The role of geography in the complex diffusion of innovations

Article *in* Scientific Reports · September 2020

DOI: 10.1038/s41598-020-72137-w

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Spatial diffusion and churn of social media

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Innovative ideas, products or services spread on social networks that, in the digital age, are maintained to large extent via telecommunication tools such as emails or social media. One of the intriguing puzzles in social contagion under such conditions is the role of physical space. It is not understood either how geography influences the disappearance of products at the end of their life-cycle. In this paper, we utilize a unique dataset compiled from a Hungarian on-line social network (OSN) to uncover novel features in the spatial adoption and churn of digital technologies. The studied OSN was established in 2002 and failed in international competition about a decade later. We find that early adopter towns churn early; while individuals tend to follow the churn of nearby friends and are less influenced by the churn of distant contacts. An agent-based Bass Diffusion Model describes the process how the product gets adopted in the overall population. We show the limitations of the model regarding the spatial aspects of diffusion and identify the directions of model corrections. Assortativity of adoption time, urban scaling of adoption over the product life-cycle and a distance decay function of diffusion probability are the main factors that spatial diffusion models need to account for.

Collective behavior, like massive adoption of new technologies or the churn from old ones, are social contagion phenomena and as such they are complex[1]. Individuals are influenced in their actions by more than one of their neighbors in the social web. This feature was already realized in the 60s and incorporated in the Bass model of innovation diffusion[2]. The Bass differential equation framework reflects the distinction between exogenous and peers' influence and it is consistent with the notion that few early adopters are followed by a much larger number of early and late majority adopters and at last, by few laggards[3]. The Bass model has been extensively used to describe diffusion process and forecast market size of new products and the peaks of their adoption[4].

Later, the importance of the social network structure has become increasingly clear in the mechanism of peers' influence. This is especially so for systems, in which individuals take a certain action only when a sufficiently large fraction of their network neighbors have taken that action before[5–8]. Complex contagion models, in which the adoption depends on the ratio of the adopting neighbors[1,9], have been efficiently applied to characterize diffusion of on-line behavior[10] and on-line innovations[11,12]. Nevertheless, how social networks foster diffusion is still a matter of discussion[13] and it is currently debated whether the close network neighborhood of egos or rather its community structure is important for diffusion[14,15]. New agent-based versions of the Bass model incorporate the effect of peer influence and complex social contagion through networks and describe diffusion process better than the differential equation framework[16].

However, a very important question of behavioral diffusion have been largely overlooked: How does complex contagion proceed in geographic space? Classic studies of spatial diffusion emphasize the role of settlement size and physical distance by showing that adoption rate grows relatively fast in large towns and locations that are close to the origin of the innovative technology[17,18]. Spatial diffusion has long been argued to take place through social networks and the canonical view on how diffusion happens in space is very similar to other processes on networks, such as finding the route to a geo-located individual through social ties[19]. Indeed, contagion – like routing – is thought to first occur between two large settlements across large distances and then become more and more local over time as it reaches small towns as well[18]. Nevertheless, three non-trivial problems demands further research so that the Bass agent-based diffusion can describe spatial aspects of adoption. First, the role of assortativity of adoption time has been shown to influence the spatial forecasting power of network models[20], but the argument still needs empirical verification with observed social network data. Second, the nature of urban scaling of adopters over the product life-cycle[21] demands better understanding because the model forecasts are not independent from the spatial distribution of early adopters. Third, it is necessary to investigate the role of physical distance in the era of on-line innovations, though the widely spread view that spatial constraints become subordinated in the cyberspace has been repeatedly disproved[22].

While much effort has been devoted to innovation diffusion, considerably less studies deal with the opposite process of churning[23–27]. When churn becomes collective, the life-cycle of the product or technology may approach its end[25,26]. Recent studies have shown that in such cases the contagious mechanism of churn is similar to the one of diffusion[23,27,28]. Nevertheless, how churn happens in space is less clear. We can expect that users let old products go and transit to new ones in large cities earlier, where new competing products are launched[29]. We can also expect that social influence is stronger from co-located and geographically proximate friends than from friends in distant locations[22,30–32].

In this paper, we link the classic approach of spatial spreading to social contagion in the Bass diffusion framework. We describe the processes of spatial diffusion and churn at unprecedented scale with several empirical observations. We explore how the number of adopters and churners follow general urban scaling laws of innovation[21] over the life-cycle of a product and investigate the role of physical distance between ties when churning a product consecutively[27]. In the next step, we fit an agent-based Bass model (Bass ABM) to global diffusion dynamics and examine how the model describes spatial adoption dynamics. Because agents are heterogenous regarding how fast they follow their peers[33], we test how assortativity in terms of adopters types[3], in comparison to other characteristics of local networks, influences the model forecast of adoption peak in each town[20]. Finally, we evaluate Bass ABM with empirical data in terms of urban scaling of adoption over the product life-cycle[21], and distance decay of social diffusion[22,30–32,34], which are key for diffusion in geographical space.

We analyze iWiW, a Hungarian online social network (OSN) established in early 2002. The number of adopters was limited in the first three years but started to grow quickly after a system upgrade in 2005 when new functions were introduced (e.g. picture uploads, public lists of friends etc.). iWiW was purchased by Hungarian Telecom in 2006 and became the most visited website in the country by mid 2000's. Facebook arrived to the country in 2008 and outnumbered iWiW in terms of daily visits in 2010, which was followed by collective churn and finally, the servers of iWiW were closed down in 2014. In sum, more than 3 million users registered a profile on iWiW over its life-cycle and reported more than 300 million friendship ties on the website. Until 2012, to open a profile new users needed an invitation from registered members.

Our dataset covers the period from the very first adopters (June 2002) until its late days (December 2012). In addition, it contains home location of individuals, social media ties, invitation ties, and the dates of registration and last log-in for each user. The two last variables are used here to identify the date of adoption and churn, respectively. This dataset has informed previous research, showing that the gravity law applies to spatial structure of social ties[30]; that adoption rates correlate positively both with town size and with physical proximity of the original location[35]; that users central in the network churn the service later than users who are on the periphery of the network[36]; and finally that the cascade of churn follows a threshold rule[27]. The spatial aspects of diffusion and churn processes at the country scale have not been explored in spite of the fact that the data are particularly well suited to their study.

Now we turn to the detailed study of spatial diffusion and churn. Figure 1 contains descriptive information on the OSN life-cycle. After three years with few adopters, the adoption accelerates, starting in most populated towns. Churn happens very frequently at the end of the life-cycle and almost simultaneously across towns. We categorize users by their adoption time, for which we apply the rule proposed by Rogers[3], that divides adopters as: (I.) Innovators: first 2.5%, (II.) Early adopters: next 13.5%, (III.) Early Majority: following 34%, (IV.) Late Majority: next 34%, and the rest as (V.) Laggards. We see that the OSN spread almost exclusively from the original location (the capital Budapest, with an order of magnitude more inhabitants than the next size town) to various parts of the country in the early phase of the life-cycle. Later, diffusion became less mono-centric and other towns also emerged as spreaders. Our findings support the idea that spreading initially happens to large distances and becomes more local over time. This is illustrated and discussed later in Figure 2I. The number of churning users per month remain moderate until the middle of the life-cycle. Churn took off when Facebook arrived to the country and accelerated further after this international competitor gained dominance on the Hungarian market. Interestingly, the social network of churners has a similar spatial pattern like in case of diffusion and the hierarchical city network emerges when churn speeds up (Fig. 1, part b).

To explore statistical characteristics of adoption and churn, we fit two cumulative distribution functions (CDF) of both adoption and churn in Figure 2B. We find that the widely known Bass curve describes the adoption relatively well, but it

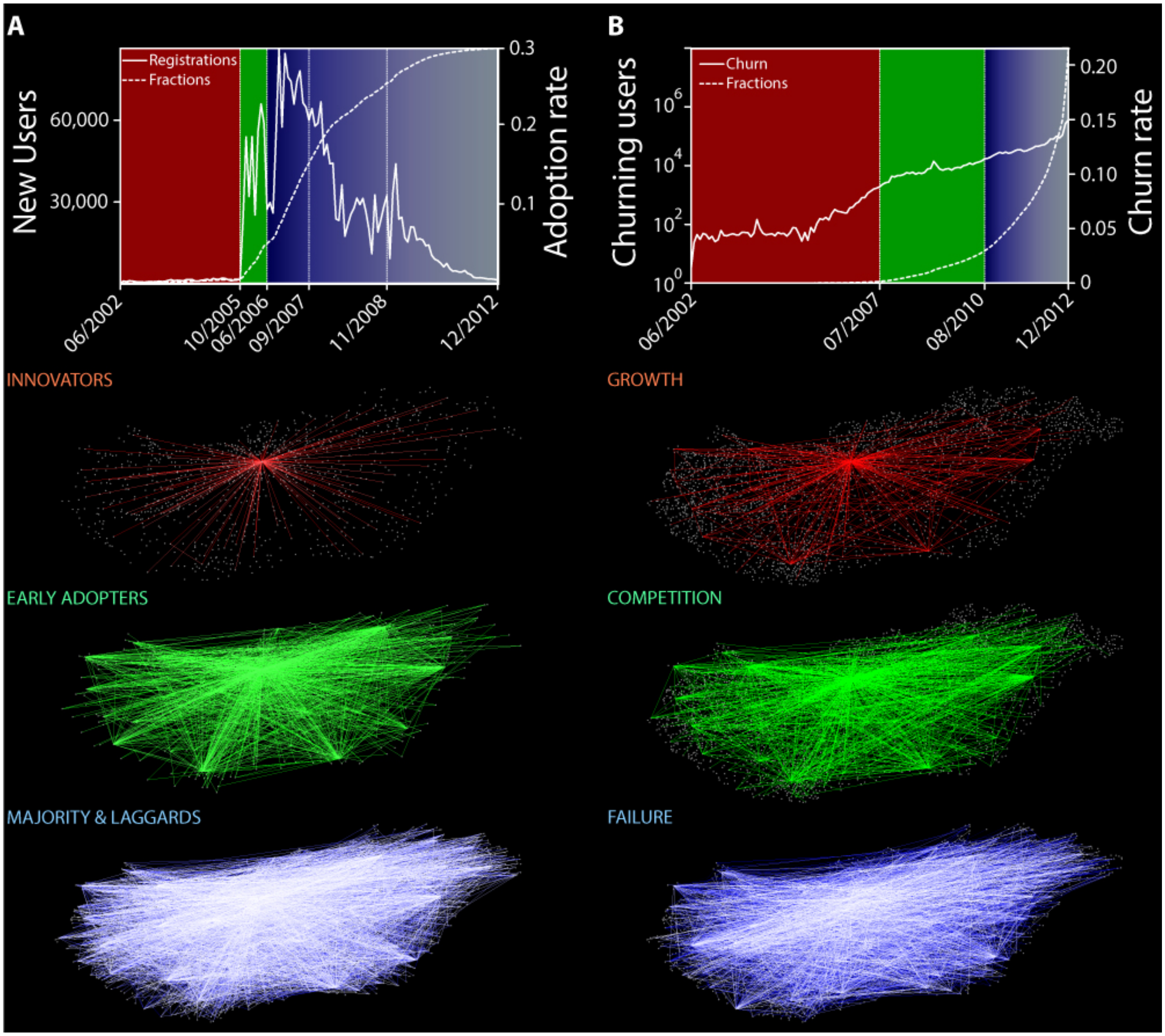

Figure 1. Adoption and churn in the OSN. **A.** Number of new users and the fraction of registered individuals among total population over the OSN life cycle. Users are categorized by the time of their registration into Rogers's adopter types: (I.) Innovators: first 2.5%, (II.) Early adopters: next 13.5%, (III.) Early Majority: following 34%, (IV.) Late Majority: next 34%, (V.) Laggards: last 16%. Spatial networks depict the number of invitations sent between locations over the corresponding periods. **B.** Number of churning users and the fraction of churned individuals among total population over the OSN life cycle. Three periods of churn are defined by iWiW's relation to Facebook: (a.) before Facebook arrival to the country (b.) competition of OSNs, (c.) Facebook has more daily visits than iWiW. Spatial networks depict the number of social ties of churning users between locations over the corresponding periods.

overestimates the adoption at the time when Facebook entered the country. The parameters of p_a (independent from the number of previous adopters; known as innovation or advertisement parameter) and q_a (dependent on the number of previous adopters; known as imitation parameter) are estimated using a non-linear regression method from the equation

$$y(t) = m\frac{1-e^{-(p_a+q_a)t}}{1+\frac{q_a}{p_a}e^{-(p+q)t}}, \quad (1)$$

where *y(t)* is the number of new adopters at time t and m is the maximum of adoption rate. The estimated parameters are q_a = 0.108; p_a= 0.00016; the model fits well the data with *SS*= 0.000245.

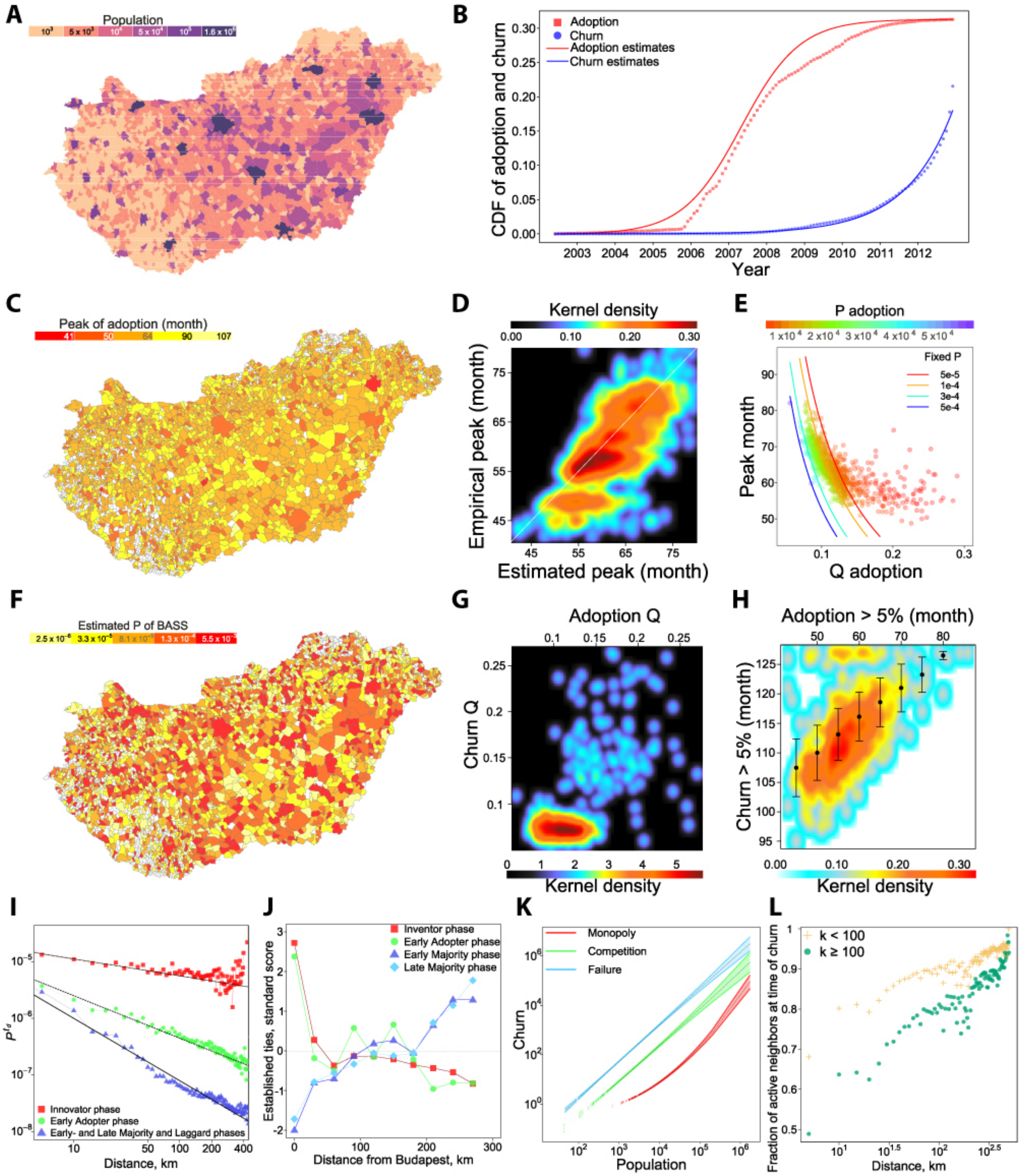

Figure 2. Empirics of diffusion and churn. **A.** Population of Hungarian towns. **B.** A Bass curve describes adoption rate CDF by a non-linear regression; while an exponential growth curve can be fitted to churn rate CDF. **C.** Adoption peaks early in large towns. **D.** Estimated peak of adoption correlates with real peak of adoption in towns. **E.** Estimated p_a and q_a result in same adoption peak as if p_a was fixed, except in early adoption cases when q_a is very high. **F.** Estimated p_a does not correlate with population size and peak of adoption. **G.** While q_a varies across towns, q_{ch} is very stable. **H.** Correlation between months of adoption take-off and churn take-off in towns.**I.** Distance decay of diffusion intensifies over the life-cycle **J.** Initially, users establish relatively many friendship ties close to the diffusion origin but the trend turns afterwards. **K.** A super-linear urban scaling curve of churn emerges early in the life-cycle. **L.** When users churn, half of their nearby friends have already churned but distant friends are still active.

Interestingly, an exponential growth function effectively explains the dynamics of churn; however, it underestimates real churn in the last month. The parameter of cumulative churn, q_{ch} was estimated by a non-linear regression from:

$$y(t) = x_0(1+q_{ch})^t, \tag{2}$$

where x_0 is the churn rate at time 0. The estimated parameters are: q_{ch} = 0.069; x_0= 3.47e-5; and the fit of the model is SS= 0.002277. We have repeated this two estimation exercises for every town and consequently estimated $p_{a,i}$, $q_{a,i}$ and $q_{ch,i}$ for every town i.

The time when adoption peaks is of general interest in spatial diffusion research[20]. Comparing the maps depicted in Figures 2A and 2C, shows that adoption peaks early in large towns but there is no spatial autocorrelation of early peaks. We have calculated the estimated month of adoption peak (T) for every town i using the estimated town-level Bass parameters defined above and the formula:

$$T_{peak-month} = \frac{\ln p_i + \ln q_i}{p_i + q_i} \tag{3}$$

Figure 2D depicts a positive correlation between the estimated and the empirical peaks in towns. Certainly, adoption peaks earlier if $p_{a,i}$ or $q_{a,i}$ increases. If either of these parameters is fixed, adoption becomes faster as the other increases. Interestingly, towns diverge from Eq. 3 for late peak times, corresponding to low $p_{a,i}$ and larger $q_{a,i}$. This means that the innovation term in the Bass model is lower and the process is driven by imitation in areas where diffusion happens later in time and as well as in less populated towns. The spatial clustering of larger $p_{a,i}$ around large towns suggest that advertisement not only has influence on adoption in large towns but also in their surroundings (Figure 2F).

The coefficient of imitation q_a varies across towns, however, as seen in Figure 2G, the rate of exponential growth in churn q_{ch} is surprisingly stable across towns. Figure 2H illustrates that churn starts early in towns that adopted early as well. This indicates that churn, similar to adoption, originates in larger towns.

The distance effect on diffusion and on-line activity is changing over the product life-cycle. In Figure 2I, we depict the probability of invitations (P_{dt}) sent to a new user at distance d and by stages of the life-cycle. The slope of the red line is -0.3 (Innovators phase), of the green line is -0.75 (Early Adopters phase), blue line is -1.1 (Majority and Laggards phase). A growing distance decay of invitation links demonstrates that diffusion first bridge distant locations but becomes more and more local over the life-cycle. The finding confirms that spatial diffusion of online products is similar to spreading of other product as Haegerstrand argued[18]. Further, we find that online activity in terms of establishing friendship ties on the website follows a "spatial wave" pattern over the life-cycle. In Figure 2J, we plot the standard score of ties established per active user at distance d from Budapest (30 km bins) and by life-cycle stages. In the early stages, users in the center of the country (around Budapest) are more active in making social ties than users in other parts of the country. However, this trend reverses in the late stages of the life-cycle when users far from the epicenter of product launch establish more social connections than the rest of the country. This finding suggests a spatial wave of using new products, which moves from the origin of innovation towards more distant locations.

To analyze urban scaling of churn, we estimate the logarithm of the number of churners accumulated over three periods in towns vs. the logarithm of the population of the town. Quadratic regression estimates with 99% confidence intervals (details in Supporting Information 3) suggest that a non-linear curve fits the data in the first half of the life-cycle and later a super-linear curve of churn forms (Figure 2K). This suggests that churn speeds up in small and middle-sized towns faster than diffusion does. Finally, we calculate the rate of active friends at distance d from the user at the time of last login. Figure 2L demonstrates that users with many friends ($k>100$) tend to churn when half of their local friends are still active. However, as distance grows, the fraction of active friends at the time of churn increases. The trend is similar in the case of users with few friends ($k\leq100$) although these users tend to churn earlier compared to their peers[27]. The trend suggests that the cascades of churn are local phenomena, in which users are more likely to follow spatially close friends than distant ones.

Further, we test an agent-based approach of the Bass model with the empirical data. In this ABM, agents are homogeneous in terms of p and q, which is the simplest specification of such models. This naturally means that users are assumed to be identically influenced by advertisements or further external effects and are equally sensitive to the influence from their social ties, captured by the fraction of infected neighbors a. The decision whether to adopt the innovation or postpone this action to a later moment is a matter of individual choice. Therefore, we keep the stochastic nature of the process, and assume that every user A decides to adopt with probability $P_{At} \in U(0,1)$ at every time t. We visit every susceptible user at every time t and infect it if p+q*a is higher than the randomly drawn P_{At}. The model belongs to the complex contagion class[1,10] because adoption over time is controlled by the fraction of infected neighbors[8,11]: as the fraction of infected neighbors increases, the

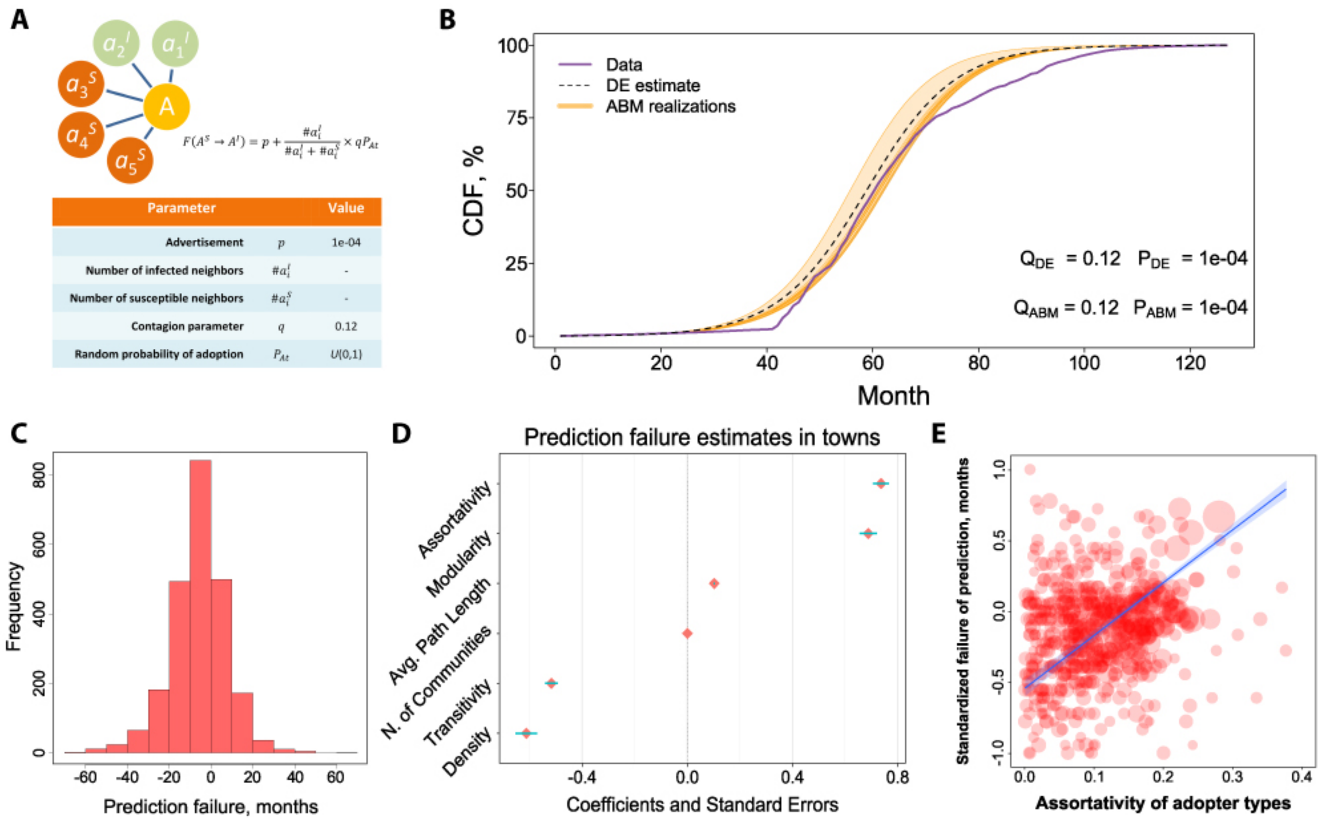

Figure 3. Complex contagion model with stochastic adoption. **A.** Adoption rules in the Bass agent-based model (ABM) and parameters. **B.** ABM realizations (solid gray lines in the shaded area) capture the CDF of adoption from the data (solid black line) better than CDF created from DE estimates. **C.** Deviance between adoption peak in towns in reality and predicted by the Bass ABM. **D.** Estimation of town-level prediction failure of ABM by simple linear regressions. Independent variables are characteristics of town-level networks. **E.** Assortative mixing of adopter categories by Rogers correlates with the standardized failure to predict the month of adoption peak in the town. Size of the dots denote the log of town population.

agent becomes more likely to adopt the innovation. For the sake of computation, we simulate the process in a 10% sample of the original data. To construct the sample, we kept the spatial distribution and the network structure of the data and stratified the social media users by towns and network communities, which were detected from the global network with the Louvain method[37]. To identify the initial levels of p and q in the ABM we run the Bass DE estimation on the sample network. These parameter values effectively approach the final fit of the ABM parameters[38]. As seeds of the diffusion, we use the actual users which adopted the OSN in the first month of the life-cycle. Both in the DE estimation and the ABM, we study 128 months. The model and parameters are illustrated in Figure 3A.

The DE estimates of p and q work well as the ABM parameters and the vast majority of ABM realizations capture the CDF of global empirical adoption better than the DE model (Figure3B). Although we find that the ABM captures the peak of adoption in a large number of towns, we also observe that differences between predicted and real time of peaks ranges widely from negative (prediction earlier than reality) to positive (prediction later than reality) (Figure 3C). In the remainder of the paper we investigate this phenomenon further in order to identify major directions for Bass ABM corrections.

We evaluated several characteristics of the town-level networks with the standardized score of prediction failure by applying simple linear regressions. Regression coefficients suggest that Bass ABM predicts the peak of adoption early in those towns where networks are relatively dense and global transitivity is relatively high (Figure 3D). On the contrary, relatively large network modularity in the town (derived from the community structure from the Louvain algorithm) delays adoption peak estimated by Bass ABM. Interestingly, we find the strongest positive correlation between prediction failure and assortative mixing of adoption time (Figure 3D). In particular, we classify each user into the adopter categories of Rogers[3] and calculate Newman's assortativity r[39] for every town. This indicator takes the value of 0 when there is no assortative mixing by adopter types and a positive value when links between identical adopter types are more frequent than links between different adopter types in the town. The positive correlation between assortative mixing and prediction failure is further illustrated by applying a linear regression weighted by town population (described in details in the Methods section), which is important in order to consider size differences across towns. This finding in Figure 3E illustrates that our ABM predicts adoption earlier in the majority of small towns, where we find no assortative mixing. However, assortative mixing is an empirical characteristic of the actual diffusion process, which we show in Supporting Information 1. Therefore, in large towns, where Innovators and Early Adopters are only loosely connected to Early- and Late Majority and Laggards, the Bass ABM predicts adoption relatively late. This finding suggests that assortativity in terms of adoption probability influences diffusion, which makes the spatial prediction problem difficult to solve.

In Figure 4, we identify other key limitations of the Bass ABM and directions for model correction: velocity of imitation, urban scaling and distance decay. Regarding the velocity of imitation in the network, we find that the average difference of adoption time between the user and his/her direct connections in the network is smaller in reality than in the ABM (Figure 4A). This is because the assortative mixing is higher in the data than in the ABM (Figure 4B). These findings together suggest that the diffusion cascade is much faster in reality than in the ABM. We find that distance decay of social ties of users who adopt early (Innovator and Early Adopter type) is larger in the ABM than in reality. This observation in Figure 4C suggests that the innovation spreads with more propensity to distant locations in early phases of the life-cycle than the Bass ABM would

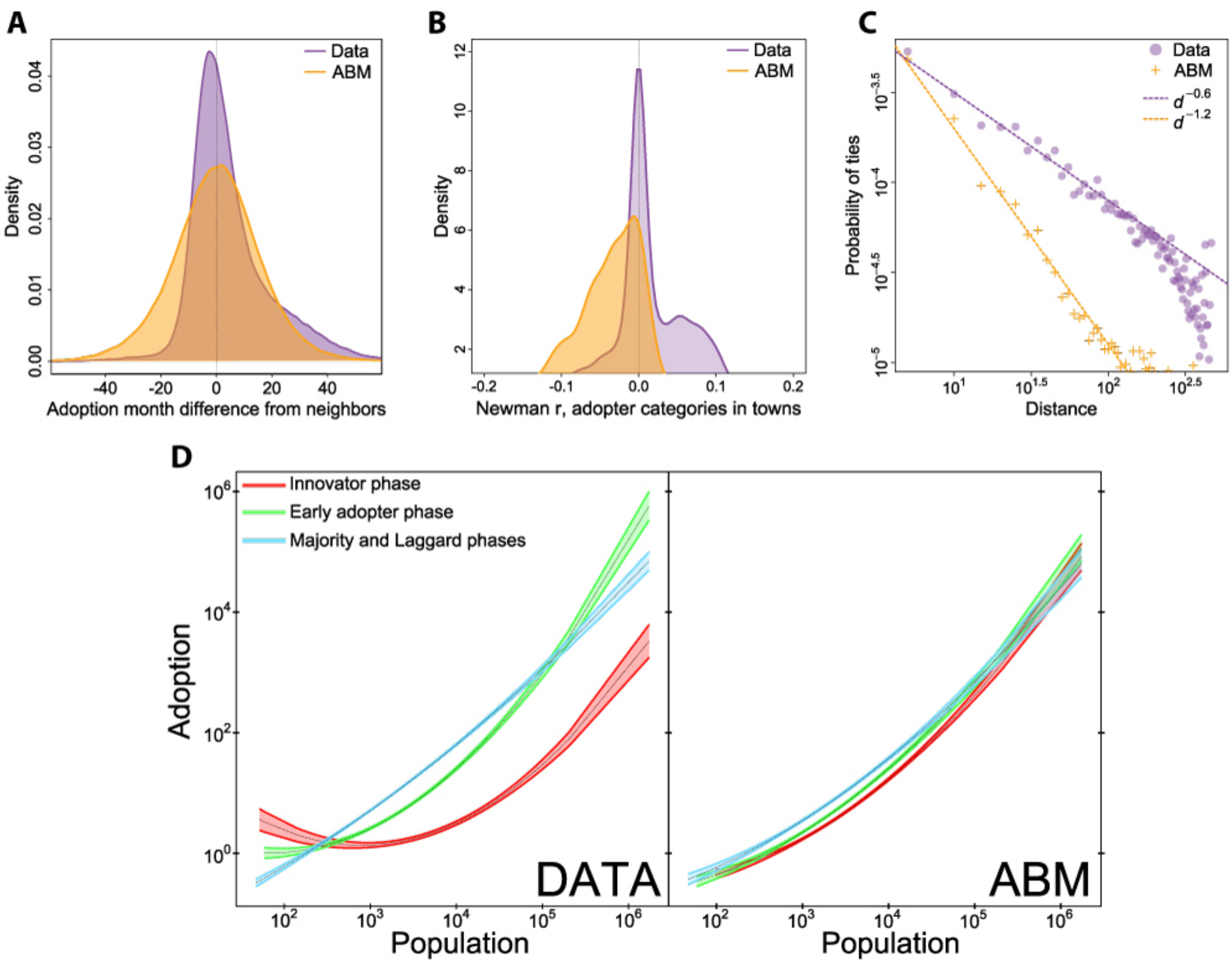

Figure 4. ABM versus reality. **A.** Difference of adoption time (measured in months) between the user and his/her direct connections is smaller in reality than in the ABM. **B.** Assortative mixing (measured by Newman's r) is higher in towns if users are categories to adopter types by the data than by the ABM. **C.** The distance decay of social ties of Innovators and Early Adopters is larger in ABM than in reality. **D.** In reality, superlinear urban scaling of adoption emerges only at the Majority and Laggards phases of the life-cycle. In the ABM, urban scaling of adoption does not differ across stages of the life-cycle.

suggest. Finally, in Figure 4D, we use quadratic regression to estimate the number of users with the size of the town. We find that superlinear scaling emerges at the middle of the life-cycle in the data; while scaling does not differ across stages of the life-cycle in the ABM. This finding is in line with the classic idea of the Haegerstrand-type of spatial diffusion[18], in which innovation appears in large centers first and then diffuses to smaller towns.

Taken together, we study spatial diffusion and churn over the life-cycle of an online product at a country scale. Diffusion follows the patterns proposed by Haegerstrand[18]. We observe that urban scaling of the number of adopters with population emerges at the middle of the life-cycle and spreading becomes more local over time. Churn starts in towns that adopt earlier, but spread very fast across the entire network[27]. Spatial proximity plays an important role in the churn cascades, as users follow local ties in churning, which makes the super-linear scaling of churn appear faster than the super-linear scaling of diffusion case.

A Bass-inspired complex contagion agent-based model fits global diffusion and we uncover novel empirical features missing from the mainstream model, which are necessary to control for to improve spatial prediction. First, assortative mixing in adoption is necessary to predict the peaks in towns, similarly observed in Twitter in the USA.[20]. Also, users follow their similar ties faster in reality than in the model, which produces higher assortative mixing in the adoption time. Second, urban scaling of Innovators and Early Adopters differ across reality and the model. Finally, contagion in the early stage of the life-cycle occurs easier between two distant locations in reality than in the ABM. These latter two notions raise nontrivial problems of prediction because the spatial distribution of Innovators and Early Adopters is the main unknown in practice.

Methods

Nonlinear least-square regression with the Gauss-Newton algorithm was applied to estimate the parameters in Equations 1 and 2. In order to identify the bounds of parameters search in the ABM, the method needs starting points to be determined, which were $p_a = 0.007$ and $q_a = 0.09$ for Equation 1 and $x_{ch} = 10^{-6}$ and $q_{ch} = 0.08$, for Equation 2.

Identical estimations were applied in a loop across towns, in which the Levenberg-Marquardt algorithm[40] was used with maximum 500 iterations. It is important to apply this estimation method because the parameter values differ across towns, and therefore town level solutions may be very far from the starting values set for the country scale estimation. Initial values were set to $p_{a,i} = 7*10^{-5}$ and $q_{a,i} = 0.1$ in case of Equation 1 and $x_{ch,i} = 10^{-6}$ and $q_{ch,i} = 0.1$ in case of Eguation 2.

To test how assortative mixing influences the spatial prediction of the diffusion ABM in Figure 3C, we estimate prediction failure with Newman's r with ordinary least square estimator and used the number of OSN users in the town as weights in the regression.

To characterize urban scaling of adoption and churn in Figures 3 and 4, we applied the ordinary least square method to estimate the formula $y(t) = \alpha x + \beta x^2$, where $y(t)$ denotes the cumulated number of adopters and churners over time period t by and x is population in the town.

Data tenure is controlled by a non-disclosure agreement between the data owner and the research group. Access can be requested by email to the corresponding author.

Acknowledgements

Balazs Lengyel acknowledges financial support from the Rosztoczy Foundation and the Eotvos Fellowship of the Hungarian State. Riccardo Di Clemente as Newton International Fellow of the Royal Society acknowledges support from The Royal Society, The British Academy and the Academy of Medical Sciences (Newton International Fellowship, NF170505).

Author contributions statement

B.L. and M.G. designed the research, B.L. and R.D.C. conceived the experiments, B.L., R.D.C. and M.G. analyzed the results. All authors wrote and reviewed the manuscript.

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Supporting information

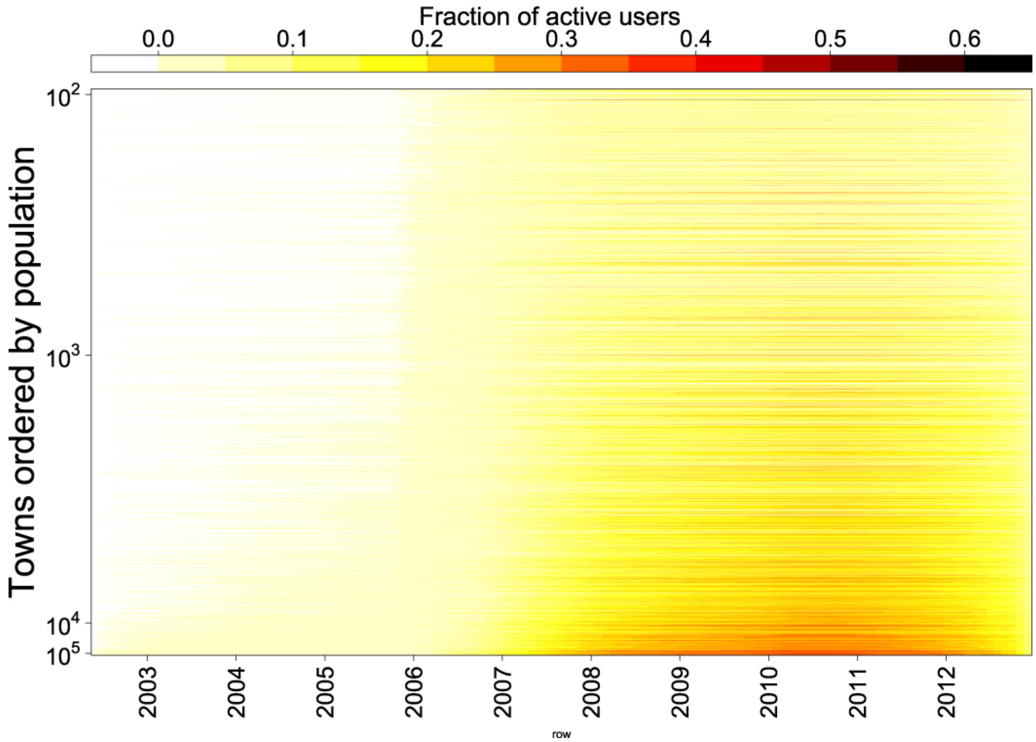

Figure S1. Active users in towns along the product life-cycle.

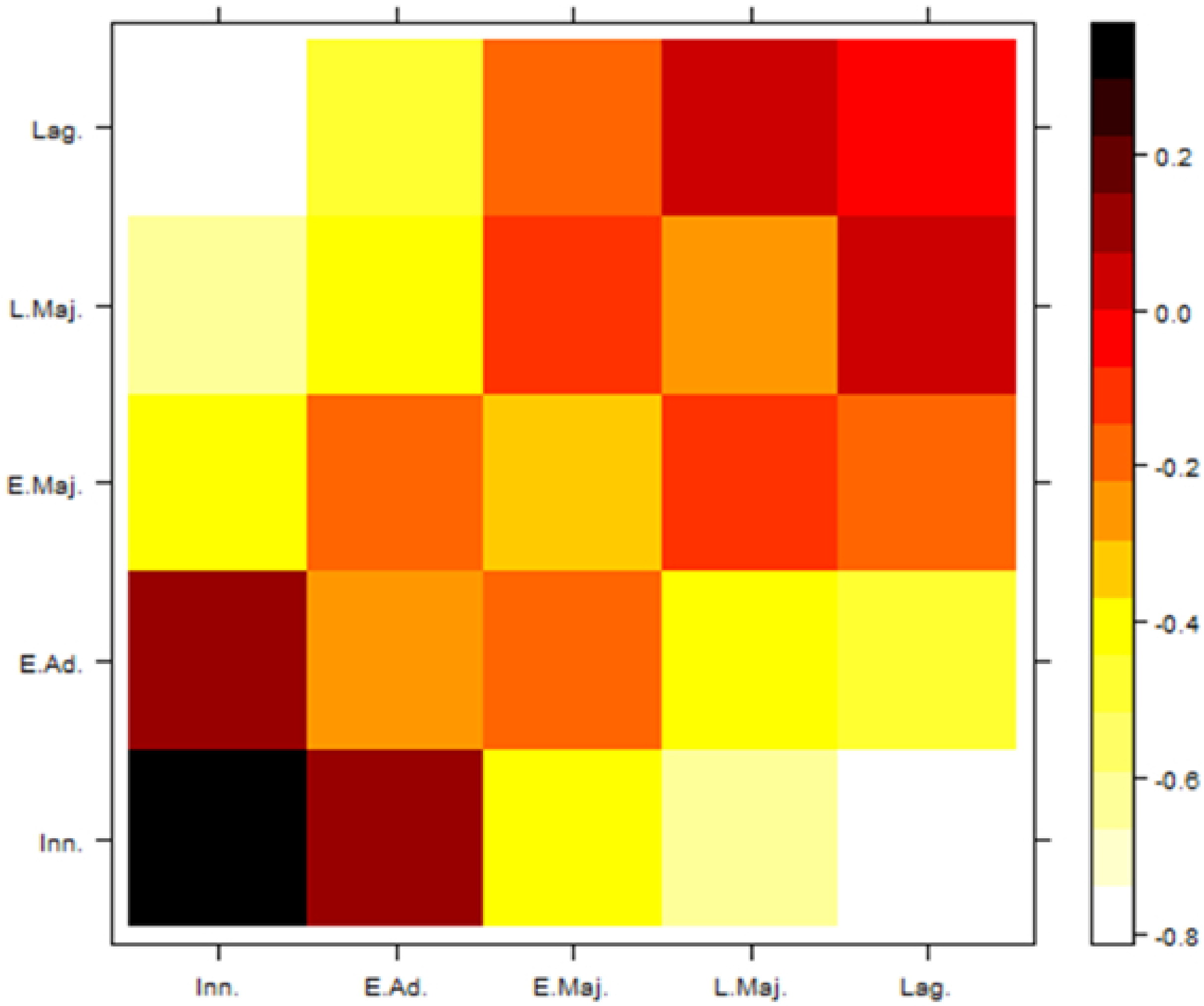

Figure S2. Assortative mixing of adoption categories. We calculated the number of links between groups W_{ij} and compared it to the expected number of ties $E(W_{ij})$ for which uniform distribution of links across the groups is assumed and is calculated by $\frac{\sum_j W_i * \sum_i W_j}{\sum W_i j}$. We have transformed the $\frac{W_i j}{E(W_i j)}$ ratio into the (-1; 1) interval using the $\frac{x-1}{x+1}$ formula. This indicator is positive if the observed number of ties exceed the expected number of ties and negative otherwise. The plot suggests that assortative mixing fragment the network into categories of Innovators and Early Adopters who are only loosely connected to Late Majority and Laggard users.

Table S3. Urban scaling of adoption and churn along the life-cycle: linear and quadratic regressions with ordinary least squares estimation.

	Adoption (log)					
	Innovator phase		Early Adopter phase		Majority and Laggards phase	
Population (log)	0.636***	-1.660***	1.079***	-0.474***	1.015***	0.533***
	(0.029)	(0.210)	(0.016)	(0.120)	(0.007)	(0.051)
Population (log) squared		0.317***		0.233***		0.073***
		(0.029)		(0.018)		(0.008)
Intercept	-1.623***	2.413***	-2.400***	0.117	-1.762***	-0.996***
	(0.105)	(0.378)	(0.053)	(0.199)	(0.022)	(0.083)
R-sq	0.412	0.503	0.658	0.682	0.737	0.740
N	669	669	2233	2233	7581	7581

	Churn (log)					
	Growth phase		Competition phase		Failure phase	
Population (log)	1.047***	-1.176***	1.439***	1.311***	1.480***	1.507***
	(0.022)	(0.178)	(0.022)	(0.170)	(0.014)	(0.104)
Population (log) squared		0.291***		0.018		-0.004
		(0.023)		(0.025)		(0.016)
Intercept	-3.240***	0.919***	-3.385***	-3.172***	-2.709***	-2.752***
	(0.079)	(0.339)	(0.072)	(0.289)	(0.044)	(0.168)
R-sq	0.768	0.810	0.696	0.696	0.810	0.810
N	719	719	1856	1856	2548	2548

Standard errors in parentheses. * p<0.10, **p<0.05, *** p<0.0

Supporting information 4: For a video on spatial diffusion and churn, go to https://vimeo.com/251494015