# The Cycle of Prosperity: Ensuring Equal Opportunity

Invited contribution to UN at 100 book

Alex Pentland, MIT
pentland@mit.edu
4/20/2021t

**Understanding Prosperity**

What will the UN 2030 development goals look like? What will we hope to achieve by 2045? I believe…and hope…that the 2030 goals will look very different from the 2015 goals. The reason is that the 2015 Sustainable Development Goals (SDGs) are almost entirely about avoiding harm, and have very little to say about policies that will minimize those harms. This silence is for a good reason: the development path taken by current rich countries is unlikely to be something that less developed countries can successfully follow. So what is to be done? What will be the best path to development in the future?

I suggest that the answer is that the rich data provided by the 2015 SDG metrics can provide the possibility of scientific determination of what sorts of new development policies are likely to be successful [1, 2]. For instance, privacy-safe, anonymized fine-grain data from mobile telephones, credit cards, and other data sources that are used to create the 2015 SDG metrics are already helping decision makers to tackle problems of societal importance [6, 24, 2]. Examples include monitoring socio-economic deprivation [11, 10, 6, 12] and crime levels [4, 13, 14], mapping the propagation of diseases [14, 15, 16, 9], and understanding the impact of natural disasters, environmental risks, and other emergencies [7, 8, 3, 4, 5], etc.

To gain a better understanding of what a science-based policy for prosperity development would look like we can examine smaller regions of the world that already have available such rich data. What we find from such "rich data" science is that neighbourhoods with more diverse amenities attract not only more people but importantly more diverse people, as shown in Figures 1(A) and 1(B). This diversity of people, ideas, and activities acts to increases the rate of innovation within the neighbourhood. Figure 1(C), for instance, shows that neighborhoods with more diverse amenities (and consequently more diverse visitors) have greater *year-on-year GDP growth.*

This effect accounts for up to *half* the variation in GDP growth even after controlling for population density, city centrality, and housing prices. That is, diversity in amenities (or, nearly equivalently, diversity of people visiting the neighborhood) is usually a *more* powerful predictor of growth than density, geographic centrality, or housing price. This data is from a large European metropolitan area' data from three other continents is similar [28].

These three figures show what appears to be the central cycle of development: diverse amenities attract large and diverse flows of people, which create opportunities for investment in new amenities and subsequent increased flows of people. However, this doesn't fully explain why people move to or work in neighborhoods with more amenities, which are after all more expensive and crowded.

Why is the preference for diverse amenities so universal? The reason may be that neighborhoods with more diverse amenities, which bring in more diverse flows of people, create greater opportunity for those who work or even just visit such neighborhoods. Figure 1(D) illustrates that people who have more exposure to diverse types of people, and thus have more access to new ideas and opportunities, make more money. Moreover, this is not just an artifact of the way the particular way access to diverse communities was measured, because you can get the same result looking at the diversity of jobs of the people they interact with, or the diversity of locations of the people that they interact with. Again, data from four continents shows similar patterns [28].

Surprisingly, the variation that has to do with education is small when compared with the variation that has to do with access to ideas from diverse communities, so it is not just rich neighborhoods or well-educated people who profit from diversity. People in all socioeconomic levels also profit from exposure to a wide variety of people and experiences, although there are systematic inequalities in this relationship [19].

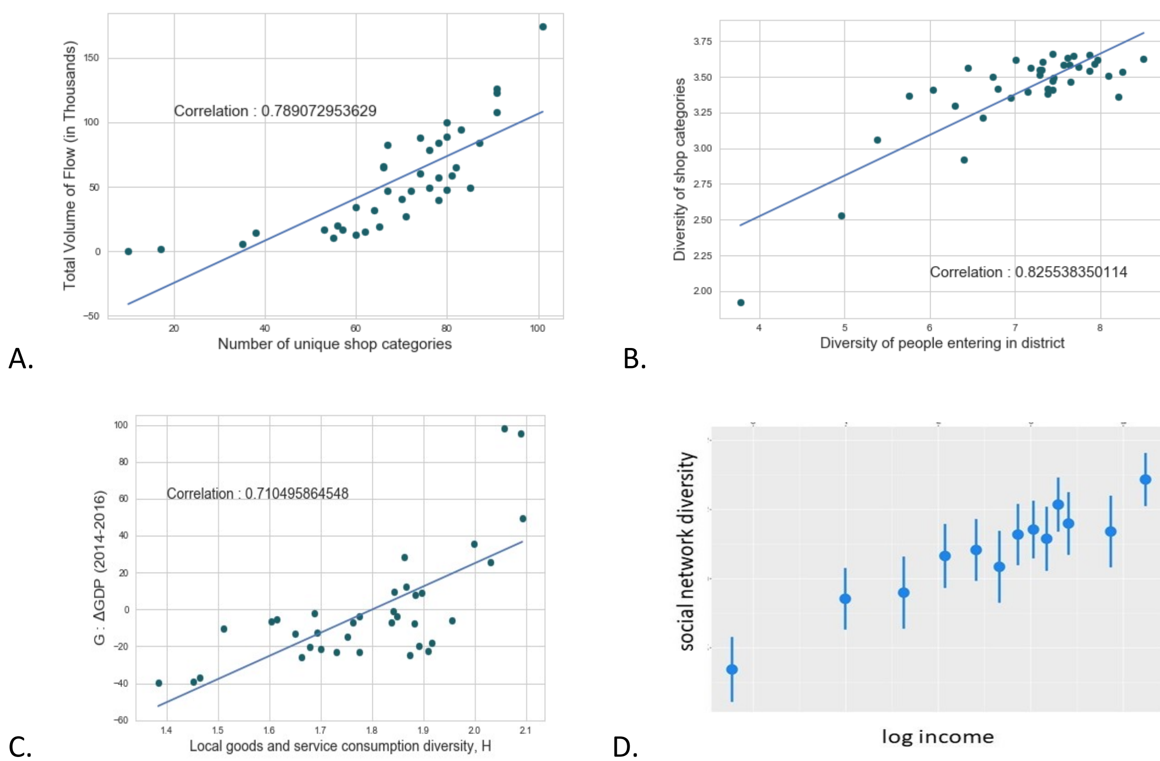

*Figure 1. (A) More diverse amenities attract more people, (B) More diverse amenities attract more diverse people (people from more different communities), and (C) greater diversity in amenities (or of people) predicts greater year-on-year GDP growth. (D) shows that people with more diverse social networks have greater personal income, showing that diversity brings wealth both for those within a neighborhood and predicts wealth for those who visit the neighborhood. Data for (A), (B), and (C) are from neighborhoods within a major European metropolitan area, data from neighborhoods within metropolitan areas on other continents is similar, and typically diversity accounts for up to half the variation in growth in GDP even after controlling for population density, centrality in city, and housing price [28]. Data for (D) is sample of 100,000 randomly chosen people in mid-income country [19].*

It is important to ask if greater network diversity *causes* greater income or whether it is the other way around. The answer is that greater network diversity indeed causes greater income on average…this is the idea of weak ties bringing new opportunities…but it is also true that greater income causes social networks to be more diverse. Wealth creation is a complex, dynamic feedback process with no one causal factor. Instead of asking about causality, it is instead better to ask about the relative strength of each part of this complex, dynamic system.

Figure 1(D) strongly suggests that access to diverse ideas is not only an important influence on the wealth generation process, but may in fact be the primary driving force. It may be best to conceive of humans as a species who are on a continual search for new opportunities [20, 22], the path to not only economic development but a more prosperous society may lay in promoting individual access to opportunities and supporting their ability to harness opportunities that they prefer.

**Exposure to New Opportunities Drives Economic Growth**

The hypothesis that diverse interaction patterns predicts the flow of new ideas from one neighborhood to another, and that the flow of ideas accounts for a substantial portion of economic growth, has recently been shown for the large-scale interactions found between nations [17, 18]. Moreover, the flow of ideas appears to be a causal factor, and not just a correlational factor, because nations with large volumes of interaction have convergence in skills, technology, and productivity over the long run.

Further, the spread of ideas is a causal factor in the spread of new types of industry between cities, as shown by our recent study looking at whether investment in high-speed rail infrastructure was a causal factor in promoting the spread of companies with specialized commercial expertise [27]. For example, when a city “X” with few information technology (IT) companies is connected by high speed rail to a city “Y” that already has many IT firms, the rail connection strongly promotes creation of more IT firms in city “X.” Applying this logic across many types of companies, this study shows that the spread of ideas because of these new rail connections *caused* an increase of company creation within specialty or category, and that this causal effect is almost 50% greater for connected cities than the general rate of company creation.

The view that physical mixing between different communities strongly influences the rate of innovation and financial growth is reinforced by a recent study in China. This study looked at factors that were important in success of new businesses by performing a survey of all the startups launched from 3,255 government-sponsored incubators throughout China [26]. This survey show that it was *cultural diversity* was the biggest factor in successful launch and funding of startups, and that diversity of industrial experience was most important in the subsequent growth and scaling of these startup companies.

**Long-term growth: intergenerational mobility**

Exposure to new ideas and behaviors also predicts long-term socio-economic success of children growing up within a neighborhood. In 2017 my MIT research group analyzed a uniquely large and complete database describing the life trajectories of at-risk children and used these data to build predictive models for life outcomes ranging from eviction from home to "grit" to school grade-point average. These data were generated by the Fragile Families Study (see https://fragilefamilies.princeton.edu/), which examined the development of 4,242 children, interviewing primary caregivers at birth and again when children are ages one, three, five, nine, and fifteen years, together with in-home assessments of the children. Several collaborative studies provided additional information on parents' medical, employment and incarceration histories, religion, child care and early childhood education. In total, 12,943 measurements were made of each child and their family, including scores on an extremely wide variety of standardized tests [29].

A total of 160 academic teams competed to use these data in order to predict life outcomes of these children. My MIT team produced the most accurate models for half of the life outcome prediction tasks (see http://news.mit.edu/2017/mit-human-dynamics-team-tops-fragile-families-challenge-1004). Despite the rich data set and state-of-art statistical methods, however, our best predictions for these life outcomes were not very accurate and in fact were only slightly better than those from a simple four-factor benchmark using only demographic characteristics and neighborhood statistics. The uncomfortable conclusion of this huge effort, as reported in the Proceedings of the National Academy of Science [29], is that you *cannot* predict children's life outcomes from any of the standard tests or interview methods applied to either the children or their families.

However, you can use neighborhood statistics to predict the probability of intergenerational financial mobility. In order to examine the "American dream" of intergenerational mobility, a group of economists, led by Raj Chetty, obtained access to 30 years of longitudinal data from the U.S. Internal Revenue Service (see http://www.equality-of-opportunity.org/ ). From these data they could compute the rate of intergenerational financial mobility across *all* U.S. Census Blocks.

Analysis of the IRS data found that 71% of the variation in financial life outcome could be predicted by characteristics of the surrounding neighborhood, specifically, the roughly four block area surrounding the child's home.  Moreover, approximately one-quarter of this neighborhood effect is "locked in" by the time the child enters kindergarten, and approximately half of the neighborhood effect is in place by the 5$^{th}$ grade. They could also analyze the outcomes of children who moved from one Census Block to another Census Block as part of a randomized lottery, thus establishing that the neighborhood effect is causal.

Why didn't interviews with parents or any of the other classic social science metrics provide similar predictive power?  Perhaps it is because the most predictive variables are ones that people generally do not have quantitative knowledge about (e.g., income distribution of people in adjoining city blocks), or are not even aware of (e.g., proportion of census forms returned, a proxy for social capital). Nor do people suspect the predictive power of these variables. Indeed, the relationships were unknown until this large-scale longitudinal computational social science analysis became available.

**Conclusion**

What these studies suggest is that the factors that we usually think about -- investment, education, infrastructure, institutions -- may not be the direct cause of prosperity.  Instead they may make a difference primarily because they help or hinder the search for new opportunities. The fundamental driver of progress in society may be the search for new opportunities, and is aided by people's skills or capital investment.

This is a fundamental shift in how we think about international development.    It suggests that promoting greater access to local opportunities and facilitating resources to harness those opportunities is the best path to building more vibrant, economically successful societies.  It suggests that we should focusing on transportation networks to make neighborhoods accessible to more diverse populations [23], invest in diverse stores and amenities in order to attract diverse flows of people [25], and promote the skills and local resources required for local residents to harness local opportunities.

Importantly, we can use local data to evaluate how to best allocate investments to maximize the expected impact on the overall prosperity and health of the neighborhood. Communities need not rely on annualized values of traditional economic indicators for planning purposes but can instead be able to make reliable estimates of what sort of efforts and investments will best contribute to achieving their vision of a prosperous neighborhood and better quality of life [2].

**References**

[1]https://www.undatarevolution.org/wp-content/uploads/2014/11/A-World-That-Counts.pdf

[2] Pentland, A., Lipton, A., Hardjono, T.,  (2020) Building the New Economy,  MIT Press (see https://wip.mitpress.mit.edu/new-economy)

[3] E. Moro, M. R. Frank, A. Pentland, A. Rutherford, M. Cebrian, and
I. Rahwan, “Universal Resilience Patterns in Labor Markets,” *Nature Communications*
3, 2021. https://www.nature.com/articles/s41467-021-22086-3

[4] Bogomolov, A., Lepri, B., Staiano, J., Oliver, N., Pianesi, F., and Pentland, A. (2014). Once upon a crime: Towards crime prediction from demographics and mobile phone data. Proceedings of the 16th International Conference on Multimodal Interaction (ICMI 2014), pp. 427-434.

[5] Jean, N., Burke, M., Xie, M., Davis, W.M., Lobell, D.B., and Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. *Science*. 353(6301), pp. 790-794.

[6] Independent Expert Advisory Group on a Data Revolution for Sustainable Development. (2014). *A world that counts: Mobilising the data devolution for sustainable development*.

[7] Lu, X., Bengtsson, L., and Holme, P. (2012). Predictability of population displacement after the 2010 Haiti earthquake. *PNAS*. 109:11576-81.

[8] Pastor-Escuerdo, D., Torres Fernandez, Y., Bauer, J.M., Wadhwa, A., Castro-Correa, C., Romanoff, L., Lee, J.G., Rutherford, A., Frias-Martinez, V., Oliver, N., Frias-Martinez, E., and Luengo-Oroz, M. (2014). Flooding through the lens of mobile phone activity. In IEEE Global Humanitarian Technology Conference (GHTC 2014).

[9] Ruktanonchai, N.W., Bhavnani, D., Sorichetta, A., Bengtsoon, L., Carter, K.H., Cordoba, R.C., Le Menach, A., Lu, X., Wetter, E., zu Erbach-Schoenberg, E., and Tatem, A.J. (2016). Census-derived migration data as a tool for informing malaria elimination policy. *Malaria Journal*. 15:273.

[10] Smith-Clarke, C., Mashhadi, A., and Capra, L. Poverty on the cheap: Estimating poverty maps using aggregated mobile communication. (2014) In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2014), pp. 511-520.

[11] Soto, V., Frias-Martinez, V., Virseda, J., and Frias-Martinez, E. (2011). Prediction of socioeconomic levels using cell phone records. In Proceedings of the International Conference on User Modeling, Adaptation, and Personalization (UMAP 2011), pp. 377-388.

[12] Steele, J.E., Sundsøy, P.R., Pezzulo, C., Alegana, V.A., Bird, T.J., Blumenstock, J., Bjelland, J., Engø-Monsen, K., de Montjoye, Y.-A., Iqbal, A.M., Hadiuzzaman, K.N., Lu, X., Wetter, E., Tatem, A.J., and Bengtsson, L. (2017). Mapping poverty using mobile phone and satellite data. *Journal of the Royal Society Interface* 14(127).

[13] Traunmueller, M., Quattrone, G., and Capra, L. (2014). Mining mobile phone data to investigate urban crime theories at scale. In Proceedings of the International Conference on Social Informatics (SocInfo 2014), pp. 396-411.

[14] Wang, H., Kifer, D., Graif, C., and Li, Z. (2016). Crime rate inference with big data. In Proceedings of the ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD 2016), pp. 635-644.

[15] Wesolowski, A., Eagle, N., Tatem A.J., Smith, D.L., Noor, A.M., Snow, R.W., Buckee, C.O. (2012). Quantifying the impact of human mobility on malaria. *Science*. 338(6104), pp. 267-270.

[16] Wesolowski, A., Metcalf, C.J.E., Eagle, N., Kombich, J., Grenfell, B.T., Bjørnstad, O.N., Lessler, J., Tatem, A.J., and Buckee, C.O. (2015). Quantifying seasonal population fluxes driving rubella transmission dynamics using mobile phone data. *PNAS*. 112(35), pp. 11114-11119.

[17] Buera, F., Oberfield, E., (2016) The Global Diffusion of Ideas, NBER Working Paper No. 21844

[18] Alvarez, F., Buera, F., Lucas, R. (2013) Idea Flows, Economic Growth, and Trade, NBER Working Paper No. 19667

[19] Jahani, E.,Saint-Jacques, G. Sundsøy, P., Bjelland, J., Moro, E., Pentland, A., (2017) Differential Network Effects on Economic Outcomes: A Structural Perspective. SocInfo (2) 2017: 41-50

[20] Krumme, C., Llorente, A., Cebrian, M., Moro, E., and Pentland, A. (2013) , The predictability of consumer visitation patterns, *Scientific Reports* volume3, Article number: 1645

[21] Madan, A., Cebrian, M., Moturu, S., Farrahi, K., Pentland, A. (2012) Sensing the" health state" of a community, IEEE Pervasive Computing, Vol. 11, No. 4, pp. 36-45

[22] Singh, V., Bozkaya, B., Pentland, A., (2015) Money Walks: Implicit Mobility Behavior and Financial Well-Being, PloS, https://doi.org/10.1371/journal.pone.0136628

[23], Pan, W., Ghoshal, G., Krumme, C., Cebrian, M., and Pentland, A., (2013) Urban characteristics Attributable to Density-driven Tie Formation *(2013) Nature Communications, V*olume4, Article number: 1961 (2013)

[24] Pentland, A., (2015) Social Physics: How social networks can make us smarter, Penguin Press.

[25} Dong, X., Suhara, Y., Bozkaya, B., Singh, V., Lepri, B., Pentland, A., (2018) Social Bridges in Urban Purchase Behavior, ACM Transactions on Intelligent Systems and Technology (TIST), Vol 9, No. 3, Article 33.

[26] Yuan ,X., Qiu, Y, Wei, Y. , & Liu, S.Y., (2017) Research on the Relationship Between Entrepreneurship Diversity and Performance of Regional Innovation Networks——Micro data analysis based on 3255 Chinese incubators, Theory & Practice, 2017(9),152-155.

[27] Gao, J Jun, B., *Pentland*, A., Zhou, T., and *Hidalgo, C., (2016)* Collective Learning in China's Regional Economic Development (2018), https://arxiv.org/abs/1703.01369.

[28] Chong, S., Bahrami, B., Chen, H., Balcisoy, S., Pentland, A., (2020) Economic Outcomes Predicted by Diversity in Cities (2020) EPJ Data Science, **9**, Article number: 17

[29] Salganic, M, et al (2020) Measuring the predictability of life outcomes with a scientific mass collaboration, Proceedings of the National Academy of Sciences 117(15):201915006
DOI: 10.1073/pnas.1915006117