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ORIGINAL PAPER

Cultural assimilation and segregation in heterogeneous societies

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Abstract
I propose a model of cultural assimilation with endogenous social networks and idiosyncratic assimilation patterns that is consistent with the empirical evidence for Europe. The model implies that assimilation is weaker in pluralistic or more culturally heterogeneous societies, and stronger in socially denser societies, but it is not influenced by the minority share. Social segregation for the minority increases with social density, with the minority share, and with the initial average cultural distance between the majority and the minority.

Keywords Culture · Distance · Evolution

JEL Classification J15 · Z10

1 Introduction

Social interactions play a crucial role in the evolution of culture for a minority. Intergroup contact and frequent exchanges can lead to a process of cultural assimilation, which promotes social trust and helps solve coordination problems, thereby fostering the provision of public goods (Alesina et al. 1999; Alesina and La Ferrara 2005), the transmission of human capital and the implementation of efficient policies (Guiso et al. 2016). Moreover, culturally assimilated minorities are less likely to form socially segregated enclaves, thereby reducing conflict. Cultural assimilation and social segregation are also key determinants of the economic and political consequences of immigration: if immigrants live in enclaves, hold on to their values, and strive to transmit them to their children, anti-immigrant feelings might arise (Dustmann and Preston 2001; Facchini and Mayda 2009), strengthening the support for nationalist parties and anti-immigration policies (Russo 2021; Tabellini 2020).

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To study the joint determinants of cultural assimilation and social segregation, I propose a calibrated epidemiological model of cultural evolution in a country where a fraction of the population is a minority, and where the majority is culturally heterogeneous. The key feature of the model is a disutility from social matchings between individuals with different opinions, either as a result of social conformism (Akerlof 1997; Bernheim 1994; Cialdini and Goldstein 2004), or because cultural differences might hinder trade (Lazear 1999), for instance making it more costly to sign contracts. The accumulation of disutilities, in turn, induces agents, both in the majority and in the minority, to change their opinions and to avoid social interactions with the individuals from whom they are culturally distant. The costs of changing opinions are idiosyncratic and issue-specific, so the model implies heterogeneous assimilation patterns, both over individuals and over traits: not all minority agents assimilate, and some cultural traits tend to be persistent. The choice over social interactions, in turn, results in the endogenous formation of social networks by homophily (Currarini et al. 2009; MCPherson et al. 2001), potentially leading to social marginalization, with further implications for the assimilation process. The endogenous social networks, together with the model calibration and with the assumption of culturally heterogeneous majorities, are new with respect to the literature on cultural transmission (Bisin and Verdier 2000, 2001; Giavazzi et al. 2019).

I propose two measures to quantify the extent of cultural assimilation in the model. The first, which I call *σ-assimilation*, is designed to compare individuals at a given point in time, and it is a measure of the average cultural distance between a minority agent and the majority. Since opinions are binary in the model, I use the Hamming distance between individual vectors of opinions to measure cultural distances, and I define an individual in the minority as more σ-assimilated if her average cultural distance from the majority is smaller. The second measure, which I call *Δ-assimilation*, is instead designed to track the evolution of assimilation over time, and it is simply computed as the first difference of the σ-assimilation measure over a pre-specified time interval. According to this second measure, there is Δ-assimilation for an individual in the minority if her cultural distance from the majority shrinks.

The model cannot be solved analytically, so I discuss a numerical solution for a calibration targeted to the European countries, for which I have joint information on values and opinions from the European Social Survey (ESS), and on demographics from the EUROSTAT census. The calibration is targeted at first-generation immigrants, for which I take the country-specific shares from census data. Using information on the immigrant's nationality, I can further construct a measure of initial cultural distances between immigrants and natives to feed in the model. The rest of the model parameters are then calibrated to match: the distribution of the frequency of social interactions for the immigrants and the distribution of the importance of tradition for immigrants, as they emerge from the ESS answers; the share of socially marginalized individuals, with few social interactions, also from the ESS.

I show that the model is able to capture several features of the data that it was not calibrated to match. Most importantly, the model is able to replicate some stylized facts, or correlation evidence, that emerges from the data. The exercise consists in computing an empirical measure of σ-assimilation of immigrants using the ESS, regressing it on some covariates and then showing that regression of the σ-assimilation measures computed on an artificial cross-section of simulated data from the model delivers the same results. In particular, I find that assimilation is weaker (higher cultural distance between the majority and the minority) in pluralistic societies characterized by a high variability of opinions within the majority. Moreover, assimilation is stronger for more socially active immigrants, but weaker in the case of immigrants whose origin country is culturally more distant, on average, from their host country. Finally, assimilation is not influenced by the immigrant share of the population. More than that, the model is able to replicate: the within-country variability of σ-assimilation; the cross-country variability of Δ-assimilation; the positive correlation between cultural assimilation and individual well-being that emerges from the data.

Once I establish the model validity in matching the empirical evidence, I use it to perform comparative statics within an environment where assimilation patterns are heterogeneous across individuals and across cultural traits. First, pluralism, that is the initial cultural heterogeneity within the majority, reduces assimilation and reduces the average size of the social networks, leading to the formation of small cultural enclaves. Second, minorities who come from countries that are culturally more distant assimilate less. Third, the immigrant share does not affect assimilation. The model also predicts more cultural assimilation in countries with high social density defined as the frequency of social interactions, although the effect is small. Social segregation, in turn, increases with social density, with the minority share, and with the initial average cultural distance between the minority and the majority. These results are robust across different model parametrizations and several model extensions.

The model, however, cannot be used to perform a welfare analysis on the potential social desirability of cultural assimilation. The main reason is that it abstracts from the trade-off associated with cultural diversity discussed by Ashraf and Galor (2013): diversity hinders the transmission of human capital and increases the transaction costs related to within-country interactions, but it also fosters creativity and, therefore, technological change. Moreover, assimilation is not necessarily desirable because the very idea of cultural assimilation abstracts from a judgment about the kind of culture that prevails in the long run. For instance, there can be assimilation of a minority to a culture of violence and discrimination, with potentially severe social and economic consequences.

The rest of the paper is organized as follows: Section 2 briefly reviews the related literature. Section 3 describes the model and the calibration procedure. Section 4 explains the construction of cultural assimilation measure, both in the model and in the data. Section 5 summarizes the tests of the model fit to the data. Section 6 illustrates the model comparative statics. Section 7 discusses several robustness checks and model extensions. Section 8 concludes. The appendix discusses additional results from the empirical analysis. An additional on-line Appendix discusses additional results and further model extensions and provides details on the construction of the vectors of opinions that define culture.

A small note before proceeding: in the paper, I use the word assimilation, instead of integration, to be consistent with the previous literature but without any particular political or moral judgment on the process of assimilation.

2 Related literature

This paper is related to the economic, sociological, and anthropological literature on cultural evolution. The main contribution in the construction of a calibrated epidemiological model with endogenous social networks and with a culturally heterogeneous majority that is consistent with the empirical evidence on assimilation in Europe.

I build on the seminal paper by Lazear (1999) (and on its dynamic extension by Konya 2005), borrowing the assumption of a positive gain from cultural assimilation stemming from lower transaction costs. Bisin and Verdier (2000, 2001) model cultural evolution as a result of the interaction between the vertical transmission within the family and the horizontal transmission outside the family, resulting in persistent cultural traits because of homogamous marriages. A similar framework appears in Panebianco (2014), who focuses on inter-ethnic attitudes. Giavazzi et al. (2019) merge the Lazear (1999) and the Bisin and Verdier (2000, 2001) models, to study the speed of cultural evolution in the US, while Algan et al. (2022) use a similar model to explain the prevalence of Arabic names in France. In a related contribution, Adda et al. (2019) show that granting legal status to immigrants reduces intermarriages. The main innovation with respect to these contributions consists in proposing a calibrated model with endogenous network formation that, consistently with the data, delivers both heterogeneity in assimilation and social segregation.

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 shares many features with those approaches, but it extends the analysis to the endogenous formation of social networks, making it also close to the literature on network[1] formation (Currarini et al. 2009, among others), on the importance of networks for immigrants' assimilation (Verdier and Zenou 2017). More broadly, my analysis is related to the economic literature on identity formation (Akerlof and Kranton 2000; Benabou and Tirole 2011; Shayo 2020 and on the recent literature on the evolution of narratives (Shiller 2017).

Grosjean (2011) proposes a gravity model of cultural integration, showing that cultural change can be slow. My model implies instead relatively fast assimilation, in line with the evidence in Manning and Roy (2010) and Cameron et al. (2015). Abramitzky et al. (2020) show instead that the speed of assimilation, in the US, did not change much over time. In a related contribution, Fouka et al. (2022) show that the inflow of a relatively more distant minority can ease the assimilation and reduce the segregation of the less distant minorities. Giuliano and Nunn (2021) propose and test a different theory of cultural evolution based on environmental similarity, showing that culture persists in case of climatic stability. I abstract from these features. Sato and Zenou (2020) propose a model of cultural integration that focuses on residential

[1] see also the models of peer-effects in networks by Patacchini and Zenou (2012) and to the model of conformism in Boucher (2016).

patterns within cities, a feature from which I also abstract, even if my model could be extended to residential, rather than only social, segregation.

With respect to the measurement of cultural assimilation, Meng and Gregory (2005) and Bisin et al. (2008), among others, quantify assimilation using intermarriages; Constant et al. (2009) propose a measure of ethnic identity based on language and self-identification; Arai et al. (2009) and Abramitzky et al. (2020) measure assimilation with the frequency of ethnic names; Aleksynska (2011) uses civic participation; Manning and Roy (2010) use a self-assessed measure of assimilation. With respect to these works, I measure cultural assimilation by leveraging a large amount of information on several cultural traits as it emerges from ESS survey questions, and I distinguish between a static and a dynamic measure of assimilation. My measures of assimilation are related to the social antagonism framework developed by Desmet et al. (2017), but, differently from them, I propose a specific metric for cultural assimilation at the individual level.

Several empirical studies highlight the persistence of culture, also among minorities and among immigrants, and my model is consistent with this evidence. Examples include Giuliano (2007) for living arrangements, Fernandez and Fogli (2005) for fertility and labor market participation, Guiso et al. (2006) and Algan and Cahuc (2010) for trust, Becker et al. (2014) for trust and (low levels of) corruption, Botticini and Eckstein (2005) for education preferences, Voigtlander and Voth (2012) for antisemitism, and Luttmer and Singhal (2011) for preferences for redistribution. My model is consistent with this persistence.

3 The model

The scope of this section is to proposes a simple theoretical framework to think about assimilation in culturally heterogeneous societies. I first describe the model setup (Section 3.1), and then the details of the calibration procedure (Section 3.2).

3.1 Model setup

A fictional country is inhabited by N citizens[2] indexed by $i \in \{1, 2, \ldots N\}$. A fixed fraction $\lambda < 0.5$ of the population belongs to a cultural minority (identifier MN), while a fixed fraction $(1-\lambda)$ to a majority (identifier MJ). The citizens match socially, every period, with a total of $z_i = \lfloor \gamma_i N \rfloor$ individuals to discuss and exchange ideas, where γ_i is an individual measure of social participation. Social participation 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 by agent i is fixed, I assume that the identity of those individuals changes. I denote with J_{it} the set of individual identifiers of the agents that match with agent i at time t, with cardinality $|J_{it}| = z_i$. Without

[2] 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).

this feature, the model will deliver less heterogeneity in assimilation with respect to the observed one.

There is a total of M issues to potentially discuss in social matchings, and the opinions are binary. I denote with $q_{it}^m \in \{0, 1\}$ the opinion 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 every day is important. The assumption of binary opinions simplifies the analysis, but it is restrictive. In the on-line Appendix, I discuss a model extension to multiple opinions, which delivers similar results. I assume that the issues differ in their salience, which I define as a 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 opinions of agent i, which is the model equivalent of culture. Both assumptions are designed to match the wide heterogeneity in assimilation over different issues observed in the data.

The agents' utility function is very stylized[3]: they simply derive a disutility when they discuss an issue with an agent who holds a different opinion. There are two possible interpretations of the disutility. The first entails the notion of social conformism (Akerlof 1997; Bernheim 1994; Cialdini and Goldstein 2004), with individuals that prefer to think and behave as the majority and that are negatively affected in case they realize that they do not. The second is related to the possibility of "missed trade" (Lazear 1999), in the sense that it is more difficult, or more costly, to sign contracts with commercial counterparts that come from different cultural backgrounds. For simplicity, I normalize[4] the per-matching disutility to one (wlg). I define the disutility of agent i over the issue m, in a given period t, as:

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

where the Θ_{ijt}^m are z_i independent draws from a Bernoulli distribution with probability θ^m. The agents are characterized by a rule-of-thumb reaction to the accumulation of disutility, which works along two dimensions: changing opinions and avoiding social interactions. In both cases, the model features tipping points. To capture the empirically observed variability in assimilation, both over individuals and over issues, I assume that the agents have an idiosyncratic switching cost, which I model as an individual and issue-specific, total disutility threshold $\hat{H}_i^m$, above which an agent switches ($h_{it}^m > \hat{H}_i^m$). Agents with high thresholds typically hold on to their opinions even in case of frequent disagreements; they are closely tied to their heritage, perhaps because of their upbringing. Viceversa, the agents with low thresholds are the conformist. These thresholds will be calibrated leveraging the survey information on the importance that different individuals attribute to the tradition. Since the opinions are binary, a switch simply entails changing from disagreement to agreement and viceversa. In this

3 See Shayo (2009); Stark et al. (2018) and Sato and Zenou (2020) for more extensive utility function specifications in models of identity formation.

4 An alternative normalization would be to have a strictly positive utility in case of interactions with individuals with the same opinions. As long as the difference between this positive utility and the disutility from interactions in case of different opinions is similar, the model will behave similarly.

baseline model, I assume, for simplicity, that past disutilities are fully discounted, as agents were memoryless: all their decisions are based on what happens in the current period. In Section 7.1, I discuss a model extension to memory, which delivers similar results.

The second reaction to disagreement is a process of social exclusion: if a matching with a given agent results in a high disutility, then all future interactions with the same agent are avoided. The implication is that the identity of the agents in social matchings is the result of previous interactions or, alternatively, there is an endogenous social network formation mechanism based on homophily (MCPherson et al. 2001). The total disutility from a matching between agents i and j, at time t, conditional on their matching, is equal to:

$$\hat{f}_{it}^{j} = \sum_{m=1}^{M} \hat{\Theta}_t^m |q_{it}^m - q_{jt}^m| \qquad j \in J_{it} \tag{2}$$

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 matchings with her from period $t+1$ onward. These flags are the result of spot interactions that lead to strong disagreements, which are akin to ideological fights. 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:

$$f_{it}^{j} = \mathbb{1}_{[\hat{f}_{i\bar{t}}^{j} \geq \zeta_i]} \qquad \text{for some} \quad \bar{t} < t \tag{3}$$

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. This endogenous network formation is an essential element of the model, which allows to capture the co-evolution of culture and social interactions. Moreover, it allows the model to match a specific feature of the data, that is the heterogeneity in social participation, both within and between countries, and the extent of socially marginalized individuals. I assume that the identity of the agents in social matchings is chosen randomly, given γ_i, but only among the non-excluded (non-flagged) individuals. For further consistency, I assume that the process of social exclusion is at work both for minority and majority agents. Furthermore, in this benchmark model, the flags are irreversible (see Section 7.1 for robustness), and they are chosen regardless of the eventual changes of opinions that happened in the period (see Section 7.1 for robustness). One possible outcome of this selection algorithm of the social network is the exclusion of all individuals, i.e., $f_{it}^j = 1 \, \forall j$ ("zero" degree, see Jackson 2010). I define this condition as social marginalization (Constant et al. 2009), and I use this information to calibrate the model.

One crucial feature of the model is that it delivers heterogeneous assimilation patterns, that is a full distribution of σ-assimilation over minority agents. In other words, not all agents from the minority assimilate even if there is convergence, on average, for the minority as a group. Moreover, assimilation is also heterogeneous by traits, and some of them are persistent even for otherwise culturally assimilated minority agents. A second distinctive feature of the model is that assimilation is also the result of intragroup contact among minority agents.

The model, because of its complexity, cannot be solved analytically, and it is not possible to formally show the existence and uniqueness of an equilibrium. The complexity, in turn, is a consequence of the many heterogeneities, and of the joint decisions over opinions and social networks, both of which are included to make the model able to match the empirical evidence. To obtain a numerical solution, I propose a calibration to a cross-section of European countries and then show that the model is able to replicate several empirical features that it is not calibrated to match. Once a numerical solution is available, I will show that such a solution is stable across simulation rounds, proving that there is no concern about potential multiple equilibria. The details of the calibration procedure are outlined in the next Section 3.2. The uninterested reader can directly jump to Section 4 that discusses how to measure cultural assimilation.

3.2 Parameters, calibration, and solution

Paramters I simulate countries composed by a fixed measure of $N = 1000$ individuals, therefore abstracting from cross-sectional population differences. I consider a total of $M = 50$ issues to potentially discuss, with salience equal to $0.02 \cdot m$, meaning that the issue $m = 1$ is discussed in 2% of the social matchings only, while the issue $m = M$, in all matchings (the results are robust for different values of M as long as this is not too small). For the maximum social density[5] D, I arbitrarily normalize it to 5%, to have a reasonable (i.e., not too big) number of social contacts, but the results turned out to be robust for different values of D (see Section 7.1 for the cases of 2.5% and 10%), thereby proving that this arbitrary normalization is not problematic.

I set the minority share λ according to the first-generation immigrants' share from the 2011 EUROSTAT census. The initial opinions of the minority are randomly drawn from a Bernoulli distribution with parameter α, while the initial opinions of the majority from a Bernoulli distribution with parameter β. To set $0 \leq \beta \leq 0.5$, I use the average variance[6] of the natives' answers to the ESS questions, which is a large survey designed to elicit differences in cultural traits between individuals (see infra for further details). The difference between α and β is the model equivalent of the initial average cultural distance between the majority and the minority. Following the literature on the vertical transmission of culture (Desmet et al. 2017 and Spolaore and Wacziarg 2009, among others), I use micro-satellite genetic distance to set it. For each country, I compute the weighted average genetic distance[7] between the immigrants

[5] Note that, in the ESS, there is no detailed information on the identity of the individuals in social matchings (minority vs majority) that I can use in the calibration.

[6] I normalize these variances so that their maximum observed (cross-sectional) value is 0.25 (maximum variance of a Bernoulli distribution), then I set them equal to $\beta(1-\beta)$ and solve for the lower root ("agreement" and "disagreement," for beliefs, are just conventional labels).

[7] I then re-scale these distances so that their maximum is equal to 0.5, which is the maximum possible difference between α and β in the model (conventional meaning of "agreement" and "disagreement").

and the natives using the immigrants' shares by nationality from the census as weights. Given the country value of β, I use these distances[8] to set α.

Calibration The rest of the parameters are calibrated to match: the empirical distribution of social interactions, the empirical distribution of the individually assessed importance of tradition, and the extent of social marginalization.

To calibrate the individual level of social participation, or social density, γ_i, which determines the number of matchings, I look at answers to the ESS question that asks about the frequency of social interactions (answers are on a scale from 1 to 7, where 1 corresponds to "Never" and 7 to "Everyday"; summary statistics in the on-line Appendix). I assume that $\gamma = D \cdot \Gamma$, where Γ is distributed according to a Beta and where D is a scaling factor, and I set the parameters of the Beta distribution to match the empirical distribution of answers in the country.[9]

The thresholds $\hat{H}_i^m$ are instead calibrated to match the empirical distribution of the answers to the ESS question on the importance "[...] to follow traditions and customs," again consistently with the empirical analysis (summary statistics in the on-line Appendix). First, I fit a Beta distribution to the discrete answers using the same procedure as for social density, to then draw randomly, from the fitted distribution, individual average thresholds for each $i \in MN$. After that, I further draw m issue-specific thresholds $\hat{H}_i^m$, for each individual, from a Uniform distribution with a mean equal to the draw from the Beta. In case $H_i^{a,b} <= 0.5$, the draw is from $U[0; 2H_i^{a,b}]$; in case of $H_i^{a,b} > 0.5$, from $U[2H_i^{a,b} - 1; 1]$.

Finally, the threshold disutility for exclusion from social contacts is calibrated to match social marginalization as it emerges from the ESS. In particular, I look at the question that asks how often the respondent "[...] Takes part in social activities as compared to others of the same age" (summary statistics in the on-line Appendix), and take, as a target, the share of respondents that answers[10]: "Much less than most." I assume that there are two different thresholds 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). Then, 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:

$$SI_T = \frac{1}{\lambda N} \sum_{i=1}^{\lambda N} \mathbb{1}_{\left[\frac{1}{N-1} \sum_{j \neq i} (1 - f_{iT}^j) \leq K\right]} \tag{4}$$

[8] In Section 7.3, I extend the model to consider a majority composed of two groups with different agreement rates β.

[9] I implement a guess and very procedure as follows. For each couple of parameters, I draw a large number of values from the distribution, then I discretize the results on a 1–7 scale and compute the frequency of each value. I then compute the mean squared difference between the simulated and the empirical frequencies and choose the couple of parameters for which such difference is minimized.

[10] 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.

matches the empirical share of socially marginalized respondents among the minority.[11] Setting $K = 0$ results in a very small percentage of marginalized minority agents in the simulation. To fit the data, I arbitrarily set $K = 0.05$, but I extensively test the results for robustness (see Section 7.1).

Solution The benchmark simulation entails 100 rounds of T=100 periods, and I consider a window of 10 time periods, at the end of the simulation, to check for the solution stability, which is the numerical equivalent of showing the equilibrium existence. The coefficient of variation of the σ-assimilation measure over this time window is equal, on average (over countries and over simulation rounds), to 0.48%, while the coefficient of variation of the degree distribution of social networks to 3%. Both values are strong indicators of numerical stability (and that 80 periods are indeed enough for the benchmark model solution). In practice, the model simulations tend to reach, quite rapidly, a point where the configuration of assimilation and segregation is stable.

Since I cannot prove formally that the equilibrium is unique, I also checked numerically for differences over multiple simulation rounds (at T=100). The average (over countries) coefficient of variation turned out to be equal to 3% and, even more strikingly, the percentage difference between the bigger and the smaller values of σ-assimilation obtained over multiple simulations is, on average (over countries) equal to 10%. For what concerns the networks, the coefficient of variation of the country-average network degree is equal, on average (over countries), to 4.4%, and the average difference between the smaller and bigger values over different simulations is equal to 15%. Overall, the numerical differences between simulations are quite small and just driven by computational noise. In other words, there is no ground to be concerned with the possibility of equilibrium multiplicity.

4 Measuring cultural assimilation

In this section, I describe how to measure cultural assimilation, both in the model and in the data, respectively at a given point in time (Section 4.1) and over time (Section 4.2).

4.1 σ-Assimilation

In the model, I compute the average difference of opinions between the majority and the minority, that is an average cultural distance, to evaluate the extent of assimilation of a minority at a given point in time, with smaller differences indicating more assimilation. Since the opinions are binary vectors, and since the number of issues is the same for all agents, I use the Hamming distance, equal to the relative number of vector positions

[11] Calibrating the two parameters ζ^{in} and ζ^{out} to match both social marginalizations within the majority and the minority is more difficult for the model, and the calibration results are inaccurate (too many combinations 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.

with different entries. The average cultural distance of a minority agent i from the majority, at time t, is equal to:

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

where k indicates the country and 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 $\sum_m |q_{it}^{m} - q_{jt}^{m}|$ for $j \in MJ$ and $\forall i$. I call this measure σ-assimilation.

For the empirical implementation, I focus on European Social Survey (ESS) to elicit opinions on a wide array of subjects spanning from religiosity, social trust, and politics to the role of women and to the importance of human values such as tolerance and respect, although the measure can be in principle computed starting from any survey. Mimicking the computations in the model, I compute the cultural distance between the minority agent i and the majority agent j at time t as the Hamming distance between their vectors of answers to the ESS questions:

$$\bar{S}_{it}^{k} = \frac{1}{|MJ|} \sum_{j \in MJ} \frac{1}{\bar{M}_{ij}} \left[\sum_{m=1}^{\bar{M}_{ij}} \mathbb{1}_{[a_{it}^{m,k} \neq a_{jt}^{m,k}]} \right] \tag{6}$$

where $\bar{M}_{ij} \leq M$ is the number of questions answered by the (i, j) pair in country k, with i in the minority ($i \in MN$) and j in the majority ($j \in MJ$), M is the total number of survey questions, $|MJ|$ is the number of survey respondents in the majority (cardinality of the set MJ) and $A_{it}^{k} = \{a_{it}^{1,k}, a_{it}^{2,k} \ldots a_{it}^{m,k}, \ldots a_{it}^{M,k}\}$ is the full set of answers. Averaging these distances over all agents in the majority, I then obtain the average cultural distance between the minority agent i and the majority. The attractive empirical feature of the hamming distance is its capability to evaluate differences over cultural traits whose empirical measurement are not on ordinal scales, which is often the case for survey questions, as well as the possibility to aggregate over several traits measured differently.

Operationally, I focus on 28 countries[12] and on the last 5 ESS waves[13] (ESS5-2010; ESS6-2012; ESS7-2014; ESS8-2016; ESS9-2018) because of the joint availability of EUROSTAT data that I use both in the empirical analysis and to calibrate the model. I only excluded the questions that ask for subjective assessments related to feelings (feeling of happiness etc.), and questions about personal experiences (victim of robberies, etc.), that are not related to what people think, as well as the variables that I use as covariates to explain assimilation. The list of questions that I used is available in the on-line Appendix.

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

13 I exclude the ESS 1–4 because they refer to the period before 2010, and I have immigrant data from the EUROSTAT census in 2011. The questions asked in each survey wave are not the same, although most of them are available for the entire time span of the analysis.

I focus on a single, well-defined minority, namely immigrants, and I assume that the immigrants respondents to the ESS are representative of the population of immigrants, thereby trusting the sampling design of the ESS sample. To check if this is a good assumption, I compared the ESS sample composition for immigrants according to gender, age, and education with the EUROSTAT 2011 census data. The results are summarized in Table 1, both for the entire sample and for the countries with the biggest share of ESS immigrant respondents, and they show that the ESS sample is indeed close to representative. The only exception is for primary and tertiary education, but, in this case, the ESS sample is not representative of nearly all countries, meaning that there are no systematic relationships between being non-representative and the other features of the data that I exploit for the empirical analysis. As for the majority, I consider all ESS survey respondents who are not immigrants, whose parents were born in the country (second-generation immigrants are excluded) and who did not define themselves as part of a minority.

One potential problem is that more integrated immigrants could be more likely to respond to ESS questions or to be included in the survey in the first place, so it is indeed possible for my empirical measure of assimilation to be an upper-bound for the observed assimilation, and potentially with a lower observed variance (missing observations of non-integrated immigrants in the the tail of the distribution). However, since the data show that the sample is representative of the population of immigrants as it emerges from the census data, the bias in my measure of assimilation should be, if anything, low.

4.2 Δ-assimilation

A second approach to evaluate the extent of assimilation is to look at the changes in average cultural distance between the majority and the minority over time. In the model, the change in average cultural distance from period t to period $t + q$, for an individual i in country k, is equal to:

$$I^k_{iq} = \left[\frac{S^k_{it+q} - S^k_{it}}{S^k_{it}} \right] \tag{7}$$

with lower values corresponding to more assimilation, basically a steeper reduction of the average cultural distance from the majority. I call this second measure Δ-assimilation. Indeed, the model delivers Δ-assimilation: the cultural distance between the minority and the majority shrinks over time (negative Δ-assimilation measure), consistently with the empirical evidence of a stronger assimilation for immigrants that spent more time in the country (see infra).

The empirical counterpart of this measure is problematic to compute because there is no panel component in the ESS, meaning that it is impossible to track cultural assimilation over time for single individuals. To overcome this issue, I considered an aggregate empirical measure obtained comparing immigrants by years or cohort of immigration. The idea is that, in case of Δ-assimilation, those who spent more time in the country, everything else equal, should be less culturally distant from the natives.

Table 1 Sample statistics

	Gender		Age		Education						Obs	
	ESS	EUROSTAT	ESS	EUROSTAT	ESS			EUROSTAT			ESS	EUROSTAT
	Female	Female	Avg	Avg	Primary	Secondary	Tertiary	Primary	Secondary	Tertiary		
All	54.2	52.0	46.9	44.4	10.1	59.6	30.3	14.2	59.7	26.1	19.60	31377.20
Ireland	50.7	50.3	40.8	36.1	14.3	51.9	33.8	7.2	54.4	38.4	1.95	733.59
Switzerland	50.9	51.5	46.3	46.6	3.6	64.8	31.6	17.1	55.2	27.7	1.93	1828.33
UK	55.9	51.8	44.9	41.1	22.2	40.4	37.4	0	53.5	46.5	1.42	7938.58
Germany	50.8	52.4	44.8	45.9	2.5	63.5	34	14.7	63.6	21.7	1.49	10905.52
France	55.3	51.4	51.3	48.3	17.4	52.1	30.5	26.2	50.2	23.6	1.04	7324.13
Estonia	63.9	60.5	62.3	60.1	3	66.8	30.2	6.9	54.1	39	1.62	197.35
Sweden	52.1	51.3	47.5	44.7	9.4	54.9	35.7	14.3	56.1	29.6	1.05	1328.68

Notes: ESS refers to sample averages from the set of immigrant respondents to the European Social Survey. EUROSTAT is the average value across immigrants from the 2011 census. Gender is a dummy for female. Age is the average age. Education is in percentage terms (for Sweden it is reconstructed from the OECD immigration database). Obs is the number of immigrants in thousands (census or sample)

Formally, I compute the empirical measure of Δ-assimilation in country k, after s periods, as:

$$\bar{I}^k_{ts} = \frac{1}{J-s}\sum_{j=1}^{J-s}\left[\frac{\bar{S}_t^{j+s,k} - \bar{S}_t^{j,k}}{\bar{S}_t^{j,k}}\right] \tag{8}$$

where $\bar{S}_t^{j,k}$ is the average empirical cultural distance between natives and immigrants that spent exactly j years in the country (J maximum), s is the time span of the comparison and t is the survey wave. I implement the computation with the 9^{th} ESS wave, administered in 2018, 7 years after the period used for the model calibration, which entails having model periods of slightly less than 1 month. Since there are relatively few immigrants respondents to the ESS, I consider 5 years cohorts: $\{j \in [0,4],\ j \in [5,9],\ j \in [10,14], \ldots, j \geq 40\}$. This implies comparing immigrants that spent between 5 and 9 years in the country to immigrants that spent less than 5 years, then comparing immigrants that spent between 10 and 14 years to immigrants that spent between 5 and 9 years, etc. For robustness, I also considered cohorts of 10 years, obtaining similar results.

The empirical computations of Δ-assimilation measures on cohorts are meaningful if the individual characteristics of the immigrants in each cohort are similar, and the data confirm this, at least for the attributes recorded in the ESS (gender, marital status, number of children, years of education, hours worked, income). The only systematic difference across cohorts that I find in the data is that the immigrants that spent more years in the country are older, but this is the by-product of the cohort construction.

5 Testing the model

I propose several tests to assess the model performance at matching the empirical evidence regarding features that it was not calibrated to match. First, I analyze the model ability to replicate several stylized facts on assimilation as they emerge from the data (Section 5.1). Second, I analyze the model predictions with respect to the dynamic of assimilation (Section 5.2). Third, I test the model performance at matching the within-country variability of sigma assimilation (Section 5.3). Fourth, I show that the model is able to replicate the empirically observed positive relationship between cultural assimilation and individual well-being (Section 5.4). Unfortunately I cannot test the model performance at matching empirical data on social networks, because of the absence of detailed, and comparable, cross-country information. The only relevant available information is the fraction of socially marginalized individuals in the majority, but I use it to calibrate the model.

5.1 Stylized facts on σ-assimilation

I first establish some empirical stylized facts on σ-assimilation and then simulate artificial cross-sections in the model to show that it is able to replicate them. The scope of the empirical analysis is only to highlight the factors that are correlated with the cultural assimilation of the immigrants, and none of the results must be interpreted causally. Notice also that the empirical analysis highlighted additional empirical results, discussed in appendix, on which however I will not focus in the rest of the paper. Given the individual empirical measures of σ-assimilation $\bar{S}^k_{it}$, I run regressions of the following form:

$$\bar{S}^k_{it} = \eta_k + \delta_t + \Upsilon X_{ikt} + \Gamma Y_{kt} + \varepsilon_{ikt} \tag{9}$$

where η_k are country fixed effects, δ_t are survey wave (time) fixed effects, X_{ikt} are individual-level covariates, and Y_{kt} are country-level covariates. Since there is no panel component in the ESS, I cannot add individual fixed effects to the regression. In line with the model set-up, I consider two determinants of assimilation with country-level variability, the immigrants' share from EUROSTAT and a measure of cultural pluralism or heterogeneity[14] of the majority computed as the country-average cultural distance between each majority agent and the rest of the majority. For what concerns the determinants of assimilation with individual variability, I consider, in line with the model: the self-assessed frequency of social interaction, as it emerges from the ESS question: "How often do you socially meet with friends, relatives or colleagues"; the self-assessed importance to "[...] follow tradition and customs," again from the ESS; the microsatellite genetic distance (Cavalli-Sforza et al. 1994; Pemberton et al. 2013; Spolaore and Wacziarg 2009, 2018) between the immigrant's origin country and her host country, which I use as a proxy for the initial cultural distance[15] (Desmet et al. 2011, 2017; Spolaore and Wacziarg 2015); three additional controls for cultural similarity, namely geodesic distance between the origin and the host country capital cities, linguistic proximity[16] (from the Automated Similarity Judgment Program - ASJP) and religious distance[17] Mecham et al. 2006 between the origin and the host country of each immigrant; a dummy equal to 1 in case the immigrant has citizenship; the number of years that the immigrant spent in the country; the age at immigration; a dummy equal to one for EU born immigrants; gender, education, employment status and religious denomination.

The regression results, or stylized facts on the σ-assimilation of immigrants, are summarized in Table 2. The first evidence, which is new to the literature and which basically motivates the analysis, is that assimilation is weaker (bigger cultural distance between immigrants and natives) in case of pluralistic societies characterized by a higher variability of opinions within the majority. Second, more socially active immigrants are more assimilated (lower cultural distance from the majority), which is

[14] Given the evidence in Desmet et al. (2017), this measure of cultural pluralism can also be interpreted as a measure of ethnic heterogeneity.

[15] The implicit assumption is that the immigrants are a representative sample of the population in their origin country, which is violated if they mainly come from a minority, inducing some measurement error. The measurement error, however, is big only in case the minority accounts for a very mall fraction of the population of the origin country and/or if it is genetically very far from the rest of the population, and both conditions are realistic only in few cases.

[16] Linguistic proximity is measured as the percentage of cognate words, with similar meanings and similar roots, over a set of basic meanings.

[17] Religious distance is measured as the relative number of common nodes in religious trees that classify all religions.

Table 2 Covariates cultural assimilation

	(1)	(2)	(3)
Pluralism	0.419***	0.423***	0.417***
	(0.052)	(0.052)	(0.050)
Genetic dist	0.083**	0.072*	0.081**
	(0.041)	(0.041)	(0.038)
Meet socially	−0.055***	−0.065***	−0.071***
	(0.016)	(0.015)	(0.016)
Important tradition	−0.578***	−0.570***	−0.554***
	(0.173)	(0.168)	(0.166)
Important tradition 2	0.133***	0.131***	0.136***
	(0.024)	(0.023)	(0.023)
Immig share	0.181	0.212	0.221
	(0.236)	(0.237)	(0.229)
Year immig	−0.010***	−0.010***	−0.008**
	(0.002)	(0.003)	(0.003)
Age immig	0.004	0.003	0.004*
	(0.002)	(0.002)	(0.002)
Citizen	−0.627***	−0.612***	−0.587***
	(0.083)	(0.078)	(0.071)
Language proximity	−0.032	−0.034	−0.025
	(0.023)	(0.022)	(0.019)
Women	−0.401***	−0.441***	−0.419**
	(0.083)	(0.082)	(0.071)
Education Years	−0.067***	−0.058***	−0.050***
	(0.014)	(0.014)	(0.012)
R^2	0.263	0.269	0.274
Obs	17,524	17,461	17,368
Controls		Emp	Emp, Rel

Notes: Dependent variable is the individual measure of σ-assimilation, equal to the average cultural distance of each immigrant from the majority (see text). Pluralism is the average variance of the answers to a subset of ESS questions. Genetic Dist is the genetic distance between the origin country and the host country of the immigrant. Meet Socially is the answer to the ESS question: "How often do you socially meet with friends, relatives or colleagues." Important Traditon is the answer to the ESS question on the "Importance to follow traditions and customs," and Important Tradition 2 is its square. Immig Share is the immigrants' share in the country. Year Imm is the number of years of residence in the host country. Age Imm is the age at immigration in the host country. Citizen is a dummy equal to one if the immigrant is a citizen of the host country. Language Proxmity is a measure of language proximity between the origin country and the host country of the immigrant. Women is a dummy equal to one for females. Education Years is the number of years in formal education. All regression include: A dummy for immigrants from countries in the European Union, total population, the geodesic distance between the origin country capital city and the host country capital city, religious distance between the origin and the host country, country fixed effects and survey wave (year) effects. Controls indicates the presence of additional control variables in the regression, specifically: emp in case employment status dummies are included and rel in case of religious denomination dummies are included. The observations refer to 27 countries and 5 ESS waves (2010, 2012, 2014, 2016, 2018). Clustered standard errors at the country level in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

consistent with the analysis by Verdier and Zenou (2017) and Patacchini and Zenou (2012). Third, assimilation is stronger for immigrants that spent more time in the country, suggesting that there is cultural assimilation over time, in line with the evidence of Giavazzi et al. (2019) for the US and Manning and Roy (2010) for the UK, among others. Fourth, immigrants with a higher initial cultural distance are less assimilated, which is again in line with the result of a differential speed of assimilation by country of origin in Giavazzi et al. (2019). Fifth, assimilation does not depend on the immigrants' share in the country.[18] Sixth, cultural assimilation is a convex function of the importance assigned to tradition, which extends the result by Giavazzi et al. (2019) who find more assimilation in case of traits parents care more about. These regression results are robust across specifications, that is for alternative sets of controls. Moreover, the results are robust in case of inclusion of the square of the immigrants' share, to account for possible non-linear effects in line with the analysis in Lazear (1999), and the coefficient on the square of the immigrant share turned out to be not statistically different from zero.

To the test if the model is consistent with the empirical correlations, I simulated an artificial cross-section of individual σ-assimilation, feeding the model with random choices of the main parameters that reflect the empirical determinants of assimilation (within their empirical ranges), to then regress σ-assimilation on those parameters. The results are summarized in Table 3 for a simulation of 200 artificial countries,[19] and closely resemble the empirical results. Consistently with the empirical analysis, the largest effect is for pluralism, while the effect of social participation is only minor. The convex relationship between assimilation and the importance of tradition is a consequence of the cultural evolution process. In particular, minority agents who are very closely tied to their traditions have a high disutility threshold and rarely change opinion, resulting in less σ-assimilation. Minority agents with very small thresholds, instead, change opinion very often, and the resulting lack of stability prevents them from assimilating (Table 4).

Importantly, notice that these results can also be used to motivate the construction of the model. In particular, the relationship between assimilation and pluralism can emerge only in a model with individual heterogeneities (more on that in Section 5.3). Similarly, the endogenous choice of networks is what delivers the relationship between social participation and assimilation.

5.2 Assimilation over time

The second test of the model entails its performance at capturing the dynamics of cultural assimilation. The exercise consists in feeding the model with the observed cross-section of parameters, computing Δ-assimilation measures, and comparing them

[18] Empirically, this result could be the consequence of the effect described by Fouka et al. (2022): the inflow of a minority that is culturally more distant from the majority increases assimilation for the minorities characterized by less cultural distance, with net effects that depend both on the size of the new immigrants and on their origin country but that, in principle, are ambiguous.

[19] The number of observations in each simulation is different because the model parametrization is country-based, so different randomly chosen immigrants' shares deliver a different number of individual observations on σ-assimilation for fixed number of simulated countries.

Table 3 Regression on simulated individual data

	Bench	Robustness			
		High Dens	Family	Split	Discount (μ=0.5)
Pluralism	1.718***	1.855***	1.762***	1.809***	1.309***
	(0.051)	(0.050)	(0.049)	(0.038)	(0.041)
Genetic Dist	0.270***	0.258***	0.388***	0.296***	0.419***
	(0.028)	(0.027)	(0.025)	(0.020)	(0.026)
Meet socially	−0.902***	−0.138**	−0.687***	−0.689***	−0.346***
	(0.238)	(0.070)	(0.160)	(0.160)	(0.1138)
Important trad	−0.983***	−0.992***	−0.817***	−0.974***	−0.479***
	(0.073)	(0.074)	(0.057)	(0.059)	(0.035)
Important trad 2	0.774***	0.805***	0.650***	0.769***	0.468***
	(0.055)	(0.054)	(0.042)	(0.044)	(0.029)
Immig share	0.049	0.053	0.048	0.012	0.032
	(0.046)	(0.033)	(0.041)	(0.031)	(0.032)
R^2	0.688	0.691	0.729	0.682	0.608
Obs	15,571	15,374	16,154	15,384	15,745

Notes: Dependent variable is the individual simulated measure of σ-assimilation, equal to the average cultural distance of each immigrant from the majority, delivered by the model simulation. The parameters used at each simulation round are randomly drawn from the empirically observed ranges. Pluralism is the average variance of the answers to a subset of ESS questions. Genetic Dist is the genetic distance between the origin country and the host country of the immigrant. Meet Socially is the answer to the ESS question: "How often do you socially meet with friends, relatives or colleagues." Important Trad is the answer to the ESS question on the "Importance to follow traditions and customs." Important Trad 2 is the square of imptrad. Immig Share is the immigrants' share in the country. Bench is the benchmark model specification. High dens refers to the model with maximum social density in the country (D) normalized to 10%. Family refers to the model with families. Split refers to the model with two groups within the majority, with size $\eta = 0.5 = 1 - \eta$. Discount ($\mu = 0.5$) refers to the model with discounting of past disutilities equal to 0.5. Clustered standard errors at the (artificial) country level in parentheses. 200 artificial countries for each simulation. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

to the empirical counterparts. The results are summarized in columns (1) and (2) of Table 5. To smooth out the computational noise, I simulated 50 cross-sections and then took averages over simulation runs. The correlation between the simulated and the empirical measure of Δ-assimilation is equal to 0.612 when using 5 years cohorts, and 0.538 when using 10 years cohorts. Overall, the model captures reasonably well the evolution of cultural assimilation. This result is important because it also address one of the potential model drawbacks, which is the absence of selective return migration: non-assimilated immigrants are more likely to leave the country, meaning that the model is at risk of under-estimating assimilation over time, but the results show that this is not the case. One potential explanation is that return migration is not common in the dataset that I have, perhaps because of the relatively short time span.

5.3 Individual variability of assimilation

The third test of the model concerns its ability to match the observed within-country variability of σ-assimilation. This is particularly important because it helps motivating

Table 4 Assimilation and well-being

	(1) Data	(2) Simulation
Assimilation	−4.190***	−0.405***
	(0.717)	(0.035)
R^2	0.111	0.616
obs	17,481	15,040

Notes: Dependent variable in column (1) is the answer to the ESS question on the feeling of happiness (answers on a scale from 1 to 10). Dependent variable in column (2) is one minus the average accumulated disutility at the end of the simulation in 200 artificial countries defined by a random choice of the simulation parameters within their observed ranges. Assimilation is the individual measure of σ-assimilation (average hamming distance from the vectors of opinions of the majority). Controls included in the regression on actual data (column 1): country fixed effects, survey wave (time) effects, a dummy for citizenship, a dummy for gender, the years spent in the country, the age at immigration, the number of years in formal education, the genetic distance between the origin country and the host country of the immigrant, frequency of social interactions, importance of tradition (and its square), immigrants's share, pluralism in the majority (average variability of ESS answers) Controls included in the regression on simulated data (column 2): genetic distance between the origin country and the host country of the immigrant, frequency of social interactions, importance of tradition (with its square), immigrants' share, pluralism in the majority (average variability of ESS answers). Clustered standard errors at the real (column 1) or artificial (column 2) country level in parentheses. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$

one of the main modelling choices, namely the individual heterogeneities over opinion switching costs.

I simply check if the simulated and the empirical distributions of cultural distance between the immigrants and the natives are statistically different, running Kolmogorov-Smirnov tests of equal distributions in each country. The results are reported in column (3) of Table 5. Averaging over simulations, the null hypothesis of equal distributions cannot be rejected, at the 1% confidence level, in 61% of the cases.[20] Figure 1 plots the simulated and the empirical distribution of σ-assimilation for 9 selected countries, where the simulated distribution were re-scaled to the mean of the observed one. The countries are simply selected on the basis of their prominence, size and political importance. The graphs for the other countries in the sample are in on-line Appendix.

Overall, the model implies a slightly higher variability of assimilation with respect to the data, but it matches the distributions particularly well for many countries such as Germany and Ireland. The model however does a particularly poor job at matching the observed variability of σ-assimilation for Italy. To gain more insights on the potential determinants of the model performance along this dimension, I regressed the cross-section of euclidean differences between the simulated and the empirical distributions

[20] This figure is obtained computing the percentage of non-rejections in each cross-section simulation and then averaging over simulations. Thus it is the average number of countries for which the simulated and the empirical distributions are not statistically different at the specified confidence level.

Table 5 Evaluating the model performance

Model	Δ-Assimilation		σ-Distr	
	5y (1)	10y (2)	5% (3)	1% (4)
Benchmark	0.612	0.538	42%	61%
$K = 0.1$	0.600	0.569	31%	46%
$K = 0.01$	0.615	0.560	35%	50%
$K = 1.5$ std	0.648	0.577	36%	51%
D 10%	0.597	0.589	46%	61%
D 2.5%	0.601	0.507	42%	54%
Family	0.495	0.527	77%	85%
$\mu = 0.5$	0.719	0.645	50%	77%
$\mu = 0.9$	0.362	0.393	54%	81%
Split majority, $\eta = 0.5$	0.433	0.462	58%	69%
Split majority, $\eta = 0.25$	0.567	0.513	46%	61%

Notes: Δ-Assimilation is the correlation between the empirical and the simulated cross-sections of 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). σ-distr is the percentage of countries for which the null hypothesis of equal distributions of σ-assimilation over minority agents in the simulation and in the data is not rejected (Kolmogorov-Smirnov test, average over simulations) at the 5% level (column 3) or 1% level (column 4). Imm refers to the model calibrated for (first generation) immigrants 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 and 10y refer to the empirical computations of Δ-assimilation using 5 years and 10 years cohorts. Model specification in the fist column. K is the threshold percentage of social network members below which an individual from the minority is defined as socially marginalized (1.5 std is from the mean number of members). D is the normalization for the maximum social density in the cross-section. μ is the discounting factor for past disutilities ($\mu = 1$ for full discounting). Family refers to the model with families. Split majority is the model with two groups within the majority (η and $1 - \eta$ shares)

of cultural distance on the parameters used for the simulation. The result is that the minority share, the social density, the initial cultural distance between the majority and the minority and cultural pluralism in the majority are not statistically significant. Thus the differences between the model and the data are not systematically related to most of the mechanisms that drive assimilation in the model. The only significant variable in the regression (at the 5% level) is the shape parameter b of the Beta distributions of the thresholds $\hat{H}_i^m$, with higher values associated to smaller distances. Since b is positively related to both the mean and the variance of the thresholds, this means that the model works best in case of sufficiently high and volatile thresholds. This results is not surprising, given that, with small thresholds, opinion changes become too frequent, which translates into an excessive variability of σ-assimilation with respect to the data. In case of Italy, the problem is exactly the small threshold and the resulting instability.

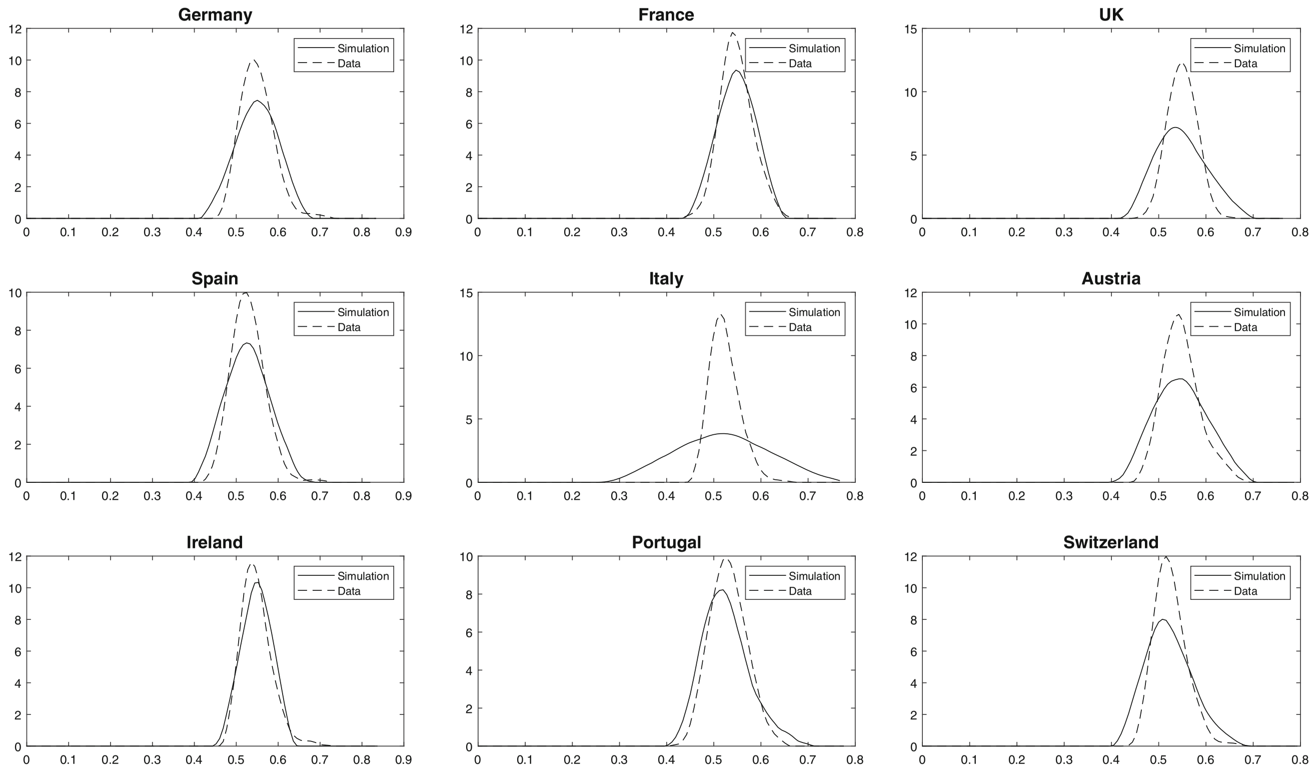

Fig. 1 Simulated and empirical distributions of cultural distance. **Notes**: Simulated (solid line) and empirical (dashed line) distributions of cultural distance for 9 selected countries. Simulation for immigrants. Empirical measures for immigrants who have spent at least 10 years in the country. Simulated distributions re-scaled to the mean of the empirical ones

5.4 Assimilation and well-being

The last test of the model performance entails the relationship between cultural assimilation and individually assessed well-being. As empirical measure of well-being, I use the ESS questions that asks about the feeling of happiness; in the model, I simply look at the accumlated disutility. The results are summarized in Table 4 and show that, both in the model and in the data, assimilation and well-being are positively correlated. In greater detail, column (1) of Table 4 reports the results of the regression of the ESS question on happiness on the empirical measure of σ-assimilation with the same empirical specification of Eq. 9. Column 2 reports instead the results of the regression of a simulated model indicator of individual well-being, equal to 1 minus the average disutility over all issues at the end of the simulation, on the individual measures of σ-assimilation and on the parameters used for the simulations, in the spirit of the exercise summarized in Section 5.1. In both cases, the regression coefficient on σ-assimilation is negative and strongly significant: the bigger the average cultural distance from the majority, the lower the well-being.

6 Comparative statics

In this section, I discuss the comparative statics, starting from a benchmark calibration with the cross-sectional median values of the main model parameters. I look at the response of 4 outcomes: the distributions of σ-assimilation over minority agents at the end of the simulation (kernel estimate), the median and the interquartile range of the distribution of Δ-assimilation (in percentage terms, with a linear smoothing), the degree distribution of the social networks at the end of the simulation (normalized number of social contacts, kernel estimate) and the average segregation of minority agents, measured as the ratio of social contacts within the minority to total social contacts.

Pluralism The first comparative static is for pluralism, that is for the variance of opinions within the majority equal to $\beta(1-\beta)$, which is central to the analysis. The results are in Fig. 2. Since the majority agents are allowed to change opinion, the comparative statics must be intended with respect to the initial level of pluralism.

More (initial) pluralism in the majority impairs both σ and Δ assimilation. To get the basic intuition, consider a single minority agent that disagrees about a given issue in a society in which a share $\beta > 0.5$ of the population agrees (smaller values of β do not lead to any action), and in which majority agents are so attached to their opinions that they never change them. The bigger is the value of β, the bigger is the probability, for a minority agent, to accumulate disutilities from purely random social interactions and, therefore, the more likely is the agent to switch, therefore reducing his cultural distance from the majority. But the bigger is β the smaller is the level of pluralism in this country, which explains the result. So the lower levels of assimilation in heterogeneous societies, in the model, does not stem from the endogenous network formation channel and from the endogenous opinion changes in the majority.

In a model with endogenous network formation, there is an additional important effect of pluralism, again going through the increased volatility of the cultural identity

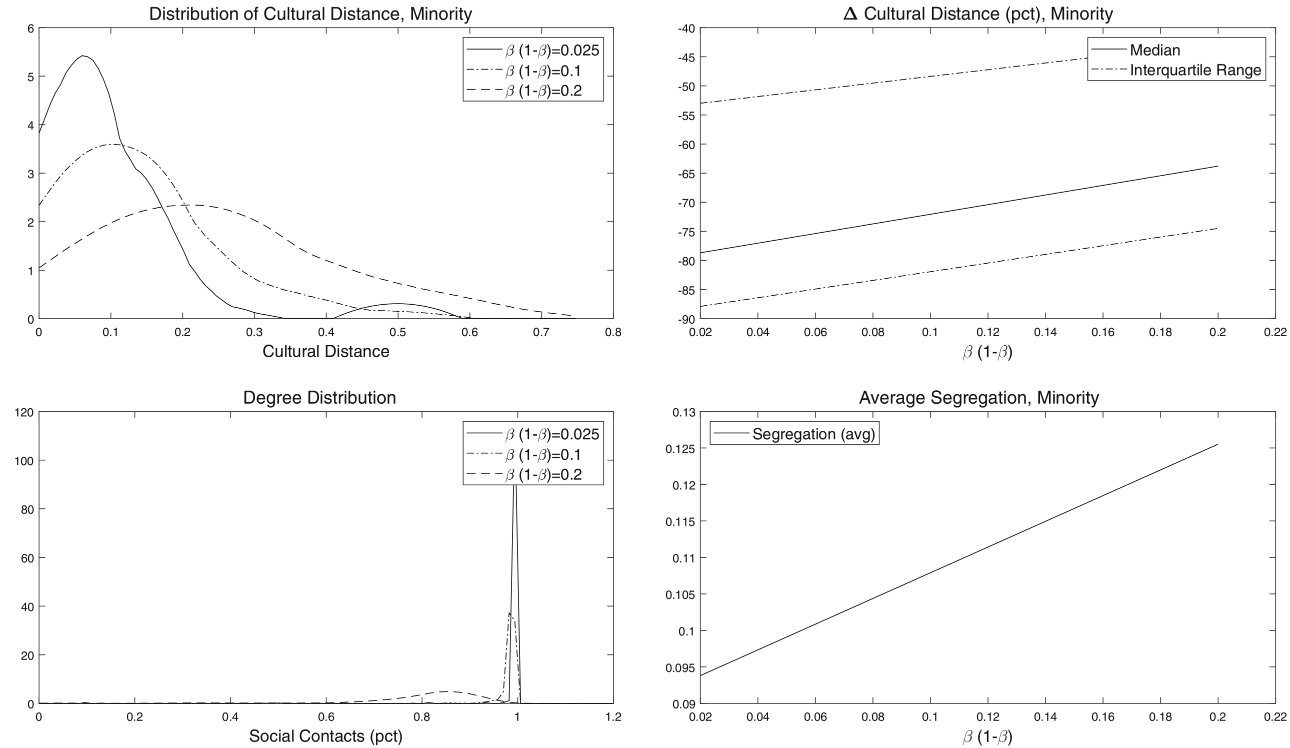

Fig. 2 Comparative statics: pluralism. **Notes**: $\beta(1-\beta)$ is the variance of opinions in the majority (see text). Upper-left panel: kernel density estimates of the simulated distributions of cultural distance between the minority agents and the majority at the end of the simulation. Upper-right 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 networks (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

of the majority agents in social matchings. Since it is easier, in case of high pluralism, to match with culturally distant agents, flags become more frequent, and social networks become, on average, smaller and more segregated, thereby reducing social contacts between the minority and the majority and, therefore, further impairing assimilation. The fact that culturally heterogeneous societies become more segregated is consistent with previous literature on social networks (see Currarini et al. 2010, among others).

Overall, both Δ and σ assimilation are more difficult in pluralistic societies, and small enclaves emerge. As an empirical example, minorities in Italy are more σ-assimilated with respect to France, despite the similar cultural distance and social density, because of the cultural homogeneity of the majority. Consistently with the empirical analysis, the magnitude of the effect of pluralism on assimilation is also quantitatively large. Importantly, these comparative statics will be the same even in case of different levels of the initial cultural distance between the majority and the minority (unless of course this is very small, but that would make the problem uninteresting), in case of different levels of social participation, and in case of different minority shares. In case of minorities that come from culturally more distant countries, the effect on segregation is actually bigger, as expected. Moreover, even assuming that only minority agents are allowed to change opinions will deliver the same results.

Minority share Figure 3 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 new immigration or in case of a higher population growth rate for the minority. Bigger minorities, for fixed social participation, imply a higher probability of social interactions with minority agents, even in a framework of purely random matchings. In case of homogeneous minorities, sufficiently different from the majority, this would imply less assimilation. But in case of heterogeneous minorities, more intragroup contacts do not necessarily lead to less assimilation, since the interactions between culturally different minority agents can also trigger opinion changes. As for network formation, bigger minority shares lead to the emergence of social networks that are more segregated, and, on average, smaller especially in case of lower heterogeneity within the minority, as a consequence of less frequent flags, thereby making intragroup contacts within the minority more frequent. Less interactions of minority agents with the majority in these more segregated networks, in turn, impair assimilation. The net effect on assimilation of these contrasting forces, for empirically plausible levels of λ and α, as shown in Fig. 3, is actually very small, which is also confirmed by the evidence discussed in Section 5.1. The effect on assimilation of bigger minority shares will be a reduction only in case of very big ($\lambda > 30\%$) minorities, although, in this case, the very notion of a minority is challenged. The comparative static is consistent with the empirical evidence. For instance, Switzerland and Norway are both characterized by assimilated minorities (small average empirical σ-assimilation), although the immigrants share in Switzerland is twice as big as the one in Norway. Moreover, Poland, Hungary and Czech Republic are characterized by non-assimilated minorities even if the immigrants share is quite low.

Initial average cultural distance Figure 4 shows the comparative statics with respect to the initial average cultural distance of the minority $\alpha - \beta$. The bigger is the average

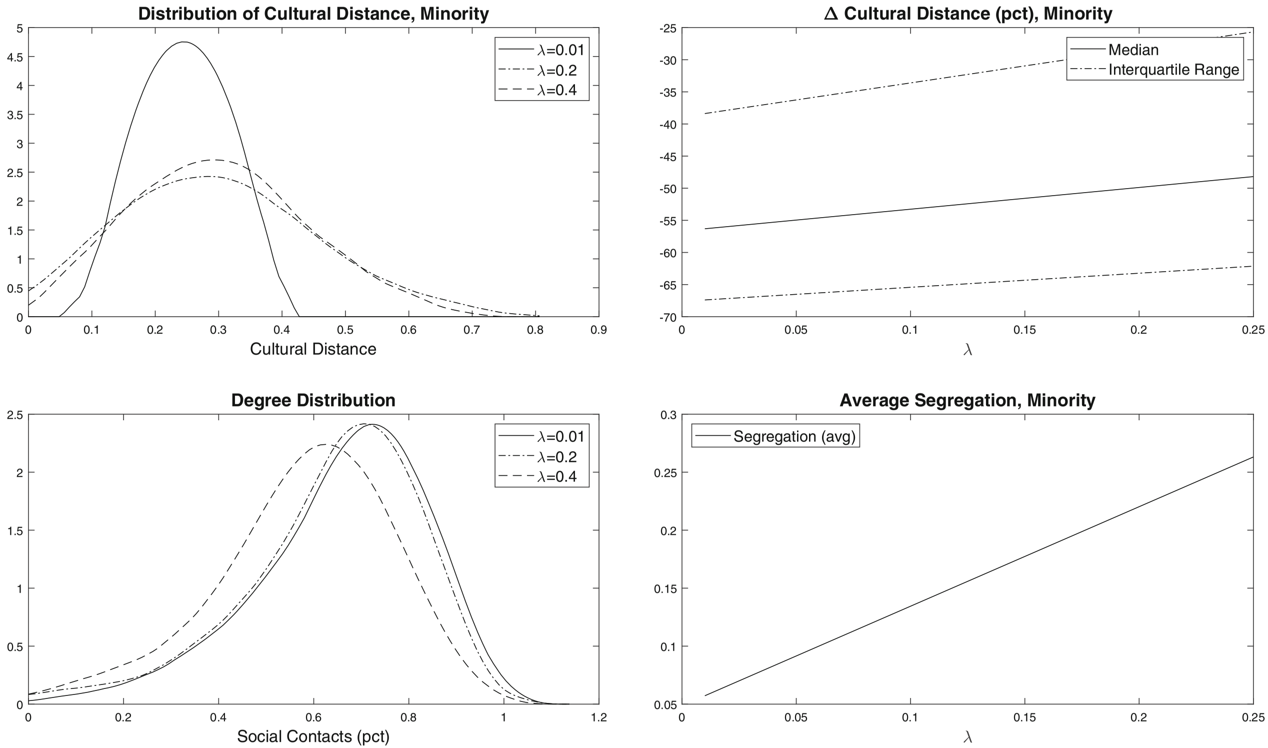

Fig. 3 Comparative statics: minority share. **Notes**: λ is the minority share. Upper-left panel: kernel density estimates of the simulated distributions of cultural distance between the minority agents and the majority at the end of the simulation. Upper-right panel: median and interquartile range of 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 networks (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

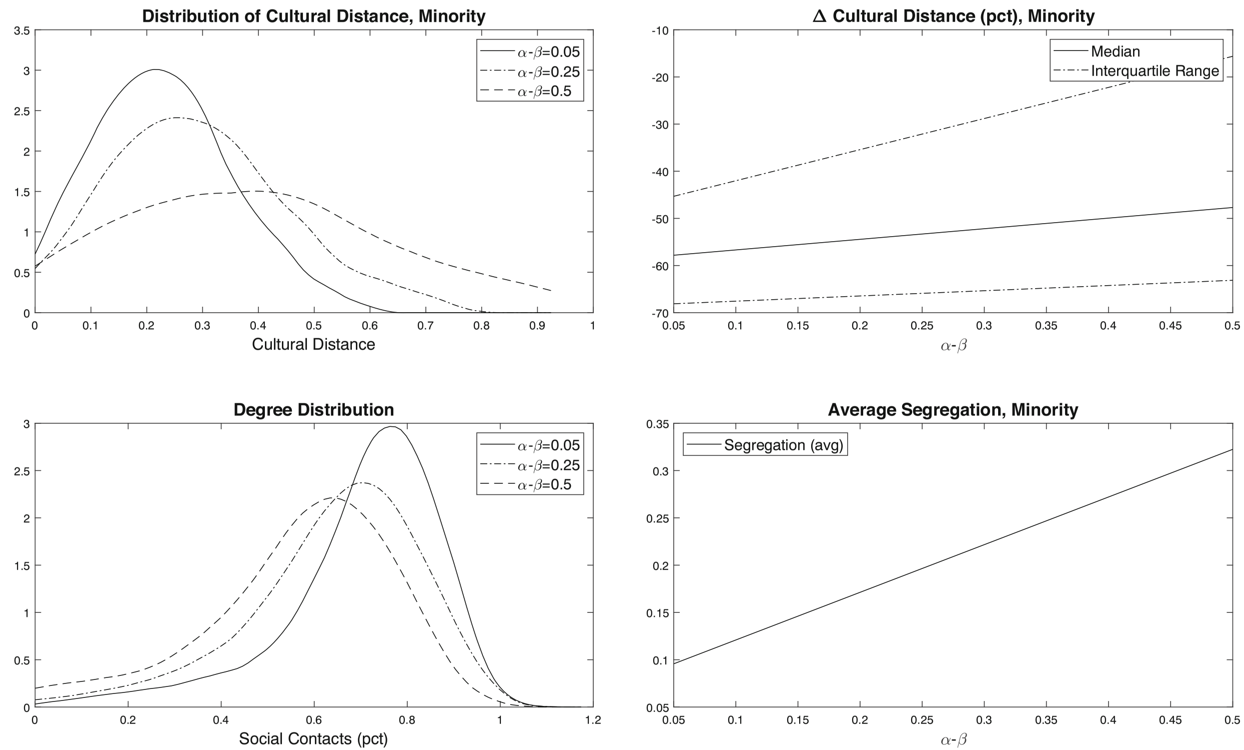

Fig. 4 Comparative statics: initial average cultural distance. **Notes**: $\alpha - \beta$ is the average cultural distance between the majority and the minority at the beginning of the simulation (see text). Upper-left panel: kernel density estimates of the simulated distributions of cultural distance 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 networks (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

initial cultural distance, the bigger is the probability of social matchings with majority agents with different opinions, meaning that opinions will change more often but also that flags become more frequent. The more frequent flags, in turn, determine the emergence of segregated social networks that, for minorities that are more different from the majority, impair assimilation. Moreover, there will also be more volatility of assimilation as a result of increasing randomness in the identity of the individuals in matchings determined by the bigger initial cultural distance. Overall, there will be a bigger share of non-assimilated minority agents, and less overall σ-assimilation, with smaller and more segregated social networks. As an empirical example, among the (potentially many) reasons why big minorities in Switzerland are more σ-assimilated than small minorities in Hungary, there is the smaller average initial cultural distance between the majority and the minority in Switzerland. Shutting down the endogenous network formation channel determines smaller effects on σ-assimilation, although the main results of less σ-assimilated minorities in case of bigger initial levels of $\alpha - \beta$ remains. The comparative statics is also similar in case of bigger minorities.

Social density Figure 5 shows the comparative statics with respect to the maximum level of social density D. Along this exercise, the average, country-level, social participation increases, but its within-country variability remains fixed. In the absence of endogenous network formation, different levels of maximum social density will not impact on assimilation, as this will only increase proportionally the number of social matchings with culturally different and culturally similar individuals. In case of endogenous network formation, a higher social density implies more opinion changes and more flags because of the more frequent matchings with culturally distant individuals. The net effect on assimilation is a small increase, because the distribution of social contacts shifts rapidly to the left, impairing assimilation, and limiting the positive effect on assimilation of increases opinion changes. Overall, socially dense societies display more σ assimilation, smaller social networks and stronger social segregation, although the magnitude of the effect on assimilation is small, consistently with the empirical evidence. In case of bigger or culturally closer minorities, the overall effect of social density on assimilation is even slightly smaller.

7 Robustness and extensions

In this section, I analyze the robustness of the results to alternative parameter values (Section 7.1), and discuss two model extensions: to families (Section 7.2) and to polarized majorities (Section 7.3). In all cases, the analysis of the model delivers similar results. Further robustness exercises can be found in the on-line Appendix.

7.1 Robustness

The baseline calibration features an arbitrary normalization of the maximum possible social density D to 5% (each agent engages at most in $0.05 \cdot N$ social matchings

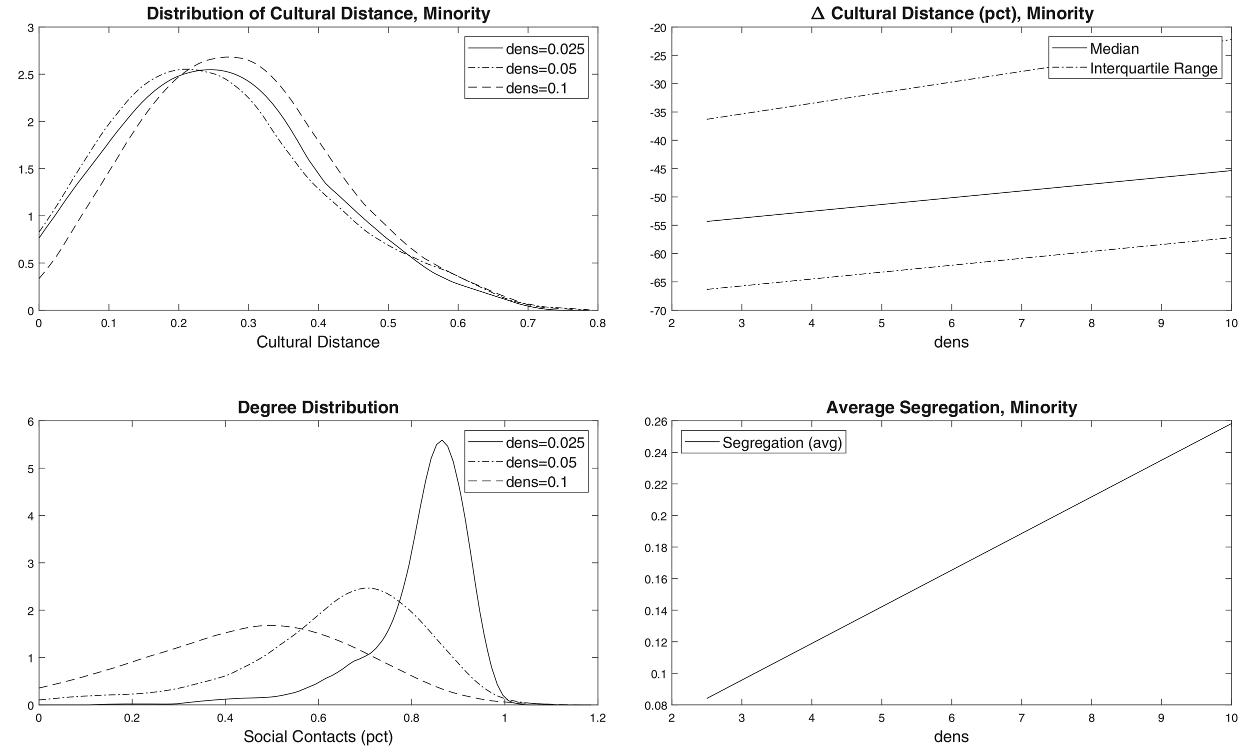

Fig. 5 Comparative statics: social density. **Notes**: dens is the normalized maximum level of social density (see text). Upper-left panel: kernel density estimates of the simulated distributions of cultural distance between the minority agents and the majority at the end of the simulation. Upper-right 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 networks (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 maximum social density. D

per period). I simulated the model with two alternative maximum density values, respectively 10% and 2.5%, and the simulation results turned out to be very similar to the benchmark (see Tables 2 and 5).

As a second robustness test, I considered a model extension to encompass memory and discounting of past issue-specific disutilities. In particular, I defined the total accumulated disutility H_{it}^m, for each agent i and issue m, as a weighted average of the actual disutility h_{it}^m and of the discounted past disutilities H_{it-1}^m:

$$H_{it}^m = \phi_i(1-\mu)H_{it-1}^m + (1-\phi_i)h_{it}^m \tag{10}$$

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. Then, I assumed that changes of opinions occur when the total disutility H_{it}^m is above the threshold $\hat{H}_{it}^m$. Within this new specification, the baseline model is a particular case with $\mu = 0$ (full memory). With discounting (shorter memories, $\mu > 0$), given the thresholds $\hat{H}_i^m$, there are less frequent changes of opinions, resulting in a slower convergence. The model performance at matching the empirical evidence, however, remains unchanged. Tables 2 and 5 show some examples for $\mu = 0.5$ and $\mu = 0.9$ and weights to past disutilities ϕ_i randomly drawn[21] from a uniform distribution between 0 and 1.

As a third test, I considered three alternative values of the thresholds number of social contacts below which the agents are defined as socially marginalized, respectively 10% of N, 1% of N, and below 1.5 standard deviations[22] from the mean of the country-level distribution of social contacts. The model performance is in line with the benchmark (see Tables 2 and 5), and the comparative statics unchanged. Note that assuming discounting of the individual disutilities which are relevant for flagging individuals, much as in the previous robustness test for the issue-specific disutilities, would result in higher thresholds to exclude individuals, without much changes in the equilibrium result.

Flags, in the model, are irreversible, which means that flagged agents cannot be re-instated in the social network in case the agent changes opinions as part of the assimilation process. To test for robustness, I considered an alternative model with reversible flags, either at a fixed exogenous rate, or with a per-period probability equal to the proportion of opinions changed in the period as follows: $\frac{1}{M}\sum_{m=1}^{M}\mathbb{1}_{\{q_{it}^m \neq q_{it-1}^m\}}$. In both cases, the results turned out to be in the line with the benchmark, even in case of a relatively high exogenous reversal probability of 0.5. The only difference, in this alternative model, is that the composition of the social networks tends to be more stable over time.

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

21 To avoid confounding effects in the interpretation of the results, I draw the individual weights independently at each simulation round (i.e., the weights are 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.

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

choose it as benchmark, is that there are not enough immigrants respondent to the ESS in each region to meaningfully calibrate the model and to reliably compute the empirical assimilation measures, whose cross-sectional variability might simply reflect differences in individual characteristics. Moreover, the classification into regions also changed in the period that I analyze, making also spatial comparisons complicated.

A potential problem with the computation of the empirical σ-assimilation measure is that, if the number of questions answered by each pair $\bar{M}_{ij}$ is too volatile, the resulting assimilation measures are not comparable. Focusing on a common subset of questions, answered by all agents, is not a feasible solution because it will severely limit the scope of the analysis, that hinges on the complexity of the definition of culture. For the empirical application on ESS data, this is not an issue, since the number of missing answers is rather small. To ensure comparability even in case of high volatility of the number of answered questions, I introduced a small correction, basically assuming a disagreement rate, over the non-answered questions, equal to its country-level average. In greater detail, the average corrected measure of σ-assimilation for the minority agent i in country k and time t, is computed as follows:

$$\hat{S}_{it}^{k} = \frac{1}{|MJ|} \sum_{j \in MJ} \frac{1}{M} \left[\sum_{m=1}^{\bar{M}_{ij}} \mathbb{1}_{[a_{it}^{m,k} \neq a_{jt}^{m,k}]} + (M - \bar{M}_{ij})\, \Pi^{k} \right] \tag{11}$$

where Π^k is the average distance over all minorty-majority pairs in country k:

$$\Pi^{k} = \frac{\sum_{i \in MN} \sum_{j \in MJ} \left[\sum_{m=1}^{\bar{M}_{ij}} \mathbb{1}_{[a_{it}^{m,k} \neq a_{jt}^{m,k}]} \right]}{\sum_{i \in MN} \sum_{j \in MJ} \bar{M}_{ij}} \tag{12}$$

This correction is equivalent to weighting the individual hamming distances between the vectors of opinions of agents i and j proportionately to the number of answered questions. The correlation between $\hat{S}_{it}^{k}$ and $\bar{S}_{it}^{k}$ in the cross-section of individual data turned out around 0.99, as a consequence of the relatively small number of missing answers. The conclusion is that the discrepancies in the number of answered questions is not a concern.

7.2 Extension I: families

The baseline model with fully random matchings within the social network ignores the role of the relationships within the family. The motivation is that my model focuses on immigrants and, in particular, on their relationship with the majority in the host country, while family relationships are more important, perhaps crucial, drivers of cultural assimilation for second-generation immigrants (Bisin and Verdier 2000, 2001, among others). To test the model robustness, I extended it to account for family relationships, in reduced form, assuming that a fixed fraction of the social matchings takes place with the same subset of individuals drawn from the own social group, and that those individuals cannot be excluded from the social network regardless of the accumulated disutility.

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,[23] 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. Importantly, I assumed that the disutility assigned to disagreement among people within the family is equal to the disutility assigned to disagreement with people outside the family, thereby ignoring the potentially higher weight given to family interactions, especially by younger individuals.[24]

There is less overall cultural assimilation in this alternative model: the median cross-country σ-assimilation is 0.466 (std 0.075) as compared to a benchmark of 0.449 (std 0.071), while the median cross-country Δ-assimilation is -8.51 (std 5.51), versus -12.79 (std 9.24) of the baseline model without families. Putting it differently, cultural traits tend to be, on average, more persistent. The model performance at matching the stylized facts of σ-assimilation is however intact (see Table 2), and the model can still match the cross-country variability of Δ-assimilation (see Table 5). Family relationships, together with a lower level of σ-assimilation, also determine a smaller variability of σ-assimilation, mostly because there are fewer well-assimilated minority agents. As a result, the model performance at matching the within-country variability of σ-assimilation improves. As for the comparative statics, they are in line with the benchmark.

The conclusion from this exercise is that, if family relationship are important, the benchmark calibrated model will slightly underestimates the persistence of culture and it will overestimate the variability of assimilation.

7.3 Extension II: polarized majorities

The baseline model features one majority group defined by an average agreement rate β. In this ection, I extend the model to a setting with a polarized majority composed by two groups. In particular, I assume that the average 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 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. 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 alternative model, the average agreement rate among the minority tends to be, over time, in between the average opinions of the two majority groups, a result which is akin to the convergence to a "Neutral" culture in fragmented societies highlighted by

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

[24] A model with asymmetric disutilities is better suited, among others, to analyze cultural assimilation for second-generation immigrants.

Lazear (1999). (see the on-line Appendix for an illustration). The model performance (see Tables 2 and 5) and the comparative statics are close to the benchmark. The results obtained with $\eta = 0.25$ and $\eta = 0.75$ are, in all respect, similar. In conclusion, the results from the analysis are robust to the possibility of polarization in the majority.

8 Discussion and conclusion

Summarizing the results from the analysis, the model implies: (1) Less assimilation in case of pluralistic (culturally heterogeneous) majorities. (2) Less assimilation for minorities coming from culturally distant countries. (3) More assimilation in ase of higher social density. (4) No effect of the minority share on cultural assimilation. (5) More average segregation for culturally distant and big minorities, for high social density and for pluralistic majorities. (6) Smaller social networks in pluralistic and socially denser societies.

The model has several implications when it is interpreted in terms of immigration (i.e., with a minority made up by immigrants). First, it helps understanding why immigration is more accepted in some areas or historical period rather than others. For instance, assuming that social media increase social density, in the sense of increasing the frequency of social interactions and exchanges of ideas, than the model predicts less assimilation and, therefore, less acceptance of immigration when the use of socials is widespread. This can explain the strong anti-immigration responses in Europe following the refugees crisis (2014–2017). Second, the model can be used for policy predictions. For instance, it implies that restrictive immigration policies 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 influence assimilation.

The question, however, is if assimilation is a legitimate policy objective to pursue and, as already stressed from the introduction, the model is ill equipped to perform this analysis. The main reason is the absence of one of the positive effects of cultural diversity, highlighted, among others, by Ashraf and Galor (2013), namely its possibility to foster creativity and technological change. Moreover, assimilation to a culture that does not promote, say, creativity, and patience, will not be beneficial for long-run growth even if, per se, assimilation will determine lower transaction costs between individuals.

The methodology that I propose to assess cultural assimilation can also be used to quantify assimilation 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, as well as for second-generation immigrants and for other, self-assessed, minorities, The problem is that such an analysis requires larger surveys than the ESS, with a sufficiently big number of minority agents to meaningfully compute the empirical measures, together with abundant outside information to properly discipline the model. In this respect, the aggregate, country-level analysis of assimilation that I proposed is limited in scope: assimilation at the country level might hinder the presence of non-assimilated cultural enclaves among specific groups or areas.

The analysis can be also extended to residential segregation, either as an alternative to social segregation or as an additional individual choice. In the former case, minority agents would react to the accumulated disutility either changing opinions or changing neighborhood, choosing the one where the probability to match with similar individuals is higher. In the latter case, the agents would change neighborhood in case of high disutility regardless of the small social networks. The problem with both extension is that the calibration requires survey data at a very fine geographical level in order to capture, say, the nuances of neighborhood choice within a city. The clear direction for future research is to attempt a more disaggregated analysis, perhaps developing an ad-hoc survey.

The epidemiological model can also be used to study the emergence of fads or, in general, the diffusion of ideas among specific groups. For instance, it can rationalize the selective prevalence of a xenophobic attitude conditional on the use of social media, on the population density and on the identity of the immigrants in the city or neighborhood. Alternatively, it can be used to explain technology adoption. These are all potential avenues for future research.

One drawback of the analysis is that I do not propose an empirical validation of the model results with respect to social networks. The main reason is that such an analysis requires comparable cross-country data on social network formation and evolution over time, ideally in a context of increasing immigration, which I do not have. A further direction for future research is assessing the model performance at explaining the observed social networks.

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Data availability All data used for this research are publicly available. All the codes needed to replicate the results will be made available upon request.

Declarations

Conflict of interest The author declares no competing interests.

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