the concept of envy is compatible with many of the sociological theories of hate crimes, for example realistic group conflict theory (Green et al. 2001). In economics, besides Glaeser (2005), Cameron (2009) makes a significant contribution by analyzing hate from a heterodox perspective. Nonetheless, without an exhaustive and accurate endogenization the model is incomplete. The already tenuous inferences of causality are weakened and it is

[3] We also refer the interested reader to McCarthy and Cohen's (2002) review of the debate in the literature, highlighting the advantages of an economic neoclassical approach in complementing specific theories with general insights, with only a few assumptions, mainly rationality.

impossible to describe the long run developments of hate crime incidence, from the "creation" of hate to when the crime is committed.

We argue that this incompleteness is justified. Given our aim of understanding the relationship between economic conditions and the incidence of hate crimes, if indeed one exists, we can look at either the long or short run interaction. It is difficult to study both at the same time; the determinants of long run trends do not necessarily perfectly coincide with the determinants of short run trends. Furthermore, since accurate hate crime statistics have only recently started to be compiled, it is not possible to study long-run trends and test theories with any degree of accuracy. Therefore, we choose to see the long-run trend as exogenous, and focus on the short run. An analogy can be drawn to neoclassical macroeconomic models of growth, where the short-run model, explaining the output gap, differs from the long-run model, explaining potential output growth. Although the short-run macroeconomic model of growth follows neatly from the long-run model, our understanding of what determines fluctuations in economic growth in the short run in many ways predate the long-run growth models we have today. With hate crimes, as with other phenomena, it is reasonable and more convenient to start with the measurable and conceivable, that is short-run fluctuations, and only when there is enough data we can move on to developing and testing models explaining long-run trends.

4. Empirical Method

This section outlines the empirical method we adopt to test the hypotheses presented in the previous section. We start by discussing the definition of what constitutes a hate crime in this study; where we adopt an operational definition, which is slightly broader than the most common definitions in the literature. Next we discuss our research design. In the third subsection, we discuss the merits and pitfalls of testing theories of individual behavior using aggregate data, motivating our chosen level of aggregation. Finally, we present our econometric models, two regression specifications to test hypothesis 1-5 and 1-6 respectively.

What is a Hate Crime?

We adopt an operational definition to match the definition in our data, which is collected by a third party. The definition we adopt is given by the Swedish National Council for Crime Prevention (*Brottsförebyggande rådet*, henceforth BRÅ). BRÅ is the agency tasked with collecting and compiling statistics on hate crimes in Sweden. BRÅ's definition, (2014, p. 21, own translation) is as follows:

> Crime against a person, group, property, institution or a representative of these, that is motivated by fear of, animosity towards or hate of the victim based on the color of skin, national or ethnic background, religious creed, sexual identity as well as gender identity that the perpetrator believes, knows or perceives the persons or groups as having.

The definition implies a broad conception of applicable target, broader than the most common definition in the literature that considers hate crimes to be only those crimes perpetrated against a subordinated minority, that is majority-minority hate crimes (Green et al., 2001). Our definition allows us to study all types of hate crimes without pre-specifying the background of the perpetrator or victim. We see this as an advantage of the adopted definition as more common definitions tend to ignore a significant proportion of hate crimes, for example minority-majority hate crimes. A weakness of our chosen definition is that it excludes the physically or mentally disabled as an applicable target group. Ideally, the definition would include this group as well, in line with some of the broader definitions in the literature (Craig 1999, p. 139).

The definition specifies that illegal conduct of any kind constitutes a hate crime as long as it is motivated by hatred towards the victim because of her actual or perceived social identity. It is in line with the definition in the literature, where there is a consensus: any crime towards a member of an applicable target group is considered a hate crime as long as it is motivated by hate (Green et al., 2001; see BRÅ, 2014, p. 21-22). So, in essence, what distinguishes a hate crime from any other type of crime is the motivation. In the literature, a hate crime is any crime motivated by scorn for the perceived social characteristics of the victim, so called bigoted motivation (Green et al., 2001). A significant schism between definitions in Sweden, where we conduct our study, and the US, where a majority of previous studies of this kind have been undertaken, is that hate speech is considered a crime in the former, but not in the latter. In general, European legislation views hate speech as a crime, whereas it is protected by the first amendment in the US (Kahn, 2012).

At the same time, there is a significant discussion as to what extent the crime must be motivated by bigotry, that is whether bigotry must be the exclusive motive for a crime (Berk, 1990). Considering all crimes in which bigotry is manifested would not be appropriate. Consider for example a robbery in which the criminal insults the victim by using a racial slur;

this is hardly what we are interested in studying. Ideally, we would like to study crimes exclusively motivated by hate; this is practically very difficult if not impossible. It is possible however, with a degree of accuracy to identify crimes where the primary motivation is bigotry, which is inherent in BRÅ's definition and method of data collection (see BRÅ, 2014, p. 21-22), as well as the most common definitions in the literature (Green et al., 2001). The discussion on how to identify a hate crime is further developed in section 5, where we will introduce the hate crime data used in this study.

Research Design

All previous studies that we have reviewed are observational studies; specifically they are all correlational studies. Due to ethical, legal and practical limitations, our study is also correlational. The weakness of an observational design is that we cannot observe and control for potential confounding variables. Thus, causal inferences cannot due to endogeneity problems; rather the evidence either supports a postulated association or does not. Hence, the findings of observational studies must be interpreted with care.

The fact that all previous studies have been observational does not mean another research design is untenable, although we find it difficult to apply in our scope and with our limited resources. Green and Spry (2014) find that empirical studies of hate crimes, not just those testing how economic conditions might affect their incidence, have been almost exclusively observational. They attempt to address the issue by suggesting how to move towards a more design-based direction. Experimental designs such as randomly varying crime prevention, messaging (using mass media to broadcast more or less hateful messages) and randomly changing power arrangements have been used in studies of "regular" crime. We believe that the ethical and practical difficulties of conducting ecologically valid experiments using these methods are still quite large, especially when it comes to manipulating economic conditions, for example unemployment or income. A more promising avenue is the use of quasi-experimental designs, taking advantage of discontinuities or natural experiments as Green and Spry propose. For example, comparing two otherwise equivalent regions, where one of the regions has been especially hit by an economic crisis would be of special interest. However, in such cases, researchers are dependent on the vagaries of chance to create such instances. Unfortunately, it was not practically feasible to apply any of these insights in our study.

On the Level of Aggregation

As our hypotheses concern behavior and choices at the individual level, ideally, we would prefer to test our hypotheses using individual data. However, using individual hate crime data would be a serious threat to the right to privacy of individuals and a breach of Swedish laws. Therefore, we will test our hypotheses using aggregate data.

Aggregate analysis does also have advantages and has been useful in the study of a host of phenomena in social studies, where the direct measurement of individual behavior is problematic, illegal or unethical, as discussed by Medoff (1999, pp. 966-967). Grunfeld and Griliches (1960) argue that aggregate level data is subject to smaller errors than individual data, and thus the likelihood of poorly specified individual equation is smaller. The major pitfall of studying the correlation of aggregated data is the so-called ecological fallacy. Robinson (1950) illustrates how correlation at the aggregate level might not exist or have the opposite sign at the individual level. The risk of an ecological fallacy highlights the importance of taking into account confounding factors, and especially possible omitted variables.

In Sweden, hate crime statistics are available at the national level and at county (*län* in Swedish) level, but they are not available at the level of municipality (*kommun* in Swedish). As many municipalities experience very few hate crimes per year, in order to protect the anonymity of victims and perpetrators, BRÅ does not publish municipal statistics because of legal restrictions (SFS 2001:99). As statistics are only available for a short time period due to changes in method undertaken in 2008, aggregation at the national level would lead to an insufficient number of observations for a robust test of our hypotheses. By aggregating at the county level, we can use the variance between counties to create a set of data that is more suitable for testing the derived hypotheses. Unfortunately, this sacrifices some of the value of aggregation, as Swedish counties have a relatively small population. For comparison the entire Swedish population is comparable in size to that of some of the larger states in the US.

Econometric model

To test the six hypothesis presented in section 3, we develop two econometric models. The first regression tests hypothesis 1-5 using total hate crime incidence. In the second regression we also test hypothesis six, using only data on hate crimes with a xenophobic motive. We split the regressions since it is not possible to operationalize hypothesis six when considering all hate crimes without making overly tenuous assumptions, but it is possible to do so for the specified subtype, namely xenophobic hate crimes.

County Specific Effects: Fixed or Random

The general specification of our regression is given by the following expression:

$$\ln\,(HateCrime_{it}) = \beta_0 + \beta_1 X_{1t} + \ldots + \beta_N X_{Nt} + \varepsilon_{it}$$

The dependent variable is the log-transformed total incidence of hate crimes. The independent variables are specified below. However, it is necessary to first choose the most appropriate model for our estimation. When using panel data, it is possible to control for unobservable characteristics in each panel "member" (county in our case) which could otherwise have a potential biasing effect on regression coefficients. To do this, we can apply either the fixed effects (FE) or random effects (RE) method to our regressions. The difference in these methods lies in the assumption about how the error term, $\varepsilon_{it} = a_i + u_{it}$, is related to the explanatory variables. a_i is an unobservable, time-invariant, county-specific effect, which is assumed to influence the incidence of hate crimes, while u_{it} is the idiosyncratic error term for each observation.

In a RE specification, a_i is assumed to be independent of all explanatory variables x_{it} for all $t = 1, \ldots, \mathrm{T}$. An FE specification is appropriate when this assumption does not appear to be reasonable, and correlation between the fixed effect and the explanatory factors is expected (Wooldridge, 2013). FE controls for such a correlation by demeaning the data in order to only use the so-called within variation of variables, in our example this would be the change within a county over time. The demeaning leaves FE less efficient than random effects. However, in the event of correlation between the independent variables and the county specific effect, a RE model would render biased estimates; hence, in such cases FE is preferred.[4]

In this case, we believe that a fixed effects specification is the most appropriate as there are unobservable or difficult-to-measure features that are generally time invariant, at least in the given period of analysis, but differ across counties and affect the incidence of hate crimes.

[4] For a more detailed discussion of random and fixed effects, we refer the interested reader to the detailed exposition in Wooldridge (2010).

Geographical aspects are perhaps the most important of these. A simple example would be the presence or absence of a reliable and extensive public transportation system in a county. As stated previously, hate crimes often occur at a distance from the perpetrator's domicile, thus ease of mobility lowers the costs of committing a hate crime, while it is also correlated to one of our chosen explanatory variables, namely population density. This an example of an effect that is difficult to measure, but there are also other factors mostly related to geography, such as the terrain, weather conditions throughout the year, that could be similarly conducive to criminal activity and are correlated with the variables in the model specification.

Returning to our critique of Gale et al. (2002), we provide a detailed exposition of what we believe are the flaws in their choice of estimation model. On the decision between fixed and random effects, Gale et al. argue that since they cannot determine which method is more appropriate *a priori*, it is best to perform the regression with both models and determine which is the best by performing a Hausman test. The null hypothesis under the Hausman test is that RE estimators are efficient. It is common to use the random effect specification unless the Hausman test rejects the null. This is, however, not the appropriate use of the test. Wooldridge (2013, p. 478) explains that " [i]n practice, a failure to reject means either that the RE and FE estimates are sufficiently close so that it does not matter which is used, or the sampling variation is so large in the FE estimates that one cannot conclude practically significant differences are statistically significant." Furthermore, through a series of simulations, Clark and Linzer (2012, p.2) show that "the Hausman test is neither a necessary nor a sufficient metric for deciding between fixed and random effects."

The choice of estimator should depend on the relationship to be tested, on whether there are possible time-invariant factors that might be correlated with the chosen explanatory variables, in this case across states. It is on these grounds that one can motivate the use of one estimator or the other; tests can then be used to see if our intuition is confirmed in the data. Wooldridge (2013, p.478) argues that "FE is almost always much more convincing than RE for policy analysis using aggregated data." Therefore, we estimate our regressions using the fixed effects model.

Heteroskedasticity

Another important issue in the estimation process is the issue of heteroskedasticity. In the presence of heteroskedasticity, both regression estimates and confidence intervals are likely to be biased. Therefore, we perform calculate a modified Wald statistic to test for groupwise hetereoskedasticity as is appropriate for a fixed effects regression (Baum, 2001).[5] In the event of heteroskedasticity, we correct for it by using robust standard errors; this option is included in the statistics package we are using, Stata 13.

Model Specification I

Having specified the general model, we now present the first specific model. To test our hypotheses 1-5, we specify the following regression of hate crime incidence:

$$\begin{aligned} \ln(HateCrime_{it}) = \beta_0 + \beta_1 WageAverage_{it} + \beta_2 Unemployment_{it} + \\ \beta_3 PopulationYoung_{it} + \beta_4 PoliceOfficers_{it} + \\ \beta_5 PopulationDensity_{it} + \beta_c ForeignPopulation_{it} + a_i + u_{it} \end{aligned} \tag{1}$$

[5] We tested for heteroskedasticity using the Stata package "xttest3", the interested reader can read more about it here: http://www.stata-journal.com/sjpdf.html?articlenum=st0004

The dependent variable $HateCrime_{it}$ is the total number of hate crimes per 100,000 inhabitants in a county *i* during year *t*. This data is provided by BRÅ. In our regressions, we have log-transformed the hate crime data to better fit a normal distributed error plot as well as giving a more suitable way of interpreting the results since the log transformation will let us analyze percentage increases in hate crime. Log transforming is very commonly used in criminal research for these reasons (Gale. et al, 2002; Ehrlich, 1973; Sjoquist, 1973; Zhang, 1997).

We test hypothesis 1 by using $WageAverage_{it}$, a measure of average wage income in 1000SEK; thus, no capital gains or incomes from other sources are included, only wages. Higher wages imply that a person's time is more valuable; therefore, we expect β_1 to be negative. This data is provided by Statistics Sweden.

Hypothesis 2 also deals with a person's value of time, but focuses on the more binary states of being employed or not. Unemployment implies low relative value of time and therefore we expect β_2 to be positive. The Swedish Public Employment Service supplies the data used to measure unemployment. $Unemployment_{it}$ measures the open unemployment rate, which is the percentage of the working population that is actively looking for work or in an activity program organized by The Swedish Public Employment Service (2015).

We use a measure of market wages when testing hypothesis 1. In general, young people have low market wages, if any at all, and therefore low time value. To test hypothesis 3, we want to capture this share of a county's population with low time value by adding a measure of how large the group of inhabitants between 15-24 years is, $PopulationYoung_{it}$. We expect β_3 to be positive. The data is provided by Statistics Sweden and expressed as a percentage of total county population. Our choice of using the age span 15-24 years is in line with previous studies where this age span is often used in operationalization of "young population" (see Medoff, 1999).

The risk of being apprehended when committing a hate crime makes it more costly to commit said crime, as stated in hypothesis 4. We argue that a good measure of this risk is the number of police officers per capita employed in a county. Seeing many police offers out in the streets would be interpreted by the perpetrator as increasing the risk of apprehension and therefore serves as a suitable proxy for the risk of detection. The data comes from the Swedish National Police Board. $PoliceOfficers_{it}$ measures the number of police officers per capita employed by each county, excluding police units working on a national level such as The National Bureau of Investigation and the Swedish Security Service (SÄPO). We expect that as the number of police officers increases, hate crime incidence should decrease. In short, we expect a negative sign on β_4.

Hypothesis 5 states that the time it takes for a perpetrator to identify suitable hate crime victims should be negatively related to population density. Living closer to other people increases the probability of having potential victims in the vicinity, which would lower the time needed to plan and execute a hate crime. This means that the total cost of committing hate crimes should decrease as population density, given by $PopulationDensity_{it}$, goes up. β_5 is expected to have a positive sign. The data is provided by Statistics Sweden.

Finally, we must control for time variant, county specific factors that might influence the incidence of hate crimes. In this case, the most important aspect is controlling for changes in demographic composition, that is proportion of the population that can be classified as ethnic, racial or sexual minority. It seems unlikely that the proportion of the population that is in minority in terms of sexual identity has varied significantly in the period of analysis; it is also quite difficult to quantify this change accurately as discussed previously we take it as a county level fixed effect (see Green, Strolovitch, Wong & Bailey, 2001). A time-variant factor, however, is the ethnic homogeneity of a county. This is especially important as Coleman (2008) argues that in recent decades the change in the composition of the population in Europe is mostly driven by migration. Xenophobic crime makes up a large proportion of total hate crime incidence in Sweden, approximately two-thirds. Therefore it is important to control for this factor as it is time variant and is not controlled for through fixed effects estimation. Statistics Sweden collects data on county residents' country of birth. This is measured by $ForeignPopulation_{it}$, the percentage of the population with a foreign background, here defined as having at least one parent born outside of Sweden. A database on ethnic, racial or religious background, which would also be of interest, is not available in Sweden due to the strict limitations imposed by Swedish law (SFS 2009:400, SFS 2001:99).

Model Specification II

$$\ln\left(XenoHateCrime_{it}\right) = \beta_0 + \beta_1 WageAverage_{it} + \beta_2 Unemployment_{it} + \beta_3 PopulationYoung_{it} + + \beta_4 PoliceOfficers_{it} + \beta_5 PopulationDensity_{it} + \beta_6 SD\_Vote_{it} + \beta_c ForeignPopulation_{it} + a_i + u_{it} \tag{2}$$

The first model specification is sufficient for testing hypotheses 1-5. For a test of our final hypothesis we have to undertake the non-trivial task of operationalizing the spreading of hateful messages and the degree of segregation. There are many ways in which this can be measured; a commonly used tool is a media study, whereby the most significant media publications in the geographical area of interest are studied thoroughly to establish the level and growth of hateful rhetoric (see for example Koopmans & Olzak, 2004). However, this is extremely time consuming and inappropriate for nation-wide studies ranging over several years, it is usually used for a cross section, and the results are often qualitative, not quantitative.

Consequently, a better measure is necessary; we prefer to use the support for politicians spreading hateful messages, that is support of hateful political parties, as a proxy for the spreading of hateful messages. This follows the line of argument in the work of Glaeser (2005), which our hypothesis is based on. Unfortunately, when it comes to segregation there is no publically available measure that will do for our purposes. The best available measure, the housing segregation index, compiled by Statistics Sweden, is computed in such a way that is not possible to make comparisons between counties, only within counties over time, making it inappropriate for panel analysis. A recently published reported commissioned by *Dagens Nyheter* (Örstadius, *2015*) contains an appropriate metric at the appropriate level of aggregation. However, it is only available for the thirty largest municipalities in Sweden, limiting its use for a nationwide like ours.

In the Swedish context, there is one established party that can be characterized as spreading hateful messages against minorities, namely the far right party the Sweden Democrats (SD). Specifically, SD represents an anti-immigration platform, with political messages that can be characterized as populist and xenophobic (Hellström & Nilsson, 2010; Rydgren & Ruth, 2013). In a recent vignette study, Müller et al. (2014) show that SD voters hold significantly more negative views towards foreigners, compared with voters for other Swedish parties. That is to say, there is a correlation between having xenophobic opinions and voting for SD. As it is an observational study with limited external and internal validity, any generalizations and conclusions must be made with caution.

However, we believe that the political aspect is important to integrate into our model. Furthermore, as mention in section 2, according to Green et al. (2001), there are few empirical studies that integrate the political aspect in investigating hate crime incidence, and specifically when studying its association with economic conditions. We intend to make an initial attempt, while conceding that our approach suffers from significant limitations and can be improved upon in future research. Using Glaeser's (2005) terminology we take the spreading of hateful messages by SD as the supply side, and the popular support for SD, a proxy for the acceptance of their xenophobic message, as the demand side. Thus, a higher vote for SD should be associated with more xenophobia and, all else equal, by extension to higher incidence of xenophobic crime.[6]

In our second regression model we regress log transformed xenophobic hate crimes on the same explanatory variables as before while adding the explanatory variable SD_Vote_{it} to measure support for SD over time in each county. This measure comes from the opinion poll conducted in Sweden biannually by Statistics Sweden in the Party Sympathy Poll. Randomly sampled residents in each county get to answer the question "If there were an election today, which party would you vote for?" This is the most reliable measure we can find, with a large sample of nine thousand respondents. We predict that sympathy for SD should be positively associated with incidence of xenophobic crime, meaning that we expect β_6 to be positive.

[6] An alternative would be to use the number of SD representatives on county councils. This would reveal actual preferences, instead of stated ones. However, this measure would have no variation in the chosen time period, as there is only one election during our broader period of analysis, 2008-2013.

5. Data

In this section we present the data that will be used to test the hypotheses stated in section 3. We first discuss the most appropriate measure for our dependent variable, after which we present a short overview of the data with some descriptive statistics and a short discussion of trends.

Dependent Variable: Measuring Hate Crime Incidence in Sweden

Hate crime is not defined as an offence in the Swedish code; rather, if prejudice or bias is proven to have motivated a crime the severity of the penalty is increased. At the same time, certain forms of hate crimes that would not constitute crimes without hateful motivation are classified as crimes, for example hate speech is defined and classified as a criminal offence in Swedish law (SFS 1962:700*)*. Hate crime in Swedish law is thus a unifying term for a number of crimes that fit the Swedish definition of hate crime (see the discussion in section 3). Consequently, Swedish police does not classify an offence as a hate crime, but have the option of indicating that a crime might be motivated by hatred when writing their preliminary report (BRÅ, 2014). This data is not to be considered exhaustive, and education about what constitutes a hate crime varies in both quality and quantity within Sweden's police departments. Instead it is BRÅ that is tasked with collecting and processing hate crime statistics in Sweden. BRÅ publishes two measures of hate crime statistics, calculated and self-reported hate crime statistics, which are different in how they are compiled; we will explain their differences and our motivation for choosing one of them.

Calculated Hate Crime Statistics

The primary source of hate crime statistics used in this study is published on a yearly basis in a report written by BRÅ about the current state of hate crimes in Sweden (BRÅ, 2014). We call this measure the calculated hate crime statistics. BRÅ compiles the statistics by analyzing the police reports on criminal acts of defined types, based on historical trends as acts that may possibly have hateful motivation. For example, police reports on personal robberies and beatings are analyzed while tax offenses are ignored. The police reports are screened against a collection of words and phrases commonly used in police reports describing a hate crime. Analysts at BRÅ manually examine the crime reports picked up in the screening, in order to decide whether they are in fact a hate crime and if so, what the motivation is for said hate crime, e.g. religion, ethnicity or sexuality. In the decision of whether a suspected hate crime is to be classified as such, for example as racially motivated, they use the test question: "would this crime happen if the victim had the same racial background as the perpetrator?" as a key part of the decision process (See BRÅ, 2014, p.21-22, own translation).

The calculated hate crime statistics are available at the national level and also disaggregated at county-level, which is our chosen level of aggregation. This allows us to perform panel analysis producing more robust results than time series at the national level, given the short time series for which data is available. BRÅ changed the definition of what constitutes a hate crime in 2008, rendering comparisons with earlier years impossible. Therefore we will use all available data from after the change in definition in 2008, that is to say 2008-2013. BRÅ has concluded that comparability over time should not be an issue, apart from the major changes made in 2008 (BRÅ, 2014, p. 23-24).

Since 2012, a minor change in BRÅ's method is that only 50% of the police reports are picked up as a random sample, and the results are then extrapolated to arrive at a total estimate of hate crimes. This change has led to the introduction of confidence intervals in the statistics. Generally, this is not a problem since samples are quite large, but in certain cases it must be considered, especially when analyzing counties with low hate crime incidence. We do not view this as a significant problem since the aggregated hate crime figures from counties are quite large, with the exception of Gotland, where only eight hate crimes were identified in 2013. Therefore, we have chosen to omit the county Gotland from our panel in order to avoid potentially biased results.

A problem that has been confirmed in previous research by BRÅ is that certain minorities, ethnic and religious minorities, are less likely to report crimes to the police. The reason for the lower propensity to report is fear of being not being taken seriously or being badly treated by Swedish law enforcement and other government agencies, stemming from previous experiences with Swedish law enforcement as well as prejudices they might hold (BRÅ, 2008). When minorities are systematically less prone to report crimes, the measure used for hate crime incidence in this study, which is based on crime reports, becomes skewed. Thus, there is a selection bias, which is hard to estimate, but is nonetheless significant. Unfortunately, due to the aggregate nature of the data and our lack of information as to the extent of the bias we cannot correct for it.

Self-reported Hate Crime Statistics

The second potential source of data comes from the yearly National Safety Survey (Nationell Trygghetsundersökning, henceforth NTU); although we do not use this measure, we present it here for completeness. BRÅ conducts a telephone survey with a representative sample of 20 000 Swedish residents who answer questions about their exposure to criminal activity in the past year (BRÅ, 2015). Results are then extrapolated to the whole population; for this reason, estimates are subject to large confidence intervals. There are two major drawbacks of this data source that means we cannot use it as our main source. First, NTU statistics are not disaggregated at lower levels; instead they are reported at the national level only. The data would be useful in a longer time series analysis of Sweden as a whole, however, to date, only a few years are available, making it difficult to perform any robust analysis or make any substantial conclusions. Second, the fact that NTU measures self-reported exposure to crimes, without any further checks means that crimes do not necessarily fit the definition of a hate crime. BRÅ's definition is very specific and it is unlikely that a NTU respondent's experience satisfies the stringent requirements that are applied by analysts at BRÅ. Hence, due to the advantages related to aggregation and consistency of definition we prefer the calculated hate crime statistics.

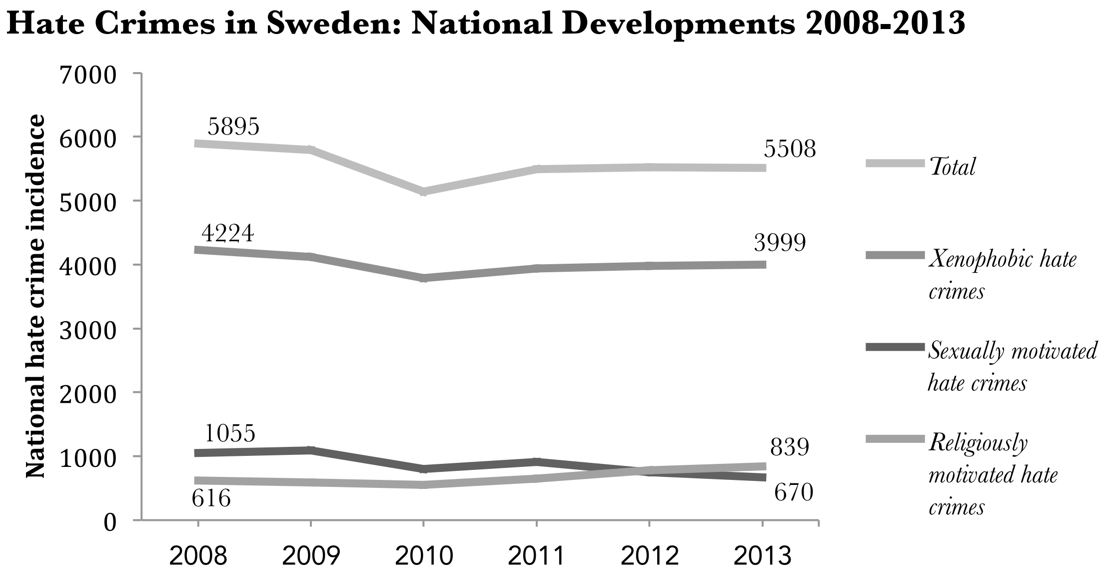

Figure 1: Calculated hate crime incidence, at the national level, by subtype according to hate crime motivation 2008-2013 (BRÅ, 2009; BRÅ 2014).

The figure above shows the national development of the hate crime incidence, in total and by subtype according to motivation, based on the calculated hate crime statistics developed by BRÅ. Total hate crime incidence is quite stable during the time period. A moderate decline up until 2010 is followed by a small uptick with total hate crime incidence increasing steadily ending on a slightly lower level in 2013 than in the beginning of the period in 2008. Xenophobic crimes follow a similar trend, with a lower incidence at the end of the period compared with the beginning. The incidence of hate crimes due to prejudice based on sexual identity fluctuates throughout the period, the incidence is lower at the end of the period of analysis than the beginning. Religiously motivated hate crimes start from a low level but are increasing during the period of analysis, unlike the other subtypes the incidence is higher at the end of the period of analysis than the beginning.

As we have already discussed, there are flaws with our measure of hate crime incidence in Sweden due to underreporting by certain minorities. This means that the empirical results from analyzing this data must be interpreted with caution. We believe that what the data lack in precision is compensated by the higher internal validity of the process through which the data is collected. We have, in total, 120 observations. Ideally there would be more data on hate crime incidence in Sweden, but comparing with previous studies, we note that although close to the lower bound, we have a comparable level of observations; thus, it should be sufficient to test our hypotheses. The fixed effects estimation method does cause our time series analysis to lose much of the variation in the data set, as it only considers the *within* variation of six observations per group while we have much more *between* variation due to the panel having 20 groups. A desirable data set would consist of a much longer time series for each group, but due to BRÅ's changes in 2008 this is impossible for us to use.

While the trend for the incidence of hate crimes is quite stable, the development of economic conditions is anything but. The Swedish recession in 2008 has been one of the deepest recessions in recent times, as argued by Hassler (2010, p.3) "the fall in Swedish GDP between 2008 and 2009 was the largest recorded since 1931. The GDP-gap was more negative 2009 than under the recession in the early 1990's." As can be seen in the table below, the national unemployment rate increased from 3.7 to 6.7 percent during the period of analysis. While an economic downturn of this size can scarcely be seen as positive, it increases the variance in our dataset and compensates for our relatively short time series. Ostensibly, a stable hate crime incidence, as the national figures show, is hard to reconcile with one of the most turbulent periods in recent Swedish economic history. However, not surprisingly, national averages do not reflect the variation in hate crime incidence at the county-level, as can be seen in Appendix I which presents summary statistics for our panel data set. In the table below, national statistics for Sweden are presented to give the reader a sense of the trends of our chosen explanatory variables during the period of analysis.

Table 1: Description of Variables and Summary Statistics on National Level, 2008-2013

Variable	Description	2008	2013
HateCrime	Crimes with an identified hate motive	5895	5508
XenoHateCrime	Crimes with an identified xenophobic hate motive	4224	3999
WageAverage	Average wage income in SEK1000, measured amongst those who have a wage	238	269.3
Unemployment	Unemployment measured in percentage of total workforce	3.7%	6.7%
PopulationYoung	Percentage of population between 15-24 years old	13.18%	12.59%
PoliceOfficers	Police officers per capita	0.002	0.002
PopulationDensity	Population/km^2	22.6	23.7
SD_Vote	Percentage of votes for Swedish Democrats as measured in the Party Sympathy Survey by Statistics Sweden	N/A[7]	9.3%
ForeignPopulation	Percentage of population with at least one parent born outside of Sweden. Used as a control variable	17.96%	20.77%

[7] 6.7% in November, 2010 when SD were included in Statistics Sweden's Party Sympathy Survey for the first time.

6. Results

For clarity, we restate our hypotheses in the form of null- and alternative hypotheses before presenting the results of our regressions in the sections that follow. We test all of our hypotheses at the 5%-level of significance. In our first regression, we test hypotheses 1-5 on hate crime incidence; the results are presented in subsections that follow. They are as follows:

$$(1)\ H_0: \beta_1 = 0 \quad versus \quad H_1: \beta_1 < 0 \quad at \quad \alpha = 5\%$$

$$(2)\ H_0: \beta_2 = 0 \quad versus \quad H_1: \beta_2 > 0 \quad at \quad \alpha = 5\%$$

$$(3)\ H_0: \beta_3 = 0 \quad versus \quad H_1: \beta_3 > 0 \quad at \quad \alpha = 5\%$$

$$(4)\ H_0: \beta_4 = 0 \quad versus \quad H_1: \beta_4 < 0 \quad at \quad \alpha = 5\%$$

$$(5)\ H_0: \beta_5 = 0 \quad versus \quad H_1: \beta_5 > 0 \quad at \quad \alpha = 5\%$$

In our second regression, we test the same hypotheses but add a sixth and perform the test on the incidence of a subtype, namely xenophobic crime. The final hypothesis is:

$$(1)\ H_0: \beta_6 = 0 \quad versus \quad H_1: \beta_6 > 0 \quad at \quad \alpha = 5\%$$

Economic Conditions and Total Hate Crime Incidence

Using model 1, presented in 4.4.3, in a fixed effects regression, with robust standard errors, we test hypotheses 1-5 using the data presented in the previous section.

Table 2: Hate Crime Incidence and Economic Conditions 2008-2013

WageAverage	-0.0134*
	(0.00676)
Unemployment	-1.038
	(2.130)
PopulationYoung	-8.772
	(12.48)
PoliceOfficers	-291.8
	(323.3)
PopulationDensity	0.00129
	(0.00825)
ForeignPopulation	9.641
	(12.96)
Constant	7.367***
	(2.088)
Observations	120
Number of counties	20
R-squared	0.215

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

As expected, *WageAverage* has a negative coefficient. However, the result is only significant at the 10% level (p-value 0.062). Among the remaining variables, *PoliceOffers*, *PopulationDensity* and *ForeignPopulation*, which is a control variable, all have the expected signs, but none are significant at any conventional level. *Unemployment* and *PopulationYoung* have different signs than expected, but both are also not significant. As none of the coefficients are significant at the 5%-level of significance, we cannot reject the null-hypotheses 1-5, when it comes to hate crime incidence. We also conduct robustness checks of our regression results, for multicollinearity and omitted variable bias. However, results do not differ in any meaningful way, see table 9 in appendix IV.

Economic Conditions and Xenophobic Hate Crime Incidence

Turning instead to our second regression, as specified in section 4.4.4, by focusing only on xenophobic hate crimes we are able to test hypothesis 6 as well as hypothesis 1-5 by including a measure of party sympathy for the Sweden Democrats. Party sympathy data for SD is only available from 2010 and onwards. Therefore our second regression is considering a shorter period: 2010-2013. The results from a fixed effects regression with robust standard errors on model 2 are displayed in table 3.

Table 3: Xenophobic Crime Incidence and Economic Conditions, 2010-2013

WageAverage	-0.0143
	(0.00974)
Unemployment	-3.664
	(6.782)
PopulationYoung	-16.27
	(25.35)
PoliceOfficers	-153.6
	(527.5)
PopulationDensity	0.0113*
	(0.00578)
SD_Vote	2.190*
	(1.119)
ForeignPopulation	1.891
	(9.877)
Constant	8.862
	(5.691)
Observations	80
Number of counties	20
R-squared	0.126

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

The variable of interest, *SD_vote*, has the expected sign, but is only significant at the 10% level (p-value: 0.065). Similarly, *PopulationDensity*, which has the expected sign, is only significant at the 10%-level (p-value: 0.066). *WageAverage* has the same sign as in the main regression but it is no longer significant. As in the previous regression, *PoliceOfficers* and *ForeignPercent*, which is a control variable, have expected signs but are not significant. *Unemployment* and *PopulationYoung* do not have the expected sign, but are also not significant. As none of the coefficients are significant at the 5%-level of significance, we cannot reject the null-hypotheses 1-6 for xenophobic crimes. We conduct robustness checks of our regression results, for multicollinearity and omitted variable bias. However, results do not differ in any meaningful way see table 10 in appendix IV.

7. Discussion

Findings

In light of our empirical analysis, the evidence does not support that economic conditions are correlated with hate crime incidence. Furthermore, we do not find a statistically significant correlation between the support for a xenophobic party and hate crime incidence, as hypothesized based on the endogenization of envy inspired by Glaeser's (2005) model that we empirically test for the first time in our study. However, we are only able to partially operationalize the hypothesis, as suitable measures of segregation are not currently available. Although correlation does not imply causation, without correlation it is not possible to have causation. Thus, our results imply that hate crime incidence is not determined by economic conditions. However, there are aspects related to our theoretical framework, method and dataset that might have a confounding effect obscuring a potential correlation.

It is important to highlight the limitations of our findings. The validity of the findings is limited to the region and time period analyzed. It is not appropriate to generalize findings from our study to other countries due to historical, cultural and not in the least legislative differences. Similarly, the findings are applicable only to the time periods analyzed, and the counties included. In general, studies such as ours suffer from low external validity, which is why it is important to perform such studies in varying geographic contexts.

The Signal and the Noise

In this section, we discuss issues that might obscure an economically significant association, especially if it is weak. With any empirical study, but especially with a correlational study, the most difficult task is isolating the signal, the true state of nature, from the noise of confounding effects that are not possible to control for. In our study we believe there are a number of weaknesses that can be sources of noise, disguising the real relationship. These can be broadly collected into three groups, deficiencies of our theoretical framework, our method or the data.

First, our failure to find support for an association might be due to a flawed theoretical framework. Our study is based on a simple model of time allocation from which we derive the hypotheses that we test empirically. If either the model is flawed, due to incorrect assumptions, or we fail to operationalize our hypotheses correctly we would incorrectly conclude that a relationship does not exist. As we discuss previously, there is reason to question the applicability of the rationality assumption that underpins our model. Nonetheless, we believe it to be appropriate, especially on the aggregate level. It might also be the case that the time-allocation model does not describe correctly the mechanism that relates economic conditions to hate crime incidence. Furthermore, an important issue in our case is a potentially flawed operationalization of the hypotheses. We might have chosen incorrect or incompatible variables or failed to include important variables. In attempting to increase the comparability of our study we have used only variables that have been used in previous studies.

Secondly, there are issues regarding research design. Endogeneity can come as a result of simultaneity, omitted variable bias (OVB), or measurement error leading to biased estimates. These biases can in turn lead to coefficients that are potentially biased towards zero, which might explain our failure to find correlation. OVB is a result of an incorrect specification of an econometric model. If the omitted variable were correlated with the dependent variable and with any variable in our set of independent variables then its exclusion would lead to biased estimates, potentially towards zero. OVB could be a result of the aforementioned theoretical weaknesses.

Finally, the quality or quantity of the data might be insufficient to perform robust testing of our hypotheses. Measurement errors, imprecise measurements of our dependent or independent variables, can lead to coefficients biased towards zero. As we mentioned before, reported hate crime statistics are significantly and systematically biased (BRÅ, 2008). This is an important issue, but it is hard to do much about it as a researcher, due to legal prohibitions. If not an issue of quality, there might be an issue of quantity, i.e. a low number of observations in our dataset. To determine if we have enough data we compare with previous studies and find that we have a comparable level of observations, although we are in the lower bound. This might still be an issue, as the number of observations, 120 for our first regression and 80 for our second, is still quite low. This is especially significant as we limit ourselves to the time series variation, due to the chosen fixed effects model of estimation. Ideally, we would like to have more observations, a longer time series and more width to our panel. However, we do not believe that the main problem is the length of our panel, that is the short time series, or breadth, the few number of counties. More likely the issue is the depth of our data.

The Depth of Data: the Level of Aggregation

We are not the first to note that the level of aggregation is important for the results of studies such as ours. Adamczyk et al. (2014, p. 17) do not find a relation between economic conditions and hate crime incidence, they suggest that a possible cause might be the level of aggregation of the data: "it is possible that [the] effect only exists on larger units of analysis like the state level (see for example, Gale et al., 2002; Medoff, 1999)". In fact, of the studies surveyed in section 2, all studies that find a find a relation use state-level or national data; studies that use county or district-level data fail to find any evidence of such a relation. However, there is no discussion in the literature as to why this might be the case, even in Adamczyk et al. (2014) the issue of aggregation is only noted in passing.

There are two possible reasons why the relationship might not be found at the lower level of aggregation, while it is found at the higher levels. On one hand, the benefits of aggregation, as we touched upon shortly in section 4, rely on a large number of observations per unit to minimize the effect of large individual errors. This is especially relevant in the case of crime statistics, as there is large variance at lower levels of analysis, with the number of reported crimes often fluctuating significantly between consecutive years. On the other hand, at lower levels of aggregation data is closer to the individual level. Arguably, it should reduce the risk of falling prey to an ecological fallacy (Robinson, 1950; Freedman, 1999), and should be better at avoiding the problem of averages. This is especially important when considering aggregated demographic data where there might be significant segregation within the units of analysis, in this case counties, along economic, ethnic, racial or religious lines. The former implies that studies that used state-level or national data, that find a relationship between hate crime incidence and economic conditions, should be given more credence than those that use disaggregated data, and do not find any relationship, while the latter implies the converse.

Without further research, it is difficult to come to a conclusion as to which is better, lower or higher levels of aggregation. Ideally, we would test the same econometric specification using data at different levels of aggregation, a multi-level analysis of sorts. Unfortunately, this is not possible in Sweden, where municipality level data is not available publically due to legal restrictions. This is not the case in other countries, for example in the US where data is available at the national, state and county levels. However, there are no multi-level studies, certain studies use county-level data while others use state-level data. Due to differences in statistical method, i.e. choice of estimation model and explanatory variables, it is hard to reconcile the findings. This is an important issue that has seemingly been ignored in the literature.

A Note on Econometric Models

Finally, we note that we have strived to present a transparent and rigorous approach to model specification and estimation based on our theoretical framework. Returning to our critique of Gale et al. (2002), we perform our main regression in random effects (RE) after running a Hausman test that confirmed the efficiency of RE-estimators. As in Gale et al. (2002), we find significant results in an RE specification. In our case, some coefficients, namely *WageAverage* (and the control variable *ForeignPercent*), become significant, see table 6 in appendix II. Similarly, we argue that a cross-section analysis, as in Medoff (1999), can lead to misleading results. In table 7, appendix II, we present the regression results of our second model specification for four consecutive years, 2010-2013. The results show, amongst other things, that significant variables one year are not significant the following years, and vice versa. Therefore, we reiterate the importance of a conservative approach, conducting panel analysis with a fixed effects estimation model, unless there are strong grounds for deviation.

Further Research

We believe that this is a fruitful and worthwhile research field. As to what research should focus on, the weaknesses we discuss above give a clear guidance as to promising avenues for future research. Concretely, this means a call for more basic research, that is a refinement and development of the theoretical framework in economics, improvements in method, mainly in terms of research design, and finally we highlight the importance of testing the same empirical models on different levels of aggregation.

As empirical studies test theories, without them it is not possible to perform empirical studies. Although the trend is promising, with some recent studies in economics on the topic of hate, more research is necessary to determine the micro-foundation of hate and how this might be affected by changes in the macro economy. This understanding would facilitate an accurate operationalization of hypotheses and empirical specification.

We argue that the micro-foundations should be tested in controlled experiments before insights are used to conduct aggregate observational studies. As we discuss in section 4, there are proponents that present tenable ways in which this can be applied in practice (Green & Spry, 2014). With a creative approach, controlled experiments can be used, within ethical limits, to empirically test the micro-foundations of envy. Observational studies, and ideally natural and quasi-experiments, can then be used to understand how individual motivation is affected by changes in the economy.

Finally, the conditionality of results on the level of aggregation highlights the importance of further research on the effect of aggregation. Thus, multi-level studies help solve the puzzle of the coincidence of level of aggregation and statistical significance. Studies should also aim to have a standardized approach so as to facilitate comparability. We cannot stress this enough, the adoption of a transparent and comparable, preferably, standardized approach to the empirical study of hate crime incidence is one of the most important issues for future research.

8. Conclusion

We set out to answer the question: *Is there an association between economic conditions and the incidence of hate crimes?* Based on hypotheses derived from a simple neoclassical economic framework we test whether this is the case for twenty Swedish counties between 2008 and 2013. The evidence does not support the thesis that there exists an association between economic conditions and hate crime incidence. Consequently, the findings are consistent with Green, Glaser and Rich (1998), Green et al. (1998) and Adamcyzk et al. (2014). They are at odds with previous studies that do find correlation (Medoff, 1999; McLaren, 1999; Falk & Zweimüller, 2011; Ryan & Leeson, 2011; Hovland & Sears, 1940). Noting the geographical and methodological limitations, we are reluctant to make generalizations outside the scope of the study. We note potential weaknesses in theory, method and, most likely, the data used in this study that can lead to negative results even if a relationship exists, especially if it is weak.

Previous research on this topic has led to inconclusive results – there is mixed evidence as to the association between macroeconomic variables and hate crime incidence. The two studies within economics that precede ours both find a correlation. We argue that this might be due to flaws in the method of these studies, specifically the choice of econometric approach. We maintain that using panel data, and a fixed effects estimation model, is the most suitable econometric approach for empirically analyzing the association between hate crime incidence and economic conditions. As it is not possible to control for confounding factors through research design, a conservative statistical approach is preferable. We note that all previous studies that find a correlation between hate crime incidence and economic conditions have been conducted at a higher level of aggregation than ours. We might be unable to detect a correlation due to the level of aggregation. Finally, the negative result might also stem from historical, cultural or legislative differences between the US, where a majority of the previous economic studies were based, and Sweden.

We call for further research to improve the theoretical framework, empirical method, with regards to both research design and econometric model. Unfortunately, we note a declining interest in empirical studies of the type we have undertaken. On the other hand, there are recent papers investigating hate theoretically (see Cameron, 2009; Glaeser, 2005). Economists are also active in drafting policy responses as to how to deal with hate crimes (see Gan et al., 2011; Dharmapala & Garoupa, 2004). However, we do not find any empirical studies that test economic theories since Gale et al. (2002). This is significant because empirical studies fill an important function mediating between theoretical understanding, or intuition, and policy formulation.

9. Summary

Using Swedish panel data at the county-level between 2008-2013, this study investigates the association between economic conditions and hate crime incidence. We summarize the contributions of our study to the literature as follows:

1) By combining insights from the existing scholarship in economics, we develop a complete model of hate crime that allows us to describe the mechanism through which economic conditions affect hate crime incidence.

2) We present a transparent, rigorous and easily replicable empirical method to test our hypotheses.

3) The study also contributes to the literature by investigating the posited association in Sweden, a country not previously covered in the literature. The research field depends on such studies to broaden the geographic scope, due to the limited external validity of studies.

4) Finally, we fail to find a correlation between economic conditions and hate crime incidence, which is consistent with some previous studies and theories that predict that no such relation exists, chiefly Green et al. (1998).

We argue that further research is necessary to improve on the theoretical framework, empirical method and data related weaknesses of our study. This is an important research field, not in the least because of its significant implications for policy.

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Appendix I: Descriptive Statistics

Table 4: Summary statistics of variables used in main regressions

Variable	Count	Mean	Std. Dev.	Min	Max
HateCrime[8]	120	3.901709	.2635047	3.332205	4.60517
XenoHateCrime[9]	120	3.580532	.277994	3.033781	4.248495
WageAverage	120	240.1442	18.39977	207.6	315.6
Unemployment	120	.083185	.0199891	.0342911	.1198804
PopulationYoung	120	.1319438	.0070903	.1174572	.1503898
PopulationDensity	120	47.50167	67.54309	2.5	331.4
PoliceOfficers	120	.0018252	.0002457	.0014323	.0027788
SD_Vote	80	0.046820	0.0257304	0	0.11
ForeignPopulation	120	.1523604	.0544655	.0645561	.3014762

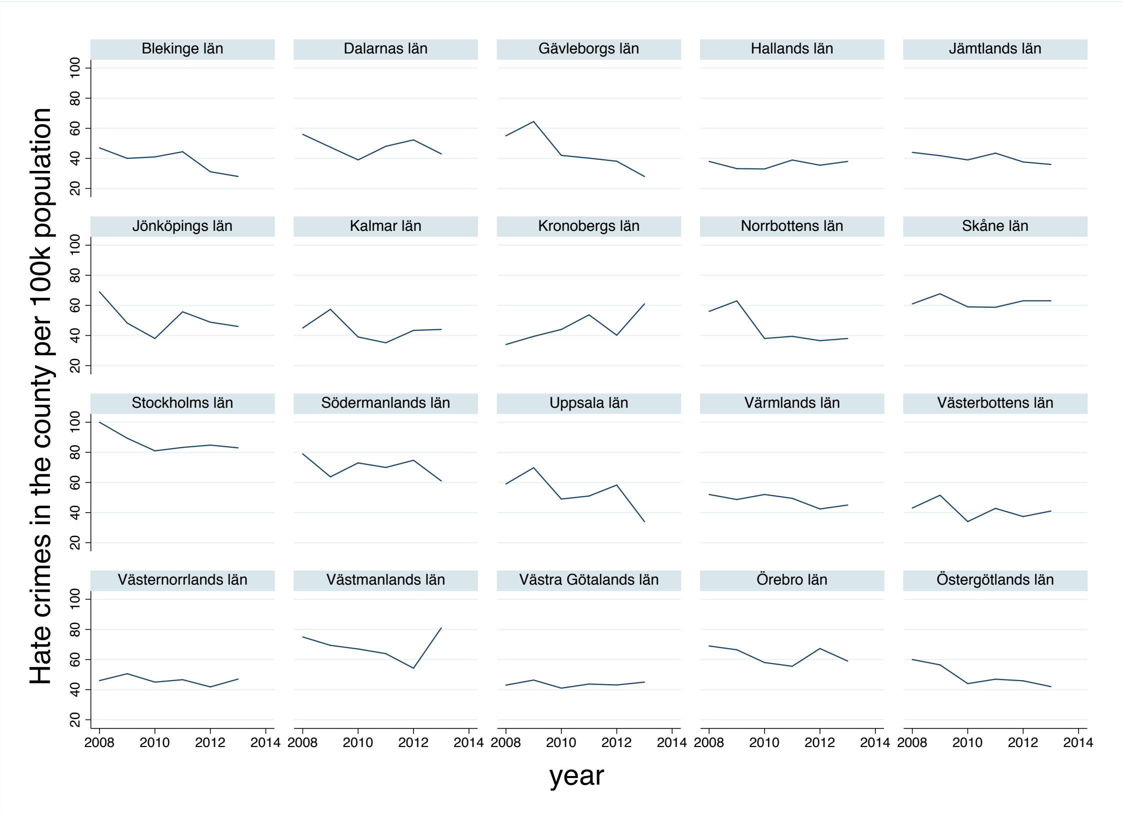

Figure 2: Hate Crime Incidence per 100, 000 residents, per County 2008-2013. (BRÅ, 2009; BRÅ 2014)

[8] Log transformed, hate crime incidence per 100 000 residents.

[9] Log transformed, xenophobic crime incidence per 100 000 residents.

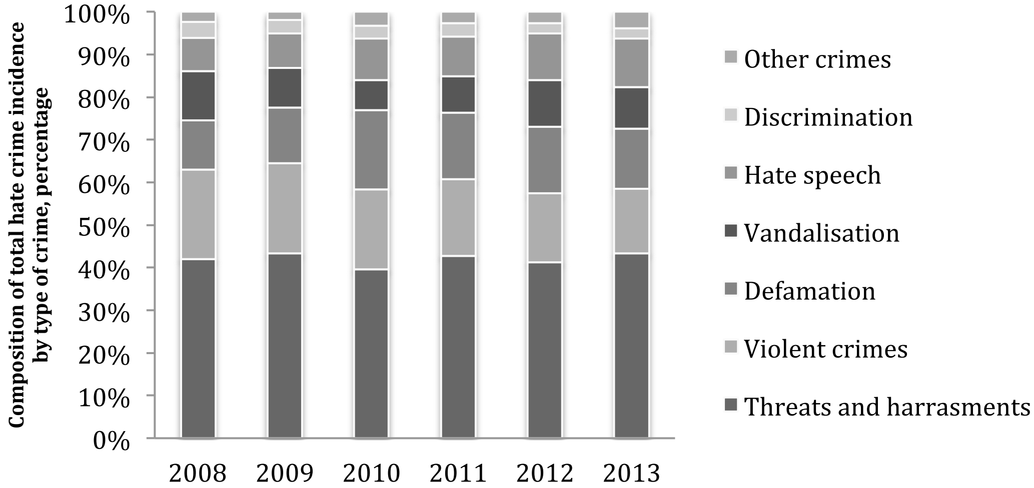

Figure 3: Composition of total hate crime incidence by type of crime committed, national figures, % of all hate crimes/year; 2008-2013 (BRÅ, 2009; BRÅ, 2014).

Table 5: Correlation table of explanatory and dependent variables

	Hate Crime	*Xeno Hate Crime*	*Wage Average*	*Unemploy-ment*	*Population Young*	*Population Density*	*Police Officers*	*SD Vote*	*Foreign Populatio*
Hate Crime	1.000								
Xeno Hate Crime	0.954	1.000							
Wage Average	0.462	0.413	1.000						
Unemployment	-0.066	-0.025	-0.420	1.000					
PopulationYoung	-0.127	-0.149	-0.268	-0.288	1.000				
PopulationDensity	0.596	0.545	0.646	-0.159	-0.232	1.000			
Police Officers	0.589	0.559	0.803	-0.330	-0.268	0.847	1.000		
SD Vote	0.061	0.088	0.180	0.178	-0.258	-0.170	-0.015	1.000	
Foreign Population	0.747	0.712	0.704	-0.222	-0.064	0.667	0.777	0.189	1.000

Appendix II: Auxiliary Regressions

Table 6: Regression Results Hate Crime Incidence and Economic Conditions 2008-2013, Random Effects

WageAverage	-0.00763***
	(0.00152)
Unemployment	-1.392
	(1.370)
PopulationYoung	-4.204
	(4.210)
PoliceOfficers	-22.08
	(203.7)
PopulationDensity	0.00131
	(0.00103)
ForeignPopulation	3.601***
	(1.022)
Constant	5.833***
	(0.744)
Observations	120
Number of county1	20

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Regression Results Xenophobic Hate Crime Incidence, cross sectional regressions, 2010-2013

	2010	**2011**	**2012**	**2013**
WageAverage	0.00548	-0.00504	0.00178	-0.00678
	(0.00580)	(0.00565)	(0.00927)	(0.00944)
Unemployment	7.877**	0.677	-3.769	-2.351
	(2.879)	(3.496)	(5.057)	(4.565)
PopulationYoung	-7.687	-1.161	0.419	-14.01
	(4.949)	(6.217)	(9.355)	(8.104)
PoliceOfficers	-345.9	6.137	192.9	475.2
	(502.5)	(355.8)	(593.8)	(480.2)
PopulationDensity	0.000277	0.000864	0.000508	-0.00125
	(0.00158)	(0.00176)	(0.00227)	(0.00274)
SD_Vote	-5.189**	-2.039	5.547	0.905
	(1.702)	(1.896)	(3.546)	(2.802)
ForeignPopulation	3.892***	3.453***	1.562	5.151**
	(0.752)	(0.983)	(2.098)	(1.798)
Constant	2.782**	4.373***	2.402	5.535*
	(1.201)	(1.430)	(1.954)	(2.668)
Observations	20	20	20	20
R-Squared	0.803	0.691	0.610	0.640

The table shows results from cross sectional regressions per year between 2010-2013 using model specification 2. Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Appendix III: Data sources

Table 8: Data sources for variables

Variables	Sources
Hate Crime	BRÅ (The Swedish National Council for Crime Prevention)
Xenophobic Hate Crime	BRÅ (The Swedish National Council for Crime Prevention)
Average Wages	Statistics Sweden
Unemployment	Arbetsförmedlingen (The Swedish Public Employment Service)
Young Population	Statistics Sweden
Police Officers	Polismyndigheten (The Swedish National Police Board)
Population Density	Statistics Sweden
SD Votes	Statistics Sweden, own calculations
Foreign Population	Statistics Sweden

Hate Crime data/Xenophobic Hate Crime data: BRÅ (2009; 2014) and BRÅ, [“Hate crimes, statistics and publications”]. (in Swedish). http://www.bra.se/bra/brott-och-statistik/statistik/hatbrott.html

Unemployment data: The Swedish Public Employment Service, [”Open unemployment and searching for employment in programs with activity support, percentages of the registered workforce”], years 2008-2014. (in Swedish) http://www.arbetsformedlingen.se/download/18.4dc389314a103f6fdb4475/1421072709427/web_%C3%A5r_andelar_ak_2008-2014.xlsx

Police Officers data: The Swedish National Police Board, [”Employee count 2001-2014”]. (in Swedish) https://polisen.se/Aktuellt/Rapporter-och-publikationer/Statistik/Publicerat---Nationellt/Polisens-personal/Antal-anstallda-2000---2013/

Population data: Statistics Sweden, [”Population, by region, civil status, gender and age”], reference code: BE0101N1 (in Swedish) http://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__BE__BE0101__BE0101A/BefolkningNy/table/tableViewLayout1/?rxid=4bd279cc-9390-43ac-b0fc-b8cf7a413892

Population Density data: Statistics Sweden, [”Population density, population and land area, by region and gender”], reference code: BE0101U1. (in Swedish) http://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__BE__BE0101__BE0101Q/UtlSvBakgTotNK/table/tableViewLayout1/?rxid=40eafa8e-3f74-4314-875b-b5447b868f92

SD Votes data: Statistics Sweden, [”Party sympathy survey”], own calculations. (in Swedish) http://www.scb.se/Statistik/ME/ME0201/2013M11/Partisympati%20i%20valkretsar.pdf

Foreign Background data: Statistics Sweden, [”Number of persons, by Swedish/foreign background and year”], reference code: BE0101AS. (in Swedish)
http://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__BE__BE0101__BE0101Q/UtlSvBakgTotNK/table/tableViewLayout1/?rxid=40eafa8e-3f74-4314-875b-b5447b868f92

Average Wage data: Statistics Sweden, [”Income from employment, by population with value, mean, thousands SEK, by region, income type, age, income class and year.”], reference code: HE0110I2. (in Swedish)
http://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__HE__HE0110__HE0110A/InkAvTjanst/table/tableViewLayout1/?rxid=4bd279cc-9390-43ac-b0fc-b8cf7a413892

Appendix IV: Robustness Check

Table 9: Robustness Check Total Hate Crime Incidence and Economic Conditions, 2008-2013

	REGRESSIONS					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
WageAverage	-0.0126*	-0.0123*	-0.000486	-0.00364	-3.51e-06	-0.0135*
	(0.00729)	(0.00671)	(0.0103)	(0.00973)	(0.00990)	(0.00735)
Unemployment	–	–	-2.689	-0.348	-1.054	-0.835
	–	–	(1.879)	(2.049)	(2.331)	(2.210)
Unemployed with Swedish background	3.199	–	–	–	–	–
	(4.353)	–	–	–	–	–
Not Working	–	2.863	–	–	–	–
	–	(1.818)	–	–	–	–
PopulationYoung	-19.17	-26.30*	–	–	–	-8.669
	(14.91)	(14.24)	–	–	–	(13.05)
15-19 years old	–	–	25.96	–	11.95	–
	–	–	(18.74)	–	(12.68)	–
20-24 years old	–	–	–	-30.54	-24.53	–
	–	–	–	(21.42)	(20.29)	–
PoliceOfficers	-457.1	-278.3	-205.8	-52.23	-49.83	-290.2
	(264.8)	(325.8)	(365.6)	(379.1)	(379.9)	(322.6)
PopulationDensity	0.00130	0.00463	-0.00820	-0.00354	-0.00650	0.00148
	(0.00738)	(0.00831)	(0.00765)	(0.00610)	(0.00730)	(0.00721)
ForeignPopulation	6.164	3.905	14.55	9.199	11.10	10.02
	(11.86)	(11.40)	(11.77)	(11.38)	(12.20)	(15.69)
*ForeignPopulation*Unemployment*	–	–	–	–	–	-1.751
	–	–	–	–	–	(18.25)
Constant	9.096***	9.226***	1.108	5.716***	3.570	7.317***
	(1.988)	(1.593)	(3.668)	(0.654)	(2.434)	(2.356)
Observations	120	120	120	120	120	120
Number of county1	20	20	20	20	20	20
R-squared	0.219	0.243	0.235	0.248	0.251	0.215

Regression (1) uses unemployment statistics for residents with Swedish background only (defined as both parents coming from Sweden) instead of overall unemployment.
Regression (2) uses the percentage of the population between 16-64 that is not working instead of overall unemployment.
Regression (3) through (5) use disaggregated percentages of PopulationYoung in all possible combinations.
Regression (6) uses the integrated variable generated by multiplying ForeignPopulation and Unemployment
Robust Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 10: Robustness Check Xenophobic Crime Incidence and Economic Conditions, 2010-2013

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
WageAverage	0.00307	-0.0307*	-0.0228	-0.0108	-0.0237	-0.0164*
	(0.0143)	(0.0160)	(0.0188)	(0.00921)	(0.0188)	(0.00921)
Unemployment	–	–	-2.447	-2.243	-2.941	8.656
	–	–	(6.453)	(6.443)	(6.605)	(16.31)
Unemployed with Swedish background	11.19	–	–	–	–	–
	(9.190)	–	–	–	–	–
Not Working	–	-10.88	–	–	–	–
	–	(6.724)	–	–	–	–
PopulationYoung	-0.851	-27.08	–	–	–	-17.81
	(27.03)	(27.70)	–	–	–	(23.50)
15-19 years old	–	–	-29.12	–	-34.00	–
	–	–	(36.32)	–	(39.35)	–
20-24 years old	–	–	–	6.751	-7.919	–
	–	–	–	(22.37)	(24.99)	–
PoliceOfficers	93.86	-313.4	-192.6	-5.891	-239.2	-53.55
	(481.3)	(558.9)	(632.2)	(494.1)	(601.1)	(625.8)
PopulationDensity	0.00203	0.0121*	0.0164*	0.00963	0.0168*	0.0115**
	(0.00598)	(0.00611)	(0.00846)	(0.00587)	(0.00869)	(0.00521)
SD_Vote	0.0213*	0.0251**	0.0196	0.0215*	0.0198*	0.0231*
	(0.0121)	(0.0115)	(0.0114)	(0.0109)	(0.0112)	(0.0111)
ForeignPopulation	0.0578	6.644	2.192	4.374	1.380	14.96
	(7.553)	(10.51)	(9.757)	(9.951)	(9.796)	(11.36)
*ForeignPopulation*Unemployment*	–	–	–	–	–	-102.4
	–	–	–	–	–	(99.62)
Constant	1.834	16.47*	10.29	4.678**	11.60	7.641
	(7.314)	(8.306)	(7.377)	(2.023)	(7.903)	(5.923)
Observations	80	80	80	80	80	80
Number of county1	20	20	20	20	20	20
R-squared	0.149	0.158	0.136	0.121	0.137	0.146

Regression (1) uses unemployment statistics for residents with Swedish background only (defined as both parents coming from Sweden) instead of overall unemployment.
Regression (2) uses the percentage of the population between 16-64 that is not working instead of overall unemployment.
Regression (3) through (5) use disaggregated percentages of PopulationYoung in all possible combinations.
Regression (6) uses the integrated variable generated by multiplying ForeignPopulation and Unemployment
Robust Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1