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Conformism, Social Segregation and Cultural Assimilation

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Abstract
I develop and calibrate a model for the joint determination of cultural assimilation and social segregation of a minority. Culture evolves as a consequence of a disutility from non-conformism in social matchings, while social networks form endogenously as a result of exclusion of individuals with different beliefs and norms of behavior. The model delivers idiosyncratic assimilation patterns and the persistence of some cultural traits. I propose two measures of cultural assimilation, one for spatial comparisons and a second to assess assimilation over time. The model implies that cultural assimilation is weaker in pluralistic and denser societies, and it is not influenced by the minority share. Social segregation increases with social density and with the minority share, and it is higher for culturally more distant minorities. I compute both assimilation measures for a cross-section of European countries and show that the model is able to match the empirical evidence on assimilation.

Keywords: Culture, Distance, Evolution.

JEL Classification: J15, Z10.

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1 Introduction

Cultural assimilation fosters social trusts and helps solving coordination problems, thereby easing economic interactions and the transmission of human capital. Cultural diversity, on the other hand, can impair public good provisions (Alesina et al. 1999; Alesina and LaFerrara 2005), especially if related to ethnic heterogeneity, and trigger conflicts (Caselli and Coleman 2012; Esteban and Ray 2011), although it can also foster the adoption of new technologies (Ashraf and Galor 2013). Cultural assimilation is also a key determinant of the economic and political consequences of immigration. If immigrants hold on to their values and beliefs, and if they strive to transmit them to their children, a culture clash might arise, and the fear that a new paradigm might replace the natives' heritage can foster anti-immigrants feelings (Dustman and Preston 2001; Facchini and Mayda 2009) that can also translate in greater support for nationalist parties (Russo 2021) or for anti-immigration policies (Tabellini 2020). Understanding the determinants of cultural evolution and assimilation is therefore crucial.

In this paper I propose a dynamic model of cultural evolution of a minority based on conformism (Bernheim 1994). The key feature of the model is a disutility from non-comformism in case of social matchings between agents with different beliefs, opinions or norms of behavior, to which the agents react both changing opinions and restricting social interactions. The costs of changing beliefs are idiosyncratic and belief-specific, so the model implies heterogeneous assimilation patterns: not all minority agents assimilate, and some cultural traits tend to be persistent. The restriction of social interactions with agents who hold different opinions, in turn, results in the endogenous formation of social networks among culturally homogeneous individuals: social segregation arises endogenously.

I consider two separate concepts of cultural assimilation. The first, which I call *σ-assimilation*, is static and relative, and it is useful to compare different countries or different areas within the country. It is based on the average cultural distance between the minority and the majority: there is more σ-assimilation in country/area A, as compared to B, if the average cultural distance between the minority and the majority is smaller in A. The second concept, which I call *Δ-assimilation*, is also based on the average cultural distance between the majority and the minority, but it is dynamic, and it useful to track the process of cultural evolution through time within a single country: there is Δ-assimilation if minority becomes culturally closer to the majority over time or, alternatively, if the average cultural distance between the minority and the majority decreases.

To quantify assimilation according to both concepts, it is necessary to start from a measure of cultural distance. Since I model binary beliefs (agreement/disagreement) over a fixed set of issues, the most natural choice is the Hamming distance, which, for two vectors of the same length, is equal to the relative number of positions with different entries (beliefs). For each agent in the minority, I compute the average Hamming distances between her vector of beliefs and the vectors of beliefs of all majority agents, to have an individual measure of σ-assimilation. Averaging at the country level, over all minority agents, I also obtain an aggregate measure of σ-assimilation that I use for cross-country analysis. As for Δ-assimilation, I simply measure it with the percentage change of cultural distance over a defined time interval, both at the individual and at the aggregate level.

I calibrate the model to a cross-section of European countries, using information from the Eurostat census and from the European Social Survey (ESS) to produce a simulated cross-section of σ-assimilation and Δ-assimilation. I show that both cross-sections are positively correlated with the empirical cross-sections of cultural assimilation computed starting from all relevant ESS questions.

The model implies that culturally more distant minorities assimilate more over time (more Δ-assimilation), although there is less overall cultural assimilation (less σ-assimilation) in countries whose minorities were initially more distant. It also implies that cultural assimilation is weaker in countries (or areas) with high social density, and in case of pluralistic, culturally heterogeneous, majorities. The minority share, instead, does not influence cultural assimilation. Social segregation increases with social density, with the minority share, and it is more pronounced for minorities with high initial cultural distance from the majority. I show that this results are robust across different parametrizations and in case of model extensions to more realistic features.

From a policy perspective, if the minority is identified with the immigrants, then the model implies two very relevant implications: immigration restrictions do not foster assimilation, and encourage immigrants settlements away from big and densely populated cities improves assimilation.

The rest of the paper is organized as follows: section 2 briefly reviews the related literature. Section 3 describes the model. Section 4 illustrates the calibration. Section 5 summarizes the simulation results. Section 6 illustrates the comparative statics and results of a regression on simulated data. Section 7 discusses several model extensions. Section 8 concludes.

2 Related Literature

This paper is related to the economic, sociological and anthropological literature on cultural evolution. I contribute to this literature: proposing a calibrated model of cultural evolution with endogenous social networks that is able to replicate the cross-sectional evidence for Europe and that delivers heterogeneous cultural assimilation patterns; highlighting that cultural assimilation, for a minority, is also the result of social contacts with agents within the minority that assimilated earlier; proposing two distinct measures of cultural assimilation, for spatial comparisons and to track cultural evolution over time, that can be computed starting from survey data.

In the seminal paper by Lazear (1999), cultural assimiliation, for a minority, is valuable because a common culture facilitates economic interactions (more trust, more trade opportunities etc.). My model is different because assimilation from conformism comes also from social interactions within the minority. Similarly to Lazear (1999), my model implies less assimilation in case of high social density and in case of culturally heterogeneous majorities but, differently from his contribution, I find no effect of the minority share on assimilation. Konya (2005) considers a dynamic extension of the model in Lazear, showing that full assimilation is possible, and efficient, only if the minority share is small. In my model based on conformism, there is assimilation also for big minorities.

Bisin and Verdier (2000 and 2001) propose a theory of cultural transmission based on the interaction between the vertical transmission of values within the family and the horizontal transmission outside the family. Since the vertical transmission is easier in homogamous families, there is an incentive to marry within the same social group, resulting in the persistence of cultural traits. In a related contribution, Giavazzi et al. (2019) merge the identity choice model of Lazear (1999) and Konya (2005) with the vertical transmission model of Bisin and Verdier (2000 and 2001), and use it to study the speed of cultural evolution in the US. I abstract from an explicit modelling of the vertical transmission within the family, but I show that all of my results are robust if a fixed share of the agents in the social networks cannot be excluded, which I interpret as a reduced form model of families.

Darity et al. (2006) and Bazzi et al. (2019) build evolutionary models of identity formation based on random matchings, showing that polarization hampers the emergence of a common culture. Kuran and Sandholm (2008) propose instead an evolutionary model where cultural evolution depends on parents' socialization, coordination gains and self-persuasion, all of which lead to culture hybridization. My model of assimilation based on conformism in random matchings shares many features with those approaches, and it extends the analysis to the endogenous formation of social networks.

Grosjean (2011) proposes a gravity model of cultural integration, showing that cultural change can be slow. My model of conformism implies instead a relatively fast assimilation, in line with the evidence in Manning and Roy (2010) and Cameron et al. (2015). Abramitzky et al. (2020) show that assimilation, in the US, today is not faster or slower today as compared to the past, where assimilation is measured by the share of non-foreign names among second generation immigrants. I propose different dynamic measure of assimilation based on survey answers, that accounts for differences in beliefs. In a related contribution, Fouka et al. (2021) show, using historical data from the US, that the inflow of a relatively more distant minority can ease the assimilation and reduce segregation of the less-distant minorities. My analysis is more stylized, being focused on a single, culturally homogeneous, minority.

Several empirical studies highlight the persistence of culture among minorities and immigrants. Among others, Giuliano (2007) shows that the living arrangements of second generation European immigrants to the US are similar to those in their home country, while Fernandez and Fogli (2005) find similar results for fertility and labor market participation choices of second generation immigrant women. Guiso, Sapienza and Zingales (2006) and Algan and Cahuc (2010) show that trust, for US immigrants, depends on their country of origin. Bisin et al. (2010) look instead at the determinants of integration, finding that muslim immigrants integrate less. My model is consistent with this persistence of cultural traits, although only for a subset of them.

3 The Model

In subsection 3.1 I explain the model in detail, while in subsection 3.2 I discuss the two concepts, and measures, of cultural assimilation.

3.1 Set-Up

A fictional country is inhabited by N citizens[1] indexed by $i \in \{1, 2, \dots N\}$, with a fixed fraction $\lambda < 0.5$ of them that belongs to a minority (identifier MN) and a fixed fraction $1 - \lambda$ to a majority (identifier MJ). All citizens match socially, each period, with a total of $z = \lfloor \gamma N \rfloor$ individuals to discuss and exchange ideas, where γ is the social density of the country. The social density depends on a variety of factors, including the degree of urbanization, the amount of social capital, the average size of schools and firms and the use of social networks. Although the total number of individuals met each period is fixed, their identity changes. I denote with J_{it} the set of all individual identifiers of the agents that match with agent i at time t, with cardinality z: $|J_{it}| = z \, \forall \, i, t$.

There is a total of M issues to potentially discuss in a social matchings, and the opinions/beliefs are binary. I denote with $q_{it}^m \in \{0, 1\}$ the belief of agent i at time t over the issue $m \in \{1, 2, \dots M\}$, with the convention that $q_{it}^m = 1$ in case of "agreement" and $q_{it}^m = 0$ in case of "disagreement". For instance, an agent might agree that becoming rich is a primary goal in life or that praying everyday is important. I assume that the issues differ in their salience, which I define as the probability θ^m to discuss them in a social matching. I denote with $Q_{it} = \{q_{it}^1, q_{it}^2, \dots, q_{it}^M\}$ the full set of beliefs over all M issues for agent i.

The agents are conformists, in the sense that they derive a disutility each time they discuss an issue with an agent who has a different belief[2]. I normalize the disutility from each

[1] I do not have population growth in the model. This is equivalent to assuming that the majority and the minority grow at the same rate. If the growth rates are different, the minority share changes, and so will the model outcomes (see the comparative statics in section 6).

[2] This model is equivalent to an alternative specification with a positive utility in case of social matchings with similar beliefs, and with changes of beliefs in case of small, per-period utility. For instance, since trade is easier in case of similar cultures, as in Lazear (1999), assimilating is a way to increase profits.

discussion and belief to 1 wlg. In a given period t, the disutility of agent i over the issue m is:

$$h_{it}^{m} = \frac{\sum_{j \in J_{it}} \Theta_{jt}^{m} \, \mathbb{1}_{[q_{it}^{m} \neq q_{jt}^{m}]}}{\sum_{j \in J_{it}} \Theta_{jt}^{m}} \tag{1}$$

where the Θ_{jt}^{m} are z independent draws from a Bernoulli distribution with probability θ^{m}. The total accumulated disutility H_{t}^{m}, for each agent i and issue m, is instead a weighted average of the actual disutility h_{it}^{m} and of the discounted past disutilities H_{it-1}^{m}:

$$H_{it}^{m} = \phi_i (1-\mu) H_{it-1}^{m} + (1-\phi_i) h_{it}^{m} \tag{2}$$

where μ is the discount rate of past disutility, and where ϕ_i and $1-\phi_i$ are the idiosyncratic weights of, respectively, past and current disutilities.

The agents react to the accumulation of disutility in two ways: changing beliefs and avoiding further social contacts with individuals who hold different views. I assume that the agents have an idiosyncratic cost for changing beliefs, which I model as an individual, and issue-specific, total disutility threshold $\hat{H}_{i}^{m}$, above which the agents switch[3] ($H_{it}^{m} > \hat{H}_{i}^{m}$). Thus the model features a tipping point. Agents with high thresholds typically hold on to their beliefs even in case of frequent disagreements; they are closely tied to their heritage, perhaps because of their upbringing. Viceversa, agents with low threshold tend to be more conformist. Since the beliefs are binary, a switch simply entails changing opinion from disagreement to agreement and viceversa. I assume that only the agents from the minority can change beliefs, so this is a model of cultural assimilation rather than a model of cultural integration. I chose this framework to have a constant benchmark to evaluate the evolution of cultural distance between the minority and the majority as a function of the primitives. Importantly, assimilation of the minority, in the model, is not only the result of interactions with the majority, but also of the interaction with other members of the minority. Thus the minority agents with more frequent contacts with majority agents assimilate more quickly, and then later foster assimilation for the other minority agents.

The second reaction to disagreement is a process of social exclusion: if a matching with a given agent results in a high disutility, the all future interactions with the same agent

[3]There is no strategic optimal choice of beliefs, but only a slow adjustment driven by conformism, but this framework is equivalent to an optimization with a constraint on the maximum possible per-period adjustment.

are avoided. Thus the identity of the agents in social matchings is the results of previous interactions or, alternatively, there is an endogenous social network formation mechanism. The total disutility from a matching between agents i and j, at time t, is equal to:

$$\hat{f}_{it}^{j} = \sum_{m=1}^{M} \hat{\Theta}_t^m |q_{it}^m - q_{jt}^m| \qquad j \in J_{it} \tag{3}$$

where $\hat{\Theta}_t^m$ are random draws from a Bernoulli distribution with parameter θ^m. When this disutility is above a threshold, the agent j is excluded ("flagged") from the social network, meaning that there will never be new mathcings with her from period $t+1$ onward. It is therefore possible to define a binary vector of "flags", for each agent i and time t, $F_{it} = \{f_{it}^j\}_{j \neq i}$, whose $N-1$ elements are equal to 1 if the total disutility $\hat{f}_{it}^j$ from a matching between i and j were above a pre-specified threshold ζ_i in a previous interaction before time t:

$$f_{it}^{j} = \mathbb{1}_{[\hat{f}_{i\bar{t}}^{j} \geq \zeta_i]} \qquad \text{for some} \quad \bar{t} < t \tag{4}$$

For consistency, I assume that $f_{it}^j = f_{jt}^i \quad \forall\, i, j$ (undirected links on the social network) at any point in time: if an agent i avoids any social contact with j, than there should be no social matching between i and j. I assume that the identity of the agents in social matchings is chosen randomly, given the social density γ, but only among the non-excluded (non-flagged) individuals.

Social networks emerge, in the model, as a result of similarity of beliefs (or non-dissimilarity). Differently from beliefs changes, I assume that this process of social exclusion is at work both for minority and majority agents. One possible outcome of this selection algorithm of social matchings is the exclusion of all other individuals from social matchings, i.e. $f_{it}^j = 0\, \forall\, j$ at some point in time (zero degree in the terminology of the social networks literature-see Jackson 2010). I define this condition as social isolation, and I use this information to calibrate the model. In this baseline model with endogenous network formation, I abstract from families. In section 7.2, I discuss a model extension where a fixed subset of agents cannot be excluded from a social network, which is a reduced-form modeling for families.

In this simple model with only a disutility from non-conformism, welfare maximization entails full assimilation of the minority. Thus all policies that induce cultural assimilation are welfare improving. This ignores the costs of changing beliefs, which I do not model explicitly, and the individual and social costs of segregation, both of which might downplay the gains from assimilation.

3.2 Measuring Cultural Assimilation

There are two possible ways to formally define cultural assimilation in this model. A first possibility entails measuring the difference between the beliefs q_{it}^m of the minority and the majority at a given point in time, and defining assimilation as a small distance. This is useful to compare different countries, or, at a lower geographical level, different subareas. I define this concept of assimilation as σ-*assimilation*. A second possibility entails instead tracking the evolution of the cultural distance between the minority and the majority over time, defining assimilation as a decreasing distance. I define this concept of assimilation as Δ-*assimilation*. In both cases, it is necessary to measure cultural distance.

The problem, then, is how to measure cultural distance. Since I have individual beliefs, I can construct a measure of cultural distance at the individual level for each minority agent. Given that the beliefs are binary, the easiest way to measure cultural distance is using the Hamming distance, equal to the relative number of different elements in the vectors of beliefs. I compute the cultural distance between each minority agent i and the majority, in each period t, as the average Hamming distance between the vector of beliefs of i, Q_{it}^m and all other vectors of beliefs in the majority Q_{jt}^m, $j \in MJ$. The country-level measure of cultural distance between the majority is a simple average of these distances over all minority agents in country k:

$$S_t^k = \frac{1}{\lambda N} \frac{1}{(1-\lambda)N} \sum_{i \in MN} \sum_{j \in MJ} \frac{1}{M} ||Q_{it}^k - Q_{jt}^k||_1 \tag{5}$$

where $||Q_{it}^k - Q_{jt}^k||_1$ is the L^1 distance (or taxicab metric) between the vectors Q_{it}^k and Q_{jt}^k, equal, for binary vectors, to the number of different elements $\sum_m |q_{it}^m - q_{jt}^m|$, $j \in MJ \quad \forall i$.

The value of S_t^k is an aggregate measure of σ-*assimilation*: there is more σ *assimilation* at time t in a given area or country A, as compared to another area or country B, if $S_t^A < S_t^B$, meaning that the minority is, on average, culturally closer to the majority in country A. The

Hamming distance is not the only possible measure of distance between binary vectors. In section 7.5, I discuss the robustness of the results to alternative measures of cultural distance.

To asses the extent of Δ-*assimilation*, I compute instead the percentage difference in cultural distances between two points in time within the same country or area. A negative difference means that the minority became culturally closer to the majority in the specified period, or Δ-*assimilated*. The measure of Δ-assimlation from period t to period $t+\Delta$, in country k, is equal to:

$$I_{\Delta}^{k} = \left[\frac{S_{t+\Delta}^{k} - S_{t}^{k}}{S_{t}^{k}}\right] \mathbb{1}_{[S_{t}^{k} \geq S_{t+\Delta}^{k}]} \tag{6}$$

with lower values corresponding to more Δ-assimilation.

4 Calibration

I calibrate the model to a cross-section of European countries, selecting a sample of 27 countries [4] based on the joint availability of the European Social Survey data and of the EUROSTAT 2011 Census data.

I simulate countries composed by a $N = 1000$ individuals for $T = 100$ periods. I therefore abstract from population differences in the cross section. I consider three alternative definitions of minority, composed, respectively, by immigrants, second-generation immigrants or by ethno-linguistic minorities. In all three cases, I set λ according to the (first-generation) immigrants share from the Census, in the absence of more detailed census data on second generation immigrants and minorities. Since λ does not significantly affect assimilation, this simplification will not induce a huge bias in the final results.

I consider a total of $M = 50$ issues to potentially discuss, with salience equal to $0.02 \cdot m$: the issue $m = 1$ is discussed only in 2% of the social matchings, while the issue $m = M$, with salience equal to one, is always discussed. In this baseline simulation, I assume that the minority agents do not discount past disutilities (full memory) setting $\mu = 0$, but I check the robustness to positive discounting in section 7.1. In the absence of more detailed information,

[4] Austria, Belgium, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland and the UK.

I draw the weights to past disutilities ϕ_i randomly from a uniform distribution between 0 and 1. To avoid confounding effects in the interpretation of the results, I draw the individual weights independently at each simulation round (ie. the weight is ϕ_{it}). Without this additional randomness, there can be minority agents who assimilate less simply because of a randomly drawn small weight to past disutilities.

I draw the initial beliefs of the minority from a Bernoulli distribution with parameter α and the initial beliefs of the other agents from a Bernoulli distribution with parameter β. To set $0 \leq \beta \leq 0.5$, I use the variance, among the majority, of the answers to a subset[5] of European Social Survey (ESS) questions. I consider the 5^{th} and 6^{th} wave held, respectively, in 2010 and 2012 because they are closer to the census year. I normalize these variances so that their maximum observed value is 0.25 (maximum variance of a Bernoulli distribution), the I set them equal to $\beta(1-\beta)$ and I solve for β taking the lower positive root ("agreement" and "disagreement", for beliefs, are just conventional labels). The variability of beliefs among the majority can be interpreted as its degree of cultural pluralism or, assuming a positive correlation between ethnicity and culture (Desmet et al 2017), as the degree of ethnic diversity or fractionalization (Alesina et al. 2003).

The difference between α and β is the model equivalent of the initial cultural distance between the majority and the minority. I calibrate it using genetic distance (Cavalli-Sforza et al. 1994; Spolaore and Wacziarg 2009), following the evidence in Desmet et al. (2011), Spolaore and Wacziarg (2015) and Desmet et al. (2017). For each country, I compute the weighted average genetic distance using the immigrants shares by nationality from the 2011 EUROSTAT census as weights. I then rescale the distances so that the maximum observed value is equal to 0.5, which is the maximum possible difference between α and β in the model ("agreement" and "disagreement" are just conventional labels). I use this distance, given the country value of β, to set α. In this benchmark specification, I assume that the majority is culturally homogeneous but, in section 7.3, I extend the model to consider a majority composed of two heterogeneous groups.

To set the thresholds $\hat{H}_i^m$, I look at answers to the ESS question (5^{th} and 6^{th} wave) on the

[5] I use all questions that ask about norms of behavior, values and beliefs, excluding the question that ask about demographics, personal information, subjective assessments (adequacy of the wage etc.) and personal experiences (victim of robberies etc.). The complete list of questions is in the appendix.

importance "[...] to follow traditions and customs". I normalize the answers range between zero and one (equally spaced) and fit[6] a Beta distribution (the most flexible on a bounded support) to the empirical distribution of answers in each country. Then I take a random draw from the fitted distribution, with country-specific parameters a and b, for each $i \in MN$. Finally I draw m issue-specific thresholds $\hat{H}_i^m$ from a Uniform distribution so that they are on average (by individual) equal to the draw from the Beta. In case $H_i^{a,b} <= 0.5$, I draw them from $U[0; 2H_i^{a,b}]$; in case of $H_i^{a,b} > 0.5$, from $U[2H_i^{a,b} - 1; 1]$.

To set the country-level social density γ, which determines the number of matchings, I look at two sources of information: the population density from the EUROSTAT 2011 census and the answer to the ESS question that asks about the frequency of social interactions. I normalize both measures between zero and one and then compute a composite index equal to the average of the two. I then arbitrarily normalize the maximum value of the computed index to 5%, to have a reasonable (i.e. not too big) number of social contacts, and I set γ equal to this re-scaled index. The average value of γ (over countries) is equal to 2.93%, meaning that agents meet, roughly 3% of the population, on average, each period. This is indeed a quite high value, but, in my rather small simulation, it is difficult to generate meaningful integration patterns with small social densities. In section 7.1 I simulate the model with two alternative upper bounds, 2.5% and 10%, and assuming heterogeneity over γ to model idiosyncratic variation in social activities.

I assume that the threshold disutility from non-conformism ζ_i above which there is the exclusion from social contacts is different for agents within or outside the social group: ζ^{in} for members of the same group (minority agents to exclude minority agents and majority agents to exclude majority agents) and ζ^{out} for members of the other group (minority agents to exclude majority agents and majority agents to exclude minority agents). For simplicity, I abstract from Idiosyncratic variability in the thresholds, although an assuming uniformly distributed thresholds with calibrated upper bounds of the distributions yields essentially the same results. I exploit again information from the ESS for calibration, looking at the question

[6]To fit the distribution, I implement a guess and verify procedure on a discrete grid of values for the two distribution parameters, simulating artificial data for each grid point, computing the distance between the simulated and the empirical value and then selecting the grid point that minimizes the distance. I also tried an alternative approach, equating the theoretical mean and variance of the Beta equal to their empirical values and then solving the non-linear system of two equations in two unknowns (with a unique solution), obtaining similar results.

that asks how often the respondent "[...] Takes part in social activities as compared to others of the same age". I consider, in particular, the share of minority respondents that answers: "Much less than most", since this is the empirical counterpart of social isolation in the model[7]. For each country, I set ζ^{in} and ζ^{out} so that, in the model, the fraction of minority agents with few social contacts at the end of the simulation:

$$SI_T = \frac{1}{\lambda N}\sum_{i=1}^{\lambda N} \mathbb{1}_{\left[\frac{1}{N-1}\sum_{j\neq i} f_{iT}^{j} \leq K\right]} \tag{7}$$

matches the empirical share of relatively social inactive survey respondents among the minority[8]. Setting $K = 0$ results in a very small percentage of isolated minority agents in the simulation. To fit the data, I set $K = 0.05$, but, for robustness (see section 7.1), I also simulated the model assuming $K = 0.1$, $K = 0.01$ and taking the percentage of minority agents with a number of potential social contact below 1.5 standard deviations[9] from the mean of the simulated distribution of potential social contacts (over minority agents).

5 Simulation Results

In subsection 5.1 I test the simulated model ability to predict the observed empirical evidence on assimilation and segregation for a cross-section of European Countries. In subsection 5.2 I discuss instead the model dynamics, both for cultural assimilation and segregation, and the characteristics of the endogenously formed social networks.

5.1 Testing the Calibrated Model

To test the model, I feed in the model the observed cross-section of the parameters described in section 4, and compare the resulting values of σ-assimilation and Δ-assimilation to their

[7] The information in this question cannot be used to gauge the extent of social segregation in the country because it only asks the respondent a comparison with other individuals in the country, without providing information about the benchmark.

[8] calibrating the two parameters ζ^{in} and ζ^{out} to match both social isolation within the majority and the minority is more difficult for the model, and the calibration results are inaccurate (too many combination of parameters deliver similar fits). Similarly, assuming four different thresholds ζ (minority to flag minority different from majority to flag majority etc.) yields too many degrees of freedom.

[9] The percentage of agents below 2 standard deviation was too small to match the data, while the percentage below one standard deviation too big.

empirical counterparts. The full cross section of parameters used for the simulation is in appendix. To smooth out computational noise, I simulate 50 cross-sections and then take medians over simulation runs. The results are summarized in table 2.

First, I evaluate the model performance with respect to σ-assimilation. To this end, I compute an empirical measure of cultural distance using the 9^{th} ESS wave administered in 2018. Since I look at the correlation between the model outcomes and the empirical measures after 7 years, each period in the model is equivalent to slightly less than 1 month. Starting from the ESS, I define as immigrants those individuals who were not born in the country, as SGI those born in the country but with either a father or a mother (or both) born outside the countries, and as minorities those who answeres "yes" to the question: "[...] Do you belong to a ethnic or religious minority." For each definition of minority, I adjust the calibrated parameters based on the ESS (see section 4) so that they match the answers of the minority under analysis.

I select, from the survey, all questions that ask about religiosity, trust, social capital, coercion, honesty, individualism, motivation, sexism, racism, politics, economics and the approach towards science and the environment, excluding only the questions that ask about personal attributes (demographics etc.) or experiences (victim of violence etc.). The full set of questions is available in the appendix[10]. Starting from these questions, I perform the same computations in equation 12. Not all survey questions have binary answers, as in the simulation. For those with more than 4 alternative answers, I restrict the ranges[11] to avoid inflating the Hamming distance measures.

A further problem with the empirical implementation of equation 12 with survey data is that the number of questions answered by each pair of agents (minority-majority) is different, with the consequence that the resulting cultural distance measures are not comparable. To correct for the potentially different number of answered questions, I assume that there is disagreement, over the non-answered questions, equal to the average, country-level, disagreement. Denoting with A_{it}^k the vector of answers to the ESS of the minority agent i, and with

[10]The questions that I use to compute cultural distance are partially different from the one that I use to calibrate β because of the different questions asked in different ESS waves

[11]In greater detail, I halve the ranges in case of of an even number of answers (10 become 5 etc.) and round to the next integer after halving in case of an odd number of answers (5 become 3 etc.). In this latter case, the assignment of the answers is such that the extremes are bunched (answers 1 and 2 in the 1-5 scale become 1 in the 1-3 scale, answers 4 and 5 become 3 and 3 does not change.)

A^k_{jt} the vector of answers of the majority agent j, both of size $\bar{M}_{ij} \leq M$, the average empirical cultural distance between the minority and the majority is:

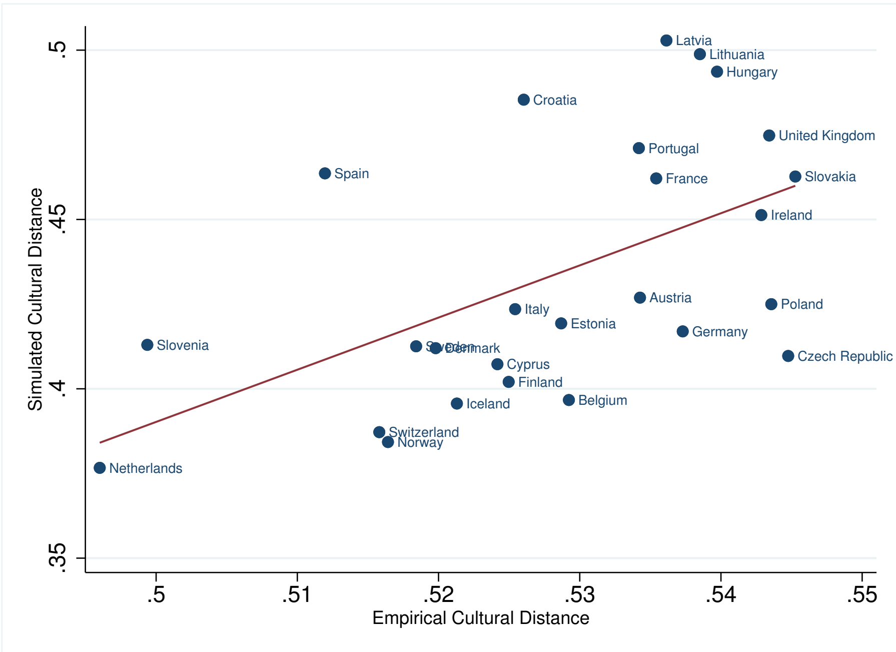
$$\bar{S}^k_t = \frac{1}{|MN|}\frac{1}{|MJ|}\sum_{i \in MN}\sum_{j \in MJ}\frac{1}{M}\left[||A^k_{it} - A^k_{jt}||_1 + (M - \bar{M}_{ij})\,\Pi^k\right] \tag{8}$$

where $|MN|$ is the number of respondents to the survey from the minority (cardinality of the set MN), $|MJ|$ is the number of respondents from the majority (cardinality of the set MJ) and where Π^k is the average distance over all minorty-majority pairs:

$$\Pi^k = \frac{\sum_{i \in MN}\sum_{j \in MJ}||A^k_{it} - A^k_{jt}||_1}{\sum_{i \in MN}\sum_{j \in MJ}\bar{M}_{ij}} \tag{9}$$

The correlation between the actual and the simulated σ-assimilation is 0.581 when looking at SGI. This is actually the most interesting group to study assimilation because they are exposed to the host country values and norms through socialization in schools at an early age, unlike most other immigrants. Figure 1 shows the scatter plot of the two measures of cultural distance, together with a linear fit. When focusing on (first generation) immigrants, the correlation is much lower, 0.337. This is actually not surprising, since immigrants, unlike SGI, are very heterogeneous: some of them immigrated recently, while others are long-term residents that spent more than 40 years in the country; some of them immigrated while very young, and attended schools in the country, while others immigrated as adults to work; some immigrants are citizens and vote in national elections, while others are granted a minimal set of rights. When computing the empirical cultural distance measure for immigrants that spent at least 7 years in the country, which is equivalent to the time span of the simulation, the correlation becomes 0.404; when restricting to immigrants that spent at least 10 years, the correlation is 0.415; for more than 15 years, 0.411. Unfortunately there are too few observations, in ESS, for immigrants that spent more than 20 years in the country to meaningfully compute an average cultural distance, which could reflect some individual characteristic. When restricting to immigrants that immigrated when less than 18, the correlation is 0.458; in case of immigration before the age of 12, the correlation is similar, 0.444. For immigrants that immigrated when less than 8, there are too few observations. Since the immigrants shares in ESS are rather small, it is also not possible to compute correlations for intersections of the above splits (young age at immigration and long span in the country). When focusing on ethno-linguistic minorities, the correlation is equal to 0.371. As for the case of immigrants, this is also a very heterogeneous group and, unlike immigrants, there is no relevant information that I can use for sample splits. For this reason, In the rest of the analysis I will focus exclusively on immigrants and SGI.

Figure 1: **Simulated and Empirical Cultural Distance**



Notes: Scatter plot of the average estimated cultural distance between second generation immigrants and natives without immigrant parents in 2018 (see text for the formula) and simulated cultural distance using 2011 data (see text for the calibration and the appendix for the full cross-section of parameters), with a linear fit.

To compute an empirical measure of Δ-assimilation, I compare the cultural distance between the immigrants and the natives separately by year of immigration: if there is Δ-assimilation, than immigrants that spent more time in the country are culturally more similar (less culturally distant) to the natives. In greater detail, I measure Δ-assimilation of a minority after δ periods, with survey data, with:

$$I_t^{emp} = \frac{1}{Y-\delta} \sum_{j=1}^{Y-\delta} \left[S_t^{j+\delta} - S_t^j \right] \tag{10}$$

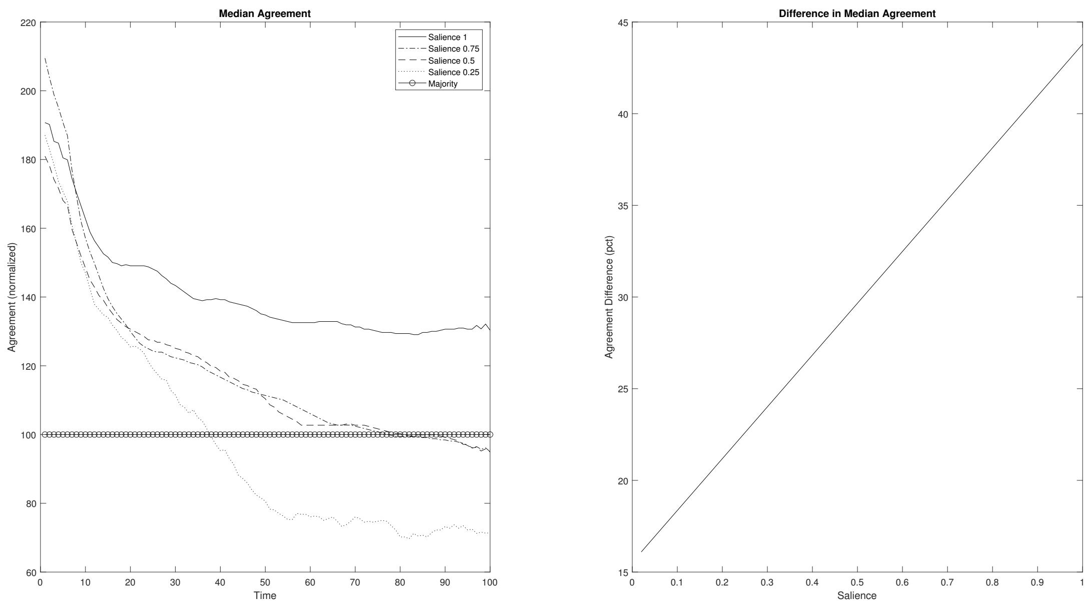
where S_t^j is the cultural distance between natives and immigrants that spent exactly j years in the country, Y is the maximum number of such years, δ is the time span of the comparison and t the survey wave used to measure cultural distance. I implement the computation with the 9^{th} ESS wave, focusing exclusively on immigrants because SGI are all born in the country (splitting by time in the country would be a split based on age) and because the only minority survey respondents for which there is information on the time spent in the country are the immigrants. Since there are not many immigrants respondents to the ESS, I compare cultural distances based on immigrants cohorts by immigration tenure, rather than based on the exact number of years. Focusing on the exact number of years results in fact in an insufficient number of observations to properly compute an average cultural distance measure, which again can reflect individual characteristics. I stat comparing 5-years cohorts: $\{j \in [0,4],\ j \in [5,9],\ j \in [10,14],\ \ldots,\ j >= 40\}$, which entails comparing immigrants that spent between 5 and 9 years in the country with immigrants that spent less than 5 years etc. The resulting correlation between the simulated and the empirical measure of Δ-assimilation is equal to 0.613. Using 10 years cohorts (10 years or less, between 11 and 20, between 21 and 30, between 31 and 40 and more than 40), results instead in a correlation equal to 0.679, while using two cohorts only (less or more than 30 years in the country), in a lower correlation of 0.476. This last bunching, however, is a little too crude, since spending 25 years in the country is not very different from spending 31 years.

All in all, the model performs better at matching the empirical measures of Δ-assimilation with respect to σ-assimilation. In both cases, however, the model yields reasonable, or better, "not counterfactual", results.

5.2 Evolution of Culture and Social Networks

Figure 2 shows an example of dynamic evolution of the median agreement rate of the minority over four issues that differ in their salience. The model is calibrated with the median values among the cross-section. Overall, the picture shows that there is assimilation, with a median agreement rate of the minority that tends towards the one of the majority (fixed by assumption). A distinctive feature of this model with endogenous social network formation is that assimilation is not necessarily stronger for more salient issues. The reason is that majority agents with different opinions over the more salient issues are excluded from the minority agents' social networks earlier and more frequently. In the example in figure 2, cultural distance is increasing in the salience, although it is also possible to have a median agreement rate that is substantially flat with respect to tsalience. An alternative model with exogenous social networks predicts instead a different pattern: with fully random matchings, there is always more assimilation for more salient issues, simply because they are more often discussed, with the result that minority agents change beliefs more often.

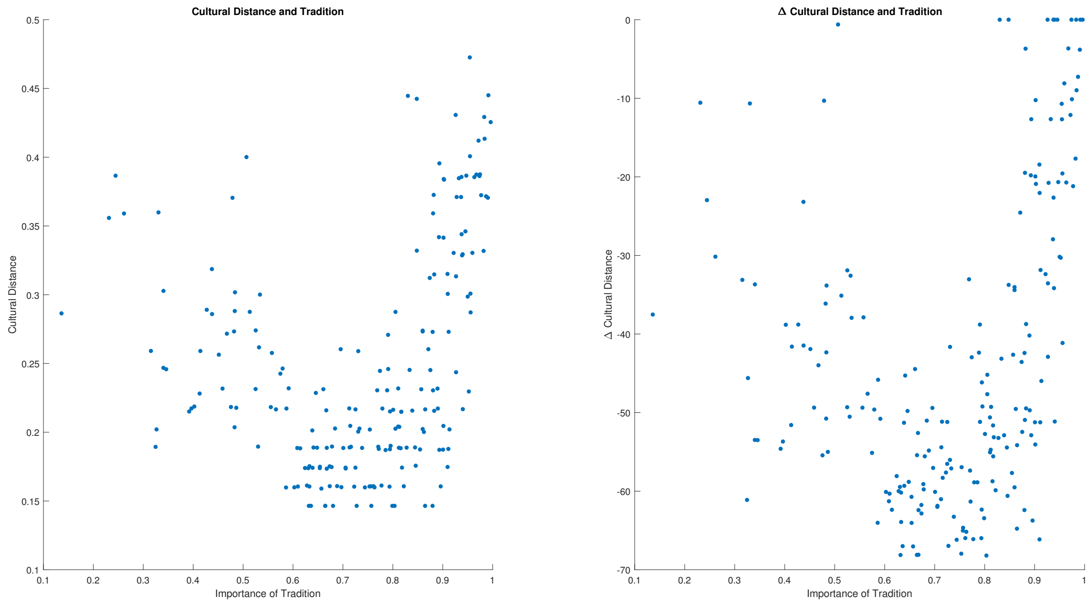
Figure 2: **Opinions and Salience**



Notes: Left panel: dynamic of the average agreement rate of the majority and of the minority conditional on salience. The agreement is normalized to be equal to 100 for the majority (equal for each salience). Right panel: Absolute value of the difference between majority and minority agreement in T in percentage terms (linear smoothing). Model calibration based on the median empirical ranges (see text).

The model implies a distribution of both Δ and σ-assimilation over minority agents. Although there is convergence in the average opinions, not all agents from the minority assimilate. The coefficient of variation of cultural distance between the majority and the minority at the end of the simulation is around 30%, stressing a considerable variability of outcomes, and it is actually three times as big than its value at the beginning of the simulation. This is because some individuals assimilate much more than others. Figure 3 shows the scatter of both σ and Δ assimilation as a function of the importance of tradition (threshold $\hat{H}_i^m$). Minority agents who are very closely tied to their original culture have a high disutility threshold and rarely change beliefs, resulting in both less σ-assimilation and less Δ-assimilation. Minority agents with very small thresholds, instead, change beliefs too often: they are constantly looking for their identity, and this lack of stability of beliefs prevents them from assimilating. Assimilation is maximal at intermediate threshold levels.

Figure 3: **Assimilation and the Importance of Tradition**

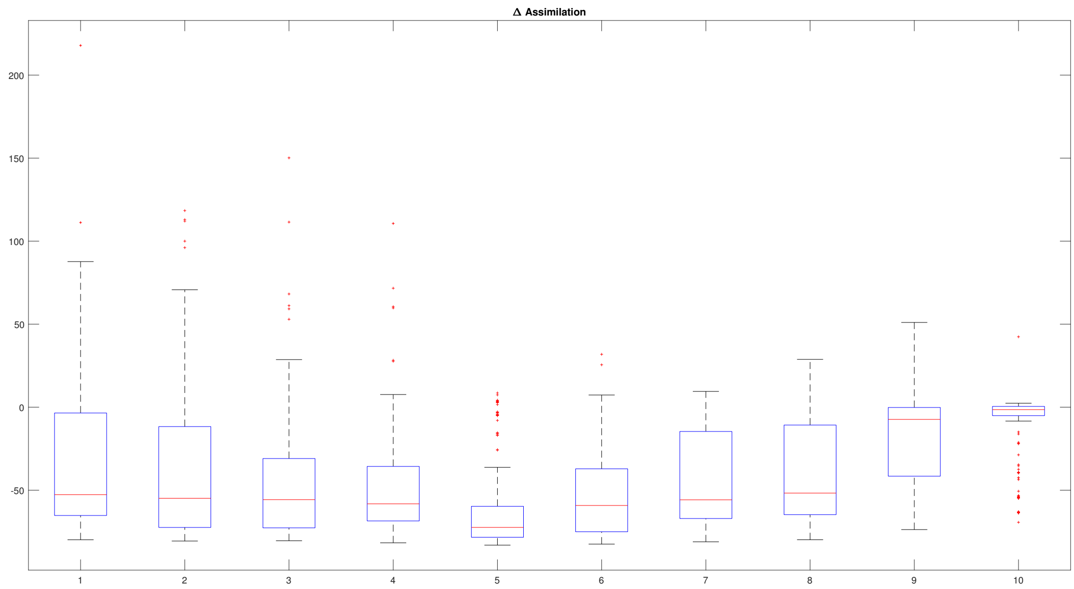


Notes: Left panel: Individual cultural distance at the end of the simulation (σ assimilation) as a function of the individual thresholds $\hat{H}_i^m$. Right panel: Change between individual cultural distance at the end of the simulation and individual cultural distance at the beginning of the simulation (Δ assimilation) as a function of the individual thresholds $\hat{H}_i^m$. Model calibration based on the median empirical ranges (see text).

The model also implies that some cultural traits are persistent. Figure 4 shows the boxplot of the percentage difference in cultural distance between the end and the beginning of the simulation by deciles of the issue-specific thresholds $\hat{H}_i^m$. To have a neat comparison, the salience of the issues is normalized to 0.5. The picture shows that there is essentially no cultural assimilation for issues over which the value attached to tradition, by the minority, is higher (high cost of changing culture).

Figure 4 shows four examples of endogenously formed social networks. To ease the visualization, I considered a small country with $N = 50$ individuals, calibrated with the cross-sectional averages of the parameter except for λ, which I set equal to 30% to have a sufficiently big number of minority agents. Minority agents can become socially isolated, although, in this

Figure 4: **Assimilation and the Importance of Tradition**



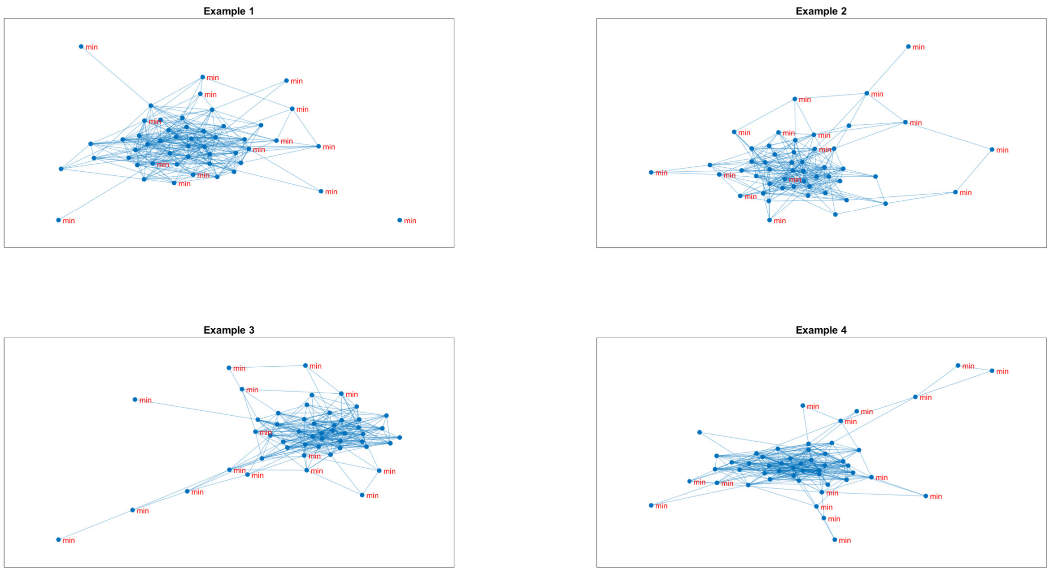
Notes: Box plot of the percentage difference in cultural distance between the end and the beginning of the simulation by deciles of the issue-specific thresholds $\hat{H}_i^m$ (on the x axis). Model calibration based on the median empirical ranges (see text). Salience equal to 0.5 for all issues.

small simulation, this does not always happen (a bigger simulation size is needed to have the calibrated fraction of isolated minority agents). Minority agents are on average, less socially connected: for a calibration based on the cross sectional medians (including λ) and a full simulation with N=1000 agents, their social contacts at the end of the simulation account, on average, for 16% of the population (14% standard deviation), while they account for 31% (10% standard deviation) for the majority. The model predicts also social segregation[12]: on average, 25% of the social contacts of the agents in the minority are other agents in the minority, while 96% of the social contacts of the majority agents are within the majority. In case of purely random social matchings, these two percentages would be equal, respectively, to λ and $1 - \lambda$, or 10% and 90% according to the median calibration.

Summarizing, the model delivers heterogenous assimilation patterns, with some cultural traits that tend to be persistent and some individuals in the minority that assimilate less or

[12]There are several ways of measuring social segregation. See Echenique and Fryer (2007) for a discussion and for a proposal of a segregation index for social networks.

Figure 5: **Social Networks**



Notes: Four examples of endogenously formed undirected social networks at the end of the simualtion. Nodes denoted with min refer to minority agents. Model calibration based on the median empirical ranges (see text). $N = 50$ total agents in the country and $\lambda = 0.3$.

do not assimilate at all. The model also predicts social segregation, with minority (majority) agents over-represented in the social networks of (minority) agents.

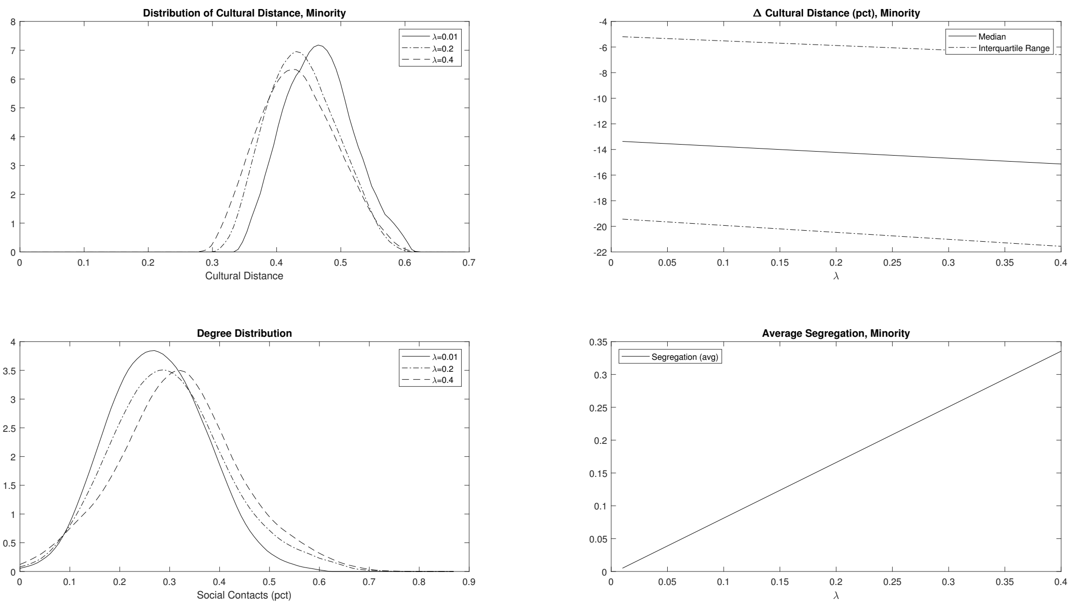
6 Analyzing the Model

To understand the importance of the model primitives on assimilation and segregation, I perform two exercises: a comparative statics, starting from a benchmark calibration based on the median parameters values among the observed cross-section (subsection 6.1), and a regression of a simulated cross section of artificial countries on the parameters used to simulated them (subsection 6.2).

6.1 Comparative Statics

Figure 6 shows the comparative statics with respect to the minority share λ. This is useful to understand how will assimilation patterns change either in case of immigration or in case of a higher population growth rate for the minority. Bigger minorities, for the same variability of beliefs, are associated with more social contacts among them, which (mechanically) increases the average size of the social networks and segregation. For a minority agent, bigger social networks imply, in turn, a higher probability to match with another minority agent with different beliefs, that assimilated earlier. There is therefore a contrasting effect on cultural assimilation, that decreases because of the smaller number of majority agents in the minority agents' social networks, but increases as an effect of more intense social contacts with minority agents that assimilated earlier. The picture shows that the overall effect is an increase of assimilation with respect to λ, but of a small magnitude. The regression evidence discussed in section 6.2 shows instead that, from a quantitative standpoint, there is no significant effect of the minority share on cultural assimilation.

Figure 6: **Comparative Statics: Minority Share**



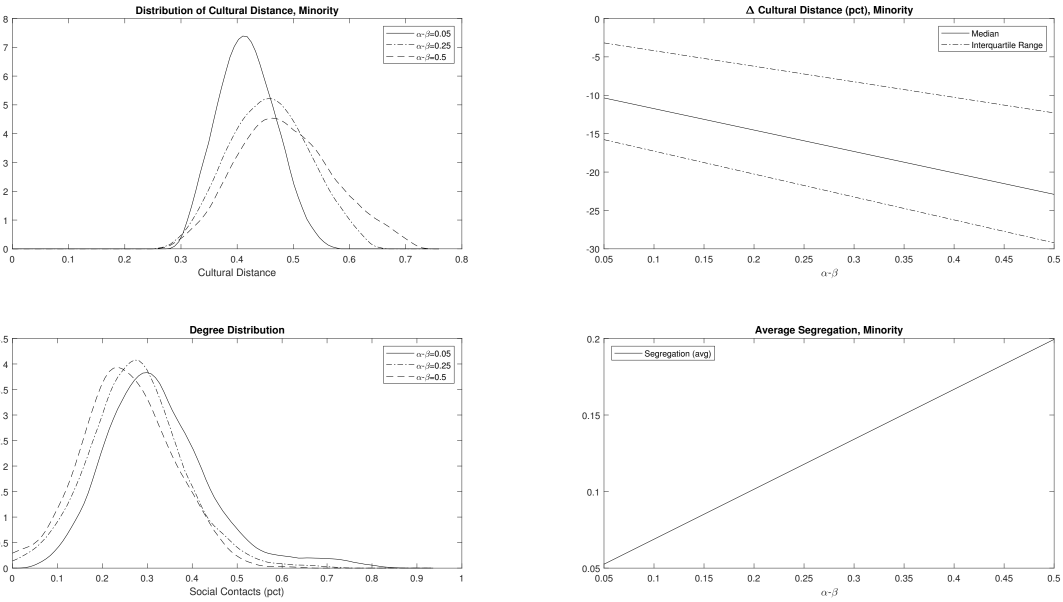
Notes: λ is the minority share. Upper-left panel: kernel density estimates of the simulated distributions of cultural distance between the minority agents and the majority at the end of the simulation. Upper-right panel: median and interquartile range of the distribution of the change in cultural distance (percentage terms, linear smoothing). Lower-left panel: kernel density estimates of the simulated degree distribution of the social network (normalized number of social contacts) at the end of the simulation (all agents). Lower-right panel: average segregation for minority agents (ratio of social contacts within the minority to total social contacts). Model calibration based on the median empirical ranges (see text) except for the minority share.

Figure 7 shows the comparative statics with respect to the initial cultural distance $\alpha - \beta$. When the minority is culturally more distant, there is a higher probability of social matchings with majority agents with different opinions, meaning that beliefs will change more often among the minority, resulting in more Δ-assimilation. This stronger assimilation over time, however, is not enough to close the initial gap in cultural distance, and the country ends up with a distribution of cultural distance that shifts to the right, with a higher share of non-assimilated minority agents and less overall σ-assimilation. There is also a higher volatility of σ-assimilation because a bigger α, for fixed β, implies also more variability of beliefs among the majority. The average number of social contacts decreases, as an effect of the higher probability to match with individuals with different opinions, and the more frequent social exclusions increase also segregation for the minority. Increasing the simulation periods to $T = 150$ periods delivers similar results, so the reason why there is less σ-integration for culturally distant minorities is not because of a limited simulation span. Culturally distant minorities are more socially segregated and, although they assimilate more over time, they end up being more culturally distant from the majority.

Figure 8 shows the comparative statics with respect to the social density γ. Higher values of γ imply both more social matchings with agents from the majority and from the minority. For fixed population size, and for fixed λ, the identity of the individuals met each period changes less often, resulting in less changes of beliefs and, therefore, less σ and Δ-assimilation. Moreover, flags to agents with different opinions are more frequent, so the distribution of social contacts shifts to the left and segregation increases, making assimilation even more difficult. Socially denser societies are characterized by weaker cultural assimilation from conformism, smaller social networks and stronger social segregation.

Figure 9 shows the comparative statics with respect to the volatility of opinions in the majority ($\beta(1-\beta)$), which can be interpreted as the degree of cultural pluralism/heterogeneity of the majority, or as the degree of ethnic fractionalization (Alesina et al. 2003), assuming that ethnicity and culture are correlated (Desmet et al. 2017). With more volatile opinions among the majority, it is easier, for a minority agent, to match with a majority agent with similar opinions and, on average, there are less changes of beliefs. Thus there is also less Δ-assimilation and a higher final cultural distance between the majority and the minority, with an effect that is quantitatively big. The total number of social contacts decreases with pluralism because flags are more frequent due to the lack of convergence of beliefs. The volatility of

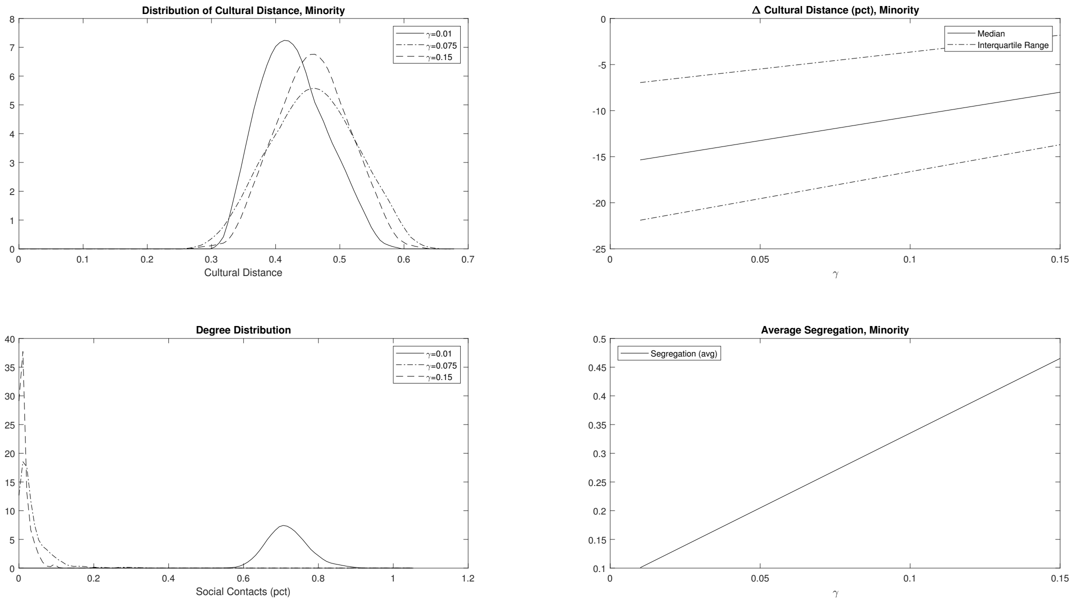
Figure 7: **Comparative Statics: Initial Cultural Distance**



Notes: $\alpha - \beta$ is the cultural distance between the majority and the minority at the beginning of the simulation (see text). Upper-left panel: kernel density estimates of the simulated distributions of cultural distance between the minority agents and the majority at the end of the simulation. Upper-right panel: median and interquartile range of the distribution of the change in cultural distance (percentage terms, linear smoothing). Lower-left panel: kernel density estimates of the simulated degree distribution of the social network (normalized number of social contacts) at the end of the simulation (all agents). Lower-right panel: average segregation for minority agents (ratio of social contacts within the minority to total social contacts). Model calibration based on the median empirical ranges (see text) except for cultural distance.

the degree distribution increases, and both small and big social networks coexist: the smaller social networks are highly segregated, while the bigger networks are hardly segregated. This is, in turn, the consequence of the increased variability of outcomes in social matchings: the minority agents that, at early stages, match with majority agents with similar beliefs, end up in relatively bigger social networks, while the opposite happens for those minority agents that match with majority agents with different beliefs. The resulting effect on the average segregation is quantitatively very small. If conformism is the only engine for integration, then both Δ integration and σ integration are more difficult in pluralistic societies: there is a higher probability to form cultural enclaves (of various sizes).

Figure 8: **Comparative Statics: Social Density**

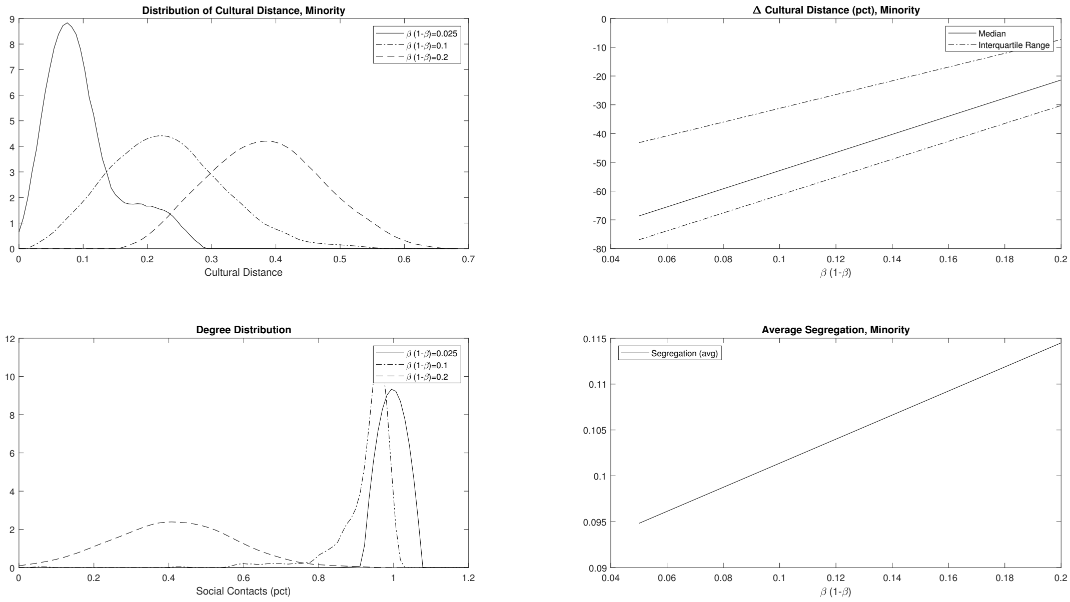


Notes: γ is the social density (see text). Upper-left panel: kernel density estimates of the simulated distributions of cultural distance between the minority agents and the majority at the end of the simulation. Upper-right panel: median and interquartile range of the distribution of the change in cultural distance (percentage terms, linear smoothing). Lower-left panel: kernel density estimates of the simulated degree distribution of the social network (normalized number of social contacts) at the end of the simulation (all agents). Lower-right panel: average segregation for minority agents (ratio of social contacts within the minority to total social contacts). Model calibration based on the median empirical ranges (see text) except for social density.

6.2 Regression on Simulated Data

To gauge the relative importance of the model primitives, I simulated artificial countries drawing random values for the baseline model parameters, to then run regressions of the assimilation and segregation measures on the parameters used in the simulation. I consider an artificial sample of 500 countries, drawing the minority share λ between 1% and 30%, the (re-scaled) average cultural distance $\alpha - \beta$ between 0.05 and 0.5, the variability of the majority agreement rate, which I use to set β, between 2.5% and 25%, the social density γ between 1% and 15%, and the parameters a and b of the Beta distribution of the thresholds (importance of tradition) between, respectively, 0.4 and 6 and 0.2 and 2. For all parameters, I considered a slightly wider range with respect to the cross section of calibration parameters. In all simulations, the two thresholds ζ^{in} and ζ^{out} to flag individuals are randomly chosen between 7 and 18. The results are summarized in table 1.

Figure 9: **Comparative Statics: Pluralism**



Notes: $\beta(1-\beta)$ is the variance of opinions in the majority (see text). Upper-left panel: kernel density estimates of the simulated distributions of cultural distance between the minority agents and the majority at the end of the simulation. Upper-right panel: median and interquartile range of the distribution of the change in cultural distance (percentage terms, linear smoothing). Lower-left panel: kernel density estimates of the simulated degree distribution of the social network (normalized number of social contacts) at the end of the simulation (all agents). Lower-right panel: average segregation for minority agents (ratio of social contacts within the minority to total social contacts). Model calibration based on the median empirical ranges (see text) except for β.

The minority share λ does not affect cultural assimilation. A bigger minority share increase only social segregation with, in particular, a 1 std deviation change in λ that determines a segregation increase equivalent to 26% of its standard deviation. More cultural distance between the majority and the minority at the beginning of the simulation implies less σ-assimilation (bigger cultural distance between the minority and the majority at the end of the simulation) but more Δ-assimilation (sharper reduction of cultural distance) and more social segregation. Quantitatively, 1 std change in the initial cultural distance predicts an increase in cultural distance at the end of the simulation of 0.035 (23% of the std of cultural distance), an increase in the absolute value of the difference between cultural distance between the end and the beginning of the simulation 0.045 (21% of the standard deviation of the change in cultural distance) and an increase of social segregation of 0.059 (18% of the standard deviation of segregation). Bigger social density predicts less σ-assimilation, less Δ-assimilation and more social segregation. Quantitatively, a one std change in γ predicts a cultural distance increase equivalent to 10% of its standard deviation, a Δ-assimilation decrease equivalent to 8% of its standard deviation and a segregation increase equivalent to 14% of its standard deviation. Thus the effect is quantitatively small. More cultural pluralism predicts less cultural assimilation and the effect is quantitatively big: a one std increase of pluralism predicts a change in cultural distance equivalent to 90% of its standard deviation, and a Δ-assimilation change equivalent to 75% of its standard deviation. Cultural pluralism increases segregation, with a 1 std change associated to a segregation increase equivalent to 28% of its standard deviation. This last result is mostly due to the smaller average network size in case of pluralism, which decreases the denominator of segregation (regressing the average network degree for minority agents on $\beta(1-\beta)$ results is a negative and strongly significant coefficient).

7 Robustness and Extensions

In this section I analyze the robustness of the results (subsection 7.1) to alternative parametrizations, and discuss three significant model extensions: a model with per-period matchings, for minority agents, with a fixed set of individuals, to model family interactions (subsection 7.2), a model with two culturally-heterogeneous groups within the majority (subsection 7.3), and a model with exogenous changes of beliefs within the majority (subsection 7.4). The correlation results between the simulated and the empirical cross-sections of assimilation are summarized in section 2. In subsection 7.5, I provide a discussion of alternatives to the Hamming distance.

7.1 Robustness

As a first robustness check, I tried restricting the empirical cross section of countries with respect to which I evaluate the model performance. The evidence is mixed. When restricting to small countries by population (below the sample median), the model performs better at matching σ assimilation of immigrants (more than 10 years in the country) and worse at matching Δ integration when measured on 5 years cohorts. When restricting to countries with small minority shares (below the median), the model performs better in all respects except Δ integration measured on 5 years cohorts. When restricting to countries with more nationalities of origin (above the median), it performs better at matching σ assimilation of immigrants and Δ assimilation on 10 years cohorts.

In the baseline calibration, I assumed no discounting of past disutilities (full memory), setting $\mu = 0$. Assuming discounting (shorter memories, $\mu > 0$), for the same thresholds $\hat{H}_i^m$, implies less frequent opinion changes, resulting in a slower convergence. The model performance at matching the empirical assimilation measures is worse than benchmark. Table 2 shows the results for $\mu = 0.5$ and $\mu = 0$, obtained doubling the length of the simulation to account for the slower evolution of beliefs. The conclusion is that the model works best in case of long memories.

I considered three alternative values of the thresholds number of social contacts K below which the agents are defined as socially excluded in the calibration (see section 4), respectively 10% and 1% of N, and below 1.5 standard deviations from the mean of the distribution of social contacts. The model performance is in line with the benchmark (see table 2), and the comparative statics unchanged.

The baseline calibration also features an arbitrary normalization of the maximum possible social density to 5%, which means that I assume that, in the country with the highest observed social density index (see section 4), each agent meets socially with $0.05 \cdot N$ individuals per period. I simulated the model with two alternative maximum density values, respectively 10% and 2.5%. The simulation results turned out to be very similar (see table 2). The comparative statics were also similar to the benchmark.

I also considered the possibility of heterogeneous social participation, modeled as an idiosyncratic fraction γ_i of the population met each period as part of social activities. For each country, I simply draw these individual γ_i from a uniform distribution between 0 and 2 times the average (country level) γ used in the benchmark simulation. I obtained similar correlations between the empirical and the simulated measures of cultural integration (see table 2) and similar comparative statics. In this alternative model, it is possible to look at the relationship between individual social participation γ_i and the individual level of σ-assimilation. This correlation is positive: more socially active individuals end up assimilating more. The cross-country median correlation between social participation and cultural distance is -0.566, with an interquartile range between -0.661 and -0.506.

One potential drawback of the analysis is that the model is calibrated at an aggregate level, ignoring potential differences across territories. I tried calibrating the model to a cross-section of NUTS 2 regions within the same countries considered in the analysis. The problem with this alternative, which is the main reason why I did not choose it as benchmark, is that there are not enough immigrants respondent to the ESS in each region to meaningfully compute the empirical Δ-assimilation measures, which requires a sufficient number of immigrants by cohort of years spent in the country, and to compute the statistics needed to calibrate the model. Moreover, the classification into regions also changed in the period that I analyze, making also spatial comparisons complicated. Calibrating the model with the available information, ignoring the above mentioned problems, results in a correlation between the empirical and the simulated measures of σ-assimilation for immigrants that spent more than 10 years in the country of 0.401, not differently from the benchmark. For SGI, the model performance is worse than benchmark, with a correlation of 0.346.

7.2 Families

The baseline model with fully random matchings within the social network ignores the role of the relationships within the family, which can be very important, perhaps crucial, drivers of cultural assimilation (Bisin and Verdier 2000 and 2001, among others). I extended the model to account for family relationships, in reduced form, assuming that a fixed fraction of the social matchings, each period, is with a fixed subset of individuals drawn from the same social group, that cannot be excluded from the social network regardless of the disutility resulting from the interactions.

More formally, for each agent i from the minority (majority), ξ_i percent of the per-period social matchings entails a subset Ξ_i of $\xi_i \gamma N$ minority (majority) agents[13], with $f_{it}^{j} = 1 \, \forall j \in \Xi_i$ at each point in time. I randomly draw the ξ_i from a uniform distribution between 0 and 1, where 0 is intended to model agents without any family relationship and 1 agents whose social contacts are only within the family. There is less cultural assimilation in this alternative model: median cross-sectional Δ-assimilation for immigrants (SGI) is -7.6% (-11.5) versus -

[13] The total number of social matchings, in the simulations, is always smaller than the number of agents in each social group.

13.29% (-14.3%) of the baseline model without families. The model performance at matching σ-assimilation is slightly worse than benchmark (see table 2). As for the comparative statics, they are in line with the benchmark, except that Δ-assimilation is flatter with respect to the initial cultural distance $\alpha - \beta$ and that the effect of this initial cultural distance on σ assimilation is more pronounced.

The conclusion from this exercise is that the benchmark calibrated model overstates the absolute value of the degree of cultural assimilation due to the exclusion of family relationships, although it is still able to reproduce the cross-sectional variability of assimilation and it is still useful to do policy analysis with comparative statics.

7.3 Heterogeneous Majorities

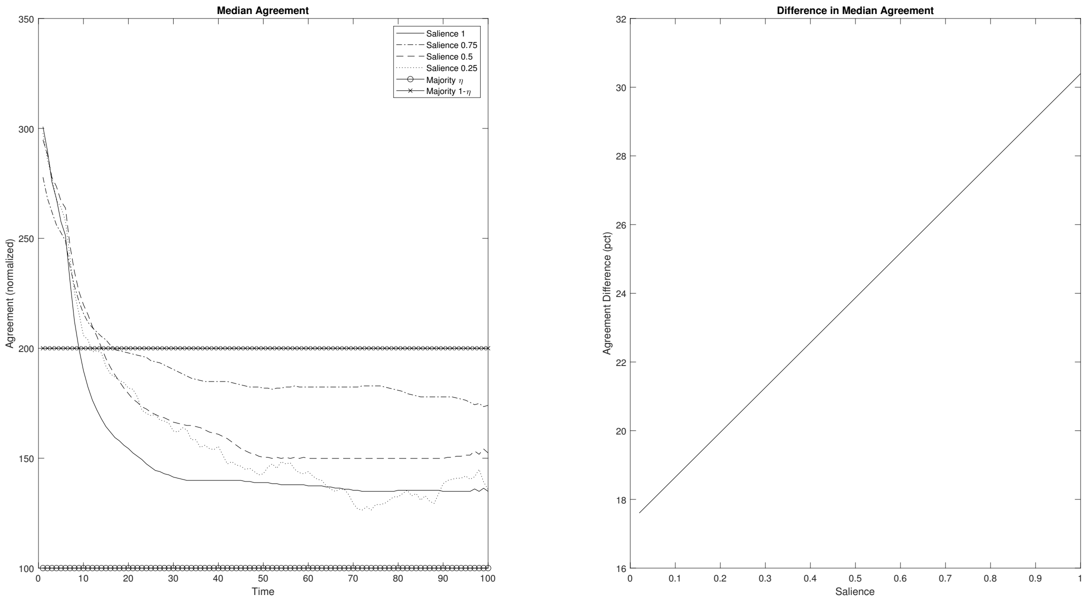
The baseline model features only one culturally homogeneous group within the majority. In this section I extend the model to a setting with a majority composed by two culturally dis-homogeneous groups[14], which is a more realistic assumption for instance for bilingual countries or for countries with more than one prevalent religion. I assume that the agreement rate among a fraction η of the majority is equal to β_η, while it is $\beta_{1-\eta}$ among the remaining fraction $1-\eta$. To preserve the main structure of the calibration, I set $\eta\beta_\eta + (1-\eta)\beta_{1-\eta} = \beta$, so that the country-level average agreement rate of the majority is the same as the benchmark. Furthermore, to have culturally diverse groups in the majority, I set $\beta_{1-\eta} = 2\beta_\eta$. To keep the interpretation of the $1-\lambda$ share of the population as the majority, I need to have both $(1-\lambda)\eta > \lambda$ and $(1-\lambda)(1-\eta) > \lambda$, which means that the model can be solved only for minority shares λ smaller than 1/3. I consider a baseline value of $\eta = 0.5$, corresponding to majority groups of equal size.

In this model, the average agreement rate among the minority tends to be, over time, in between the average opinions of the two majority groups[15]. Figure 10 illustrates an example of the dynamic evolution of opinions. The model performance (see table 2) and the comparative statics are similar to the benchmark. The results obtained with $\eta = 0.25$ and $\eta = 0.75$ are, in

[14]Extending the model to more than two groups is not worthwhile, since it would only be an alternative to the modellization of a high variance of opinions within the majority.

[15]This result is akin to the convergence to a "Neutral" culture (different from the prevalent cultures among the majority) in fragmented societies highlighted by Lazear (1999).

Figure 10: **Opinions and Salience, Heterogeneous Majorities**



Notes: Left panel: dynamic of the average agreement rate of the majority and of the minority conditional on salience. The agreement rate is normalized to be equal to 100 for the majority group with lower agreement rate (share η). Right panel: Absolute value of the difference between majority and minority agreement in T in percentage terms (linear smoothing). Model calibration based on the median empirical ranges (see text).

all respect, similar. Thus the restriction to a single, homogeneous, minority, does not influence the results.

7.4 Exogenous Cultural Evolution

One of the strong assumptions of the baseline model is that culture, for the majority, does not evolve through time. In reality, many exogenous factors such as technological change, media exposure and globalization, can influence beliefs and norms of behavior. The justification of violence against women or the perception of homosexuality and pre-marital sex are three important, and salient, examples. In this section, I discuss a model extension with exogenous changes of beliefs among the majority. More specifically, I assume that the average agreement or disagreement rate among the majority over a subset of issues decreases according to a deterministic AR(!) process. The average agreement rate in the majority at time t over the issue m is

$$G_t^m = \frac{1}{(1-\lambda)N} \sum_{i \in MJ} q_{it}^m \tag{11}$$

I model an exogenous decrease in the average agreement rate of the majority over issue m as $G_{t+1}^m = \rho\, G_t^m$ with $\rho < 1$. For the exogenous increase case, since I have binary beliefs, I simply define the average disagreement $\bar{G}_t^m = 1/((1-\lambda)N) \sum_{i \in MJ}(1 - q_{it}^m)$ and assume $\bar{G}_{t+1}^m = \rho\, \bar{G}_t^m$. Operationally, I randomly select the issues over which the beliefs evolve exogenously, so that they do not systematically differ from others in terms of salience. Moreover, I also randomly select the identity of majority agents that change opinion in each period in order to reach the desired adjustment of the average agreement rate, so that such exogenous changes are independent from all other individual characteristics.

The important result from this alternative model is that the exogenous evolution of beliefs in the majority improves the assimilation of the minority. With $\rho = 0.95$, and with an exogenous evolution for $l = 30\%$ of the beliefs, the median cultural distance between the majority and the minority over the cross section, at the end of the simulation, is equal to 0.341 (std 0.058) as compared to a benchmark, in the baseline model, of 0.447 (std 0.071). As for Δ assimilation, the difference is sharper: -32.1 (std 6.61) versus a benchmark of -13.29 (std 8.62), thus both more pronounced and less volatile. The correlations between the actual and the simulated cross sections of cultural assimilation (see table 2) are in line with the benchmark, although the model performance is less good with respect to σ-assimilation of the SGI. The comparative statics of the model are similar to the benchmark. The results are similar in case of decreasing or increasing agreement rate, and are also robust in case of a faster evolution with $\rho = 0.9$. In case of an exogenous evolution for $l = 50\%$ of the issues, both σ and Δ-assimilation are even stronger: the median cultural distance in the cross section is 0.268 (std 0.043) and the median difference in cultural distance -46.86 (std 5.53). The problem, in this case, is that the model performance at matching the empirical measures of Δ-assimilation is worse. When ρ tends to one, the simulation results are the same as the benchmark. Assuming that more than 50% of the issues have drift would be strange because of the empirical evidence on the persistence of culture.

7.5 Alternative Distances

The Hamming distance is an intuitive and convenient way of measuring cultural distance in the model, because the beliefs are binary and because it delivers a cultural distance measure at the individual level, which allows the study of the distribution of assimilation. However it is not the only possible measure of distance for binary vectors. In this section I consider several alternatives, limiting the discussion to measures that allow to study cultural assimilation at the individual level.

A first alternative to the Hamming distance is the Jaccard distance which, for two sets, is equal to one minus the Jaccard coefficient, or one minus the ratio of the number of elements in the intersection of the two sets divided by the number of elements in the union. With binary vectors of beliefs, the Jaccard measure of cultural distance is:

$$S_t^{J,k} = \frac{1}{\lambda N} \frac{1}{(1-\lambda)N} \sum_{i \in MN} \sum_{j \in MJ} \left(1 - \frac{z_{ij}^{11}}{z_{ij}^{11} + z_{ij}^{01}}\right) \tag{12}$$

where z_{ij}^{11} is the number of beliefs over which both i and j agree:

$$z_{ij}^{11} = \sum_{m=1}^{M} \mathbb{1}_{[q_{it}^m = q_{jt}^m = 1]} \tag{13}$$

and z_{ij}^{01} is the number of beliefs over which i agrees and j disagrees or j agrees and i disagrees:

$$z_{ij}^{01} = \sum_{m=1}^{M} \mathbb{1}_{[\,|q_{it}^m - q_{jt}^m| = 1\,]} \tag{14}$$

A second possible alternative measure of distance for binary vectors is the Soresen-Dice coefficient, given by $S^{D,k} = 2S^{J,k}/(1+S^{J,k})$. A third alternative entails using the Yule's colligation coefficient (a measure of association between binary vectors with the same interpretation as the correlation coefficient), constructing a distance measures as follows:

$$S_t^{Y,k} = \frac{1}{\lambda N} \frac{1}{(1-\lambda)N} \sum_{i \in MN} \sum_{j \in MJ} \frac{(z_{ij}^{11}\, z_{ij}^{00})^{1/2} - (z_{ij}^{10}\, z_{ij}^{01})^{1/2}}{(z_{ij}^{11}\, z_{ij}^{00})^{1/2} + (z_{ij}^{10}\, z_{ij}^{01})^{1/2}} \tag{15}$$

where the z^{00} and z^{10} are defined in the same way as z^{11} and Z^{01}. A fourth possibility is to use the simple euclidean distance as a metric for individual cultural distances.

The correlation between the cross-section of cultural Hamming distances (σ-assimilation) between the majority and the minority (model calibrated for immigrants) at the end of the simulation and the cross-section of cultural Jaccard distances is 0.961; the correlation between the Hamming and the Dice distances is 0.985; the correlation between the Hamming and the Yule distances is 0.937; the correlation between the Hamming and the Euclidean distances is 0.991; This very high correlation stress that the main simulation results are not specific to the cultural distance measure used.

8 Discussion and Conclusion

Summarizing the results from the analysis, the model of cultural assimilation and social segregation from conformism implies: (1) That the minority share does not influence cultural assimilation; (2) More cultural assimilation over time for culturally distant minorities, although the countries with originally more distant minorities are characterized by less overall assimilation; (3) Less cultural assimilation in case of high social density and in case of pluralistic majorities; (4) More average segregation for culturally more distant and bigger minorities and for higher social density; (5) Smaller social networks in pluralistic and denser societies.

Interpreting the model in terms of immigration, there are several policy implications. First, more restrictive immigration policies that close the borders, or that reduce the immigration quotas, will not foster cultural assimilation. Similarly, all policies whose goal is to increase the fertility rate among the natives, whenever population growth is higher among the immigrants, will not have an effect on assimilation. Second, to improve assimilation it is best to encourage immigration settlements away from densely populated areas, for instance through subsidized housing. Similarly, it is best not to locate refugees shelters in big and crowded cities.

The question, then, is if assimilation is a legitimate policy objective to pursue. In the model, any policy that fosters assimilation is desirable because it decreases the disutility from non-conformism in social matchings. However the model is too simplified to perform a welfare analysis and, in particular, it abstracts from the trade-off identified by Ashraf and Galor (2013): culturally assimilated minorities foster the transmission of human capital, but they also hinder the adoption of new technologies. The long-run effects of assimilation are, therefore, unclear, and my analysis does not offer any perspective on this issue. Assimilation is not necessarily desirable also because the concept of cultural assimilation abstracts from any evaluation or judgment relative to culture that emerges. For instance, there can be assimilation of a minority to a culture of violence and discrimination, with potentially severe social and economic consequences.

The methodology that I propose to assess cultural assimilation can also be used to quantify integration of behavior, for instance with respect to financial decisions or fertility choices, using appropriate surveys to calibrate the model and to compute the empirical assimilation measures. It can be also used to study assimilation with respect to specific subgroups of the population defined by socio-demographics characteristics, although such analysis requires larger surveys than the ESS, with a sufficiently big number of minority agents to meaningfully compute the empirical measures. In this respect, the aggregate, country-level analysis of assimilation that I proposed is severely limited in scope: assimilation at the country level might hinder the presence of non-assimilated cultural enclaves among specific groups or areas. My analysis is also inadequate to properly study segregation, and in particular residential segregation, because such an analysis requires survey data at a very fine geographical level (neighborhood). The clear direction for future research is to attempt a more disaggregated analysis, perhaps developing an ad-hoc survey.

The framework that I proposed is not necessarily specific to cultural assimilation. With few adjustments, it can be used to model fads and, in general, the emergence of common behavioral features among specific communities. One potential drawback is that conformism remains the only driver of the dynamics, although the model can be also easily extended to encompass other, more sophisticated (dis)utility functions.

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Table 1: **Regression on the Artificial Cross-Section**

	σ Integration		Δ Integration		Segregation	
	(1)	(2)	(3)	(4)	(5)	(6)
λ	0.0078	0.0077	-0.0789	-0.0886	1.0157***	1.0221***
	(0.0321)	(0.0323)	(0.0673)	(0.0674)	(0.1268)	(0.1256)
$\alpha - \beta$	0.2653***	0.2654***	-0.3579***	-0.3476***	0.4474***	0.4407***
	(0.0218)	(0.0213)	(0.0531)	(0.0486)	(0.0837)	(0.0831)
γ	0.3678***	0.3674***	0.4568***	0.4251***	1.1262***	1.1483***
	(0.0632)	(0.0642)	(0.1391)	(0.1411)	(0.2575)	(0.2561)
$\beta(1-\beta)$	2.1342***	2.1336***	2.5696***	2.5199***	1.4584***	1.4907***
	(0.0404)	(0.0424)	(0.1216)	(0.1307)	(0.1682)	(0.1676)
$a/(a+b)$		-0.0021		-0.1654***		0.1074*
		(0.0204)		(0.0623)		(0.0649)
R^2	0.853	0.853	0.617	0.634	0.496	0.499

Notes: OLS regression results for a simulated cross-section of 500 artificial countries with a random parameter choice within a pre-specified range (see infra). σ-assimilation is the median Hamming distance between the majority and the minority at the end of the simulation. Δ-assimilation is the difference between the median cultural distance minority-majority at the end of the simulation and the median at the beginning. Segregation is the average ratio of the social contacts within the minority to the total number of social contacts among all minority agents. λ is the minority share ($\lambda \in [1\%; 30\%]$). $\beta(1-\beta)$ is the volatility of the opinions among the majority ($\beta(1-\beta) \in [2.5\%; 25\%]$). $\alpha - \beta$ is the average cultural distance between the majority and the minority at the beginning of the simulation ($\alpha - \beta \in [0.05; 0.5]$). γ is the social density ($\gamma \in [1\%; 15\%]$). $a/(a+b)$ is the average importance of tradition for the minority (mean of a Beta distribution with parameters a and b ($a/(a+b) \in [0.167; 0.968]$). All regressions include the two thresholds ζ^{in} and ζ^{out}, randomly chosen between 7 and 18. All other model parameters are fixed at the calibration benchmark (see section 4). Median cultural distance (σ assimilation) is 0.311, with std 0.151 and interquartile range [0.176;0.433]. Median change in cultural distance (Δ) is -0.268, with std 0.218 and interquartile range [-0.438;-0.141]. Median segregation is 0.144, with std 0.324 and interquartile range [0.053;0.271]. Robust standard errors in brackets. ***=significant at the 1% level. **=significant at the 5% level.

Table 2: **Simulated and Actual Cross Section, Correlations**

Model	**σ-Assimilation**		**Δ-Assimilation**	
	Imm	SGI	5y Cohorts	10y Cohorts
Benchmark	0.415	0.581	0.613	0.679
Small population	0.586	0.547	0.381	0.738
Small minority share	0.682	0.723	0.565	0.842
Many origin countries	0.684	0.513	0.489	0.798
$K = 0.1$	0.407	0.566	0.614	0.688
$K = 0.01$	0.399	0.568	0.659	0.694
$K = 1.5$ std	0.417	0.624	0.625	0.669
Max density 10%	0.390	0.418	0.602	0.671
Max density 2.5%	0.418	0.539	0.564	0.621
Heterogeneous γ	0.425	0.501	0.613	0.662
Family	0.345	0.466	0.615	0.646
$\mu = 0.5$	0.335	0.377	0.647	0.646
$\mu = 1$	0.317	0.338	0.501	0.521
Split majority, $\eta = 0.5$	0.432	0.522	0.629	0.643
Split majority, $\eta = 0.25$	0.397	0.589	0.656	0.662
Drift, $l = 30\%$, $\rho = 0.95$, positive	0.483	0.467	0.601	0.624
Drift, $l = 30\%$, $\rho = 0.95$, negative	0.412	0.341	0.616	0.619
Drift, $l = 30\%$, $\rho = 0.90$, positive	0.394	0.372	0.522	0.538
Drift, $l = 50\%$, $\rho = 0.95$, positive	0.416	0.392	0.490	0.483

Notes: Correlations between the simulated and the empirical cross-sections of cultural assimilation. σ-Assimilation is the median Hamming distance between the majority and the minority (specified in the second row of the table) at the end of the simulation. Δ-Assimilation is the absolute value of the percentage difference between the median Hamming distance at the end of the simulation and the median Hamming distance at the beginning (calibration only for immigrants). Imm refers to the model calibrated for (first generation) immigrants (see text) and to the empirical computations for immigrants that spent at least 10 years in the country. SGI refers to the model calibration for second generation immigrants and to the empirical computations for second generation immigrants. 5y-Cohorts and 10y-Cohorts refers to the empirical computation of Δ-assimilation using, respectively, 5 years and 10 years cohorts (see equation 10). Model specification in the fist row of the table. Small population refers to countries with population below the cross-sectional median. Small minority share refers to countries with immigrants share below the cross-sectional median. Many origin countries refers to countries with a number of immigrants origin countries above the cross-sectional median. K is the threshold percentage of social network members below which an individual from the minority is defined as socially isolated (see section 4), and 1.5 std means below 1.5 standard deviations from the mean number of members above social networks of minority agents. Max density refers to the normalization for the maximum social density value in the cross section (see section 7.1). Heterogeneous γ refers to the model with within-country heterogeneity in social participation (see section 7.1). μ is the discounting factor for past disutilities ($\mu = 1$ means full discounting). Family refers to the model with families (see section 7.1). Split majority is the model with two groups within the majority, with shares η and $1 - \eta$ (see section 7.1). Drift is the model with exogenous evolution of beliefs in the majority, with AR(1) parameter ρ, for l percent of the issues and with increasing agreement (positive) or disagreement (negative) rate.