Fortune Monitor or Fortune Teller: Understanding the Connection between Interaction Patterns and Financial Status

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***Abstract*—We have deployed mobile phones to more than 100 participants in a community split into two phases. In this paper, we use this unique dataset to study the correlation between users' call and Bluetooth face-to-face interaction patterns, and their financial status. We show that such correlation exists on an individual level. We find that the interaction diversity measure correlates more strongly with individual's financial status compared with other social behavior measures such as the number of contacts and length of interactions, and it is much less sensitive to personality variance. We also discuss in this paper the long-lasting sociological theory that a diverse relationship leads to a more successful financial status. Our evidence tends to support a behavioral and psychological oriented theory opposite to the prevailing arguments: Social diversity exhibited by our participants are influenced by their income as well.**

***Keywords*-Sociology, Mobile Computing, Behavioral Science**

I. Introduction

Recently it is discovered that interaction diversity correlates with increased wealth, as illustrated in Eagle et al [1], and it is generally believed that diversity leads to financial gain in the literature [2] [3] [4] [5].

Two immediate followup questions arise: *The first challenge* is to study whether we can observe the same correlation at the level of individuals rather than aggregated communities. Such correlation could tremendously benefit our understanding of personal economic well-being, and would also have applications in the area of mobile commerce: merchants can use communication patterns to estimate the overall financial status of each mobile phone user, and recommend more suitable products and services as suggested by Wilska et al [6].

The second challenge is to better understand the causality of such correlations. Researchers tend to believe that a diverse relationship brings benefits such as increased information or external opportunities, among others [2] [3]. Such thinking comes from a long line of classical social science literature: Granovetter's weak tie theory [4] and Burt's social structure hole theory [5], to name two. Other additional works look into evidence in different dataset to support this type of argument [7].

The theories mentioned above imply that a strong and diverse connectivity may lead to higher economic well-being, i.e. the interaction diversity is somehow a *fortune teller*. The second implication is that individuals who come from better financial status are often those who also exhibit diverse social relationships.

We have deployed an Android-based smart phone sensing platform in a postgraduate residential community adjacent to a major research university. In addition the dataset is augmented by a comprehensive set of survey questionnaires. This study, known as the *Friends and Family Study* [8], has been conducted for over a year. In this study, rather than looking at aggregate area-level mobile data [1], we are interested in the individual-level relationship between one's financial status (defined as spending habits and household income in this study) and their social interaction diversity.

From the data of the *Friends and Family Study*, we discover that the individual call patterns and face-to-face interaction patterns are connected to one's financial status. Therefore, mobile phones can be treated as a potential *fortune monitor* for one's financial status.

We propose in this paper our theory that the causality might be in the other direction than currently attributed. The correlation observed in previous work [1] may be partially due to a more behavioral oriented mechanism: Individuals with better financial situations may exhibit more diverse social interaction patterns. Since their financial status enables them safer and more satisfying living conditions, they naturally feel more confident and secure in exploring new social potential. As a result, when their financial status declines, they might also exhibit less diversity in social interactions due to declined living situations and confidence.

We emphasize that our study pool is a very unique combination of young individuals from different countries. As a result, it remains a question if our results can be generalized to the society, and further studies on other participant pools are necessary to confirm our findings.

II. The Friends and Family Study

A. The Living Lab

Based on previous studies including the Undergraduate Dormitory Study [9], in March 2010 we initiated a living laboratory study conducted with members of a young-family residential living community adjacent to a major research university in North America. All members of the community are couples, and at least one of the members is affiliated with the university. The community is composed of over 400 residents, approximately half of which have children.

In the pilot phase of this study was launched with 55 participants in March 2010. In September 2010, the second phase of this study was launched with 85 additional participants. Participants were selected randomly out of approximately 200 applicants, in a way that would achieve a representative sample of the community and sub-communities.

The pilot phase of the *Friends and Family Study* started in early March, 2010, and it ended with more than six months of data collected. However in this work we exclude three months of data collected during the summer break because many participants were not present. This phase was also used for discovering and fixing hardware and software issues and improving our mobile platform. The second phase started on October 2010, and in this study we use the first three months of data from the second phase.

B. Methodology

The central component of the study is the Android-based software sensing platform, which records users' call logs, contact information, Bluetooth face-to-face interaction information (by scanning for surrounding Bluetooth devices every five minutes), app usage information, and GPS location data, among others [8]. The phone software also comes with a survey application for collecting additional daily information about users such as their emotions and health related measures.

Fig. 1 illustrates the phone sensing software interface and the survey interface. We also use web interface for longer monthly surveys.

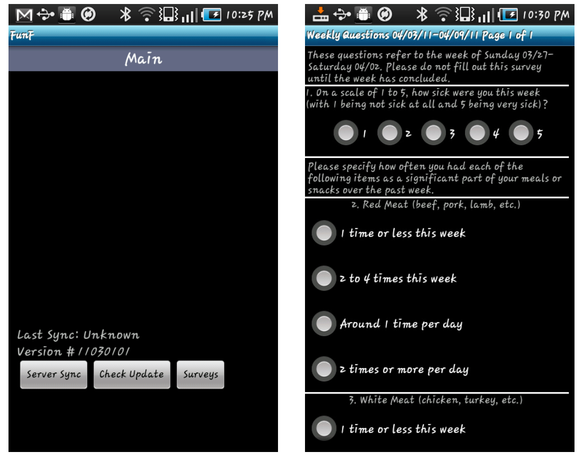
Using the call log data and Bluetooth face-to-face proximity data collected via phone sensors, we apply the same measure as in Eagle et al. [1] to compute the diversity of interactions. The diversity $D(i)$ is defined as:

$$D(i) = \frac{-\sum_{j=1}^{k} p_{ij} \log p_{ij}}{\log k}, \tag{1}$$

where p_{ij} is the interaction volume between individual i and j divided by the total interaction volume of i, and k represents the total number of contacts. Volume is either the number of phone calls for call logs or the number of hits for Bluetooth proximity.

The diversity score measures how evenly an individual's time is distributed among others. It is important to note that *high diversity does not necessarily correspond to high call volumes or large number of unique contacts*.

We compute $D_{\text{call}}(i)$ and $D_{\text{Bluetooth}}(i)$ using call logs and Bluetooth hits respectively. We count all calls including contacts outside our focused community for $D_{\text{call}}(i)$.



(a) (b)

Figure 1. In this study, our Android-based software includes both our passive sensing framework (left) and various surveys (right). Both can be remotely controlled and modified by the study manager.

Table I
THE FOLLOWING INTERACTION STATISTICS COMPUTED FROM PHONE SENSORS ARE USED IN OUR ANALYSIS FOR THIS PAPER.

Item
All Calls
Unique Contacts in Call Logs
Call Diversity ($D_{\text{call}}(i)$)
Sum of Face-to-Face Interaction Time (via Bluetooth)
Unique Bluetooth Face-to-Face Contacts
Bluetooth Face-to-Face Diversity ($D_{\text{Bluetooth}}(i)$)

For Bluetooth diversity, we only count hits within participants in this study. Each Bluetooth device has a unique MAC address, and we match MAC addresses to participants' phones in our study. It is difficult to determine whether an unknown MAC address is a phone or other devices. Therefore, we discard all hits with unknown MAC addresses. As a result, this measure only captures the communications within this study community. On average, each participant in our dataset has Bluetooth face-to-face contacts with 13 other participants. ($\sigma = 8$)

In addition to the diversity for Bluetooth interaction and calls, we also compute other raw statistics from our phone data for each participant as described in Table I.

III. The Pilot Phase: March to June, 2010

In this section, we present our analysis on data collected from 55 participants during the pilot phase from April to June 2010. For Bluetooth proximity data, we use the period from early March to mid-April, which has the most reliable and complete Bluetooth record. We use all call log data aggregated over the four months.

A. Data

In the pilot phase, we asked participants to report only their discretionary spending in the survey to measure their financial status. This idea is based on previous research which suggests that discretionary spending is correlated with family income [10], and it is not too intrusive to ask. Also, discretionary spending is commercially interesting for practical mobile based applications and commerce.

In this phase, we asked the following question in the enrollment survey:

As an INDIVIDUAL, how much do you spend per month on discretionary purchases?

Discretionary items were defined explicitly in the survey as entertainment- and hobby-related items. We ended up eliminating data from participants whose native language is not English for the analysis below, as we found that the concept of "discretionary spending" was not straightforward and clear for them.

B. Analysis

We find that discretionary spending for individual i correlates with the individual's call diversity $D_{\text{call}}(i)$ ($r = 0.35$ and $p = 0.05$), independent of number of calls. However, the correlation between discretionary spending and face-to-face interaction diversity $D_{\text{Bluetooth}}(i)$ is very significant ($r = 0.50$ and $p = 0.005$). We observe no significant correlation between the number of calls, Bluetooth hit counts, and discretionary spending. There is also no significant correlation between the number of contacts and discretionary spending, but there is very weak negative correlation between discretionary spending and the number of unique Bluetooth face-to-face contacts ($r = -0.43, p = 0.09$). We conclude that people who spend more money are likely to have a more diverse social circle, but they do not necessarily participate in more social activities, and sometimes have even less face-to-face contacts.

C. Discussion

In the pilot study we observe that interaction diversity, in particular Bluetooth face-to-face interaction diversity, correlates positively and strongly with discretionary spending. Our preliminary findings imply that people in good financial status exhibit different social behaviors than ones having lesser financial status, namely, they are likely to spend their social time more evenly distributed with different contacts.

IV. Second Phase: October to December 2010

Encouraged by the pilot study, we continued to develop the second phase of this study to further explore this type of connections and their causality implications.

In the second study, we recruited 85 additional participants, and near 70% of them just arrived the university to start their graduate study since this is the start of the fall term. Because this is a residence for families, many of these participants are generally in a more advanced stage in life than that of average university students. Many had already married and have children. A large portion of the participants were already quite successful in their careers with higher-than-average salary and life styles before coming back to this post-graduate school.

In the following analysis, we focus only on the 85 additional participants, and exclude participants from the previous phase.

A. Data

Most of the participants still have a household income from various sources such as scholarship, assistantship, family support, spouse's occupation, etc. We learned from the pilot phase that discretionary spending is limited in capturing clear financial pictures of each individual. As a result, in the enrollment survey which all new participants had to fill out before joining the second phase study, we explicitly asked two other questions in addition to the discretionary spending question used in the pilot phase:

1) *Annual household income from all sources:*
2) *Annual household income before coming back to this school:*

We decided that the questions be categorical options rather than exact amount to reduce the feeling of privacy invasion from our participants. Therefore, we ask participants to choose one of the following options for both questions: *a) Under $20,000, b) $20,000 - $45,000, c) $45,000 - $65,000, d) $65,000 - $90,000, e) $90,000+ and f) Prefer not to say.*

In addition, we collected other measurements for each participant such as the big-five personality scale [11]. We also asked in the daily phone-based survey how happy do they feel today and how stressful they feel today, both on a 7-point scale, to measure their temporal emotion dynamics.

In the second phase, we collected both Bluetooth proximity and call log data for a whole three month duration, ranging from October 2010 to December 2010, and we were able to use all of them to compute the diversity indicators as described in Section II-B.

There are 13 subjects who chose not to share their income status, and we exclude all these users in the analysis below.

B. Analysis

1) Income Distribution: Most participants decide to disclose their information on their income. We show the number of participants for different income categories in Fig. 2.

From the survey data, we notice some interesting factors for this participant pool: Currently, half of the participants have household income between $\$20,000$ to $\$45,000$ due to the fact that this is the standard stipend in this university for paid graduate students. While some participants come from a successful career and incur a sudden loss of income when coming back to school, other participants may enjoy a raise of income because of various scholarship, assistantship, family support and their spouse' work income.

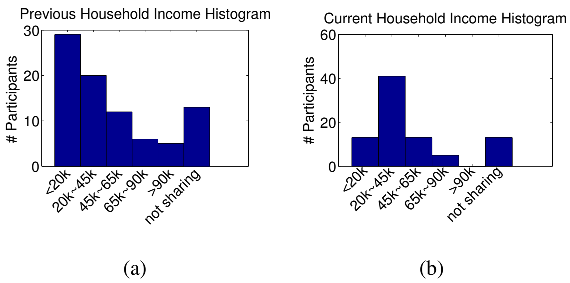


Figure 2. For both the previous (left) and current (right) household income, we show the number of participants in different income categories from the self-reported surveys.

2) Discretionary Spending: We here apply the same technique to measure the correlation between discretionary spending and phone-sensed data as described in the pilot phase of this study in Section III. To match the pilot study, we exclude data from people whose native language is not English in Fig. 3. We are able to obtain similar results: The Bluetooth diversity correlates with each individual's discretionary spending well ($r = 0.40, p = 0.03$). However, the call diversity measure does not correlate significantly with discretionary spending. From the data, we do not see see any correlation between discretionary spending and other measures listed in Table I. We realize that the correlation between the call diversity (but not number of calls) and discretionary spending is stronger in the pilot phase, and we suspect this might be attributed to the fact that most participants are newly settled in the area or even the country, while in pilot study participants have been in the community for at least half a year.

We continue to verify a previous assumption from Section III: That discretionary spending is a good indicator for financial status especially household income.

We show in Fig. 3 that the mean discretionary spending for different previous and current household income categories.

We use the median value in each of the income category as approximation of the true income (later we will refer it as "coarse income") for each participant in the regression analysis. We discover that the current income correlates with discretionary spending with $r = 0.33$ and $p = 0.08$, which matches previous work [10]. We do not see any correlation between discretionary spending and previous income ($r = 0.02, p = 0.90$). This finding suggests that discretionary spending can be partially explained by current income, but not previous income. We suspect that better financial status ensures people safer living conditions [18] [19], and people are less likely to save and more likely to spend.

Due to the limitation of the survey, we are not able to measure the exact household income. Because we only have five income brackets for regression, and participant sample size in certain income brackets is small, we emphasize here that we are adopting a significance threshold level of $\alpha = 0.10$ instead of the common $\alpha = 0.05$ in the following analysis.

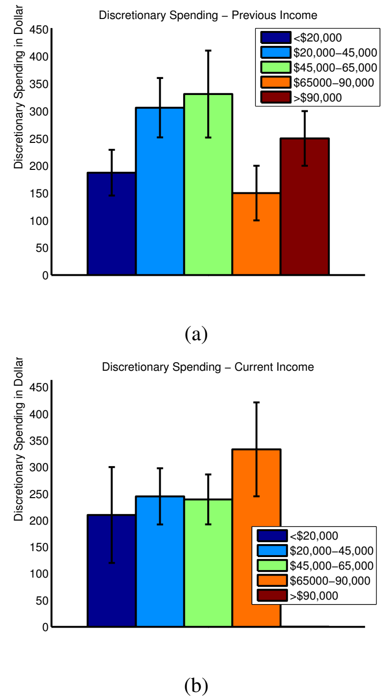
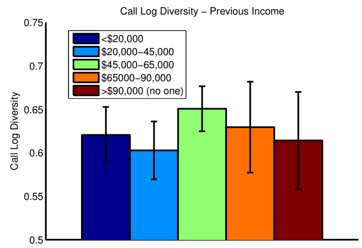


Figure 3. We illustrate that the discretionary spending for different classes of current income and previous income. The error bar is the standard error for each income category. The plots here suggest that discretionary spending is more relevant to current income.

3) Diversity in Phone Calls: We continue to study the relationship between call diversity and income here. We first compute $D_{\text{call}}(i)$ for each participant as described in Section II-B. We illustrate the mean value and standard error for different income categories in Fig. 4. There exists positive correlation between current household coarse income and call diversity ($r = 0.28, p = 0.08$). However, there is no significant correlation between previous estimated household income and call diversity ($r = 0.003, p = 0.80$). Our observations conclude that the call diversity correlates with the current household income, but it does not correlate with previous household income.

We also look at the number of phone calls for each participant, and we discovered that there is no significant correlation either between the number of phone calls and current coarse income ($r = -0.04, p = 0.70$), or between the number of phone calls and previous coarse income ($r = -0.05, p = 0.60$). Therefore, wealthier families do not necessarily make more phone calls, but they split their phone calls more evenly among their social ties.

In addition, there is no significant correlation between the number of contacts (i.e. how many different numbers one have called) and individual's previous income ($r = 0.16, p = 0.30$) or current income ($r = -0.01, p = 0.79$).



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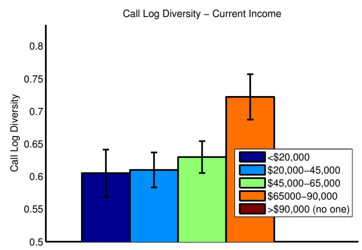
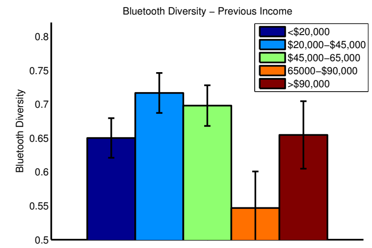


(b)

Figure 4. We show here the mean call diversity $D_{\text{call}}(i)$ and standard error for individuals in different income categories. The top plot is based on reported previous household income, and the bottom plot is based on reported current household income. Current household coarse income is correlated with call diversity ($r = 0.28, p = 0.08$), while previous household coarse income is not correlated with call diversity ($r = 0.003, p = 0.80$).



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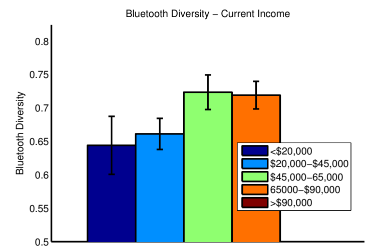

(b)

Figure 5. We show here the mean Bluetooth diversity $D_{\text{Bluetooth}}(i)$ and its standard error for individuals in different income categories. The top plot is based on previous household income, and the bottom plot is based on current household income. There exists positive correlation between current household coarse income and call diversity ($r = 0.32, p = 0.10$), but there is no significant correlation between previous estimated household income and face-to-face interaction diversity ($r = -0.28, p = 0.60$).

4) Diversity in Bluetooth Face-to-Face Interaction: We now look at the connection between income and Bluetooth face-to-face interaction diversity. As described before, the plots in Fig. 5 only include Bluetooth interactions with other participants in the study. Therefore, the interaction diversity measured here is composed of interaction only among our study participants. We illustrate the results for both previous income and current income in Fig. 5.

We notice borderline positive correlation between current household coarse income and call diversity ($r = 0.32, p = 0.10$), and we notice the correlation is much stronger within native English speakers ($r = 0.53, p = 0.06$). There is no significant correlation between previous estimated household income and face-to-face interaction diversity ($r = -0.28, p = 0.60$).

From our data, it seems that current household income is a reasonable predictor for interactions within the community. Again, we discover no significant correlation between previous income and the interaction diversity. We also find that among all participants, those who are native English speakers tend to show stronger correlation compared with participants with other native languages rather than English. This is natural, as it takes more time for international students to improve their language skills, blend into this community and form new ties with domestic participants, as previous work pointed out [12].

In addition, we observe no significant correlation between overall face-to-face interaction time and the income level ($r = 0.26, p = 0.31$ for correlation with previous income and $r = 0.08, p = 0.77$ for correlation with current income). Therefore, wealthy families do not necessarily spend more time interacting with other community members.

Interestingly, we discover there exists correlation between current income and the number all face-to-face friends (i.e. the number of other community members with whom a participant has spent time) with $r = 0.29, p = 0.08$. However, such a relationship is not observed between previous income of the participants and the number of face-to-face friends. People with higher current income do enjoy knowing a greater number of other people in the community.

V. Personality Traits

One of the most important factors which might have strong influence over social behavior is the personality variance among individuals [13]. Therefore, to further understand the mechanism in our previous findings, it is essential to investigate whether personality plays a role in interaction diversity patterns. We also examine the moderator effects for personality traits.

During this experiment, we have asked participants to report their personality by adopting an 44 question Big Five Scale developed by John et al [11]. This scale measures five different dimensions as described in Table II.

Table II
THE BIG FIVE PERSONALITY TRAITS

Dimension	Explanation
Extraversion	Encompasses such more specific traits as talkative, energetic, and assertive.
Agreeableness	Includes traits like sympathetic, kind, and affectionate.
Conscientiousness	Includes traits like organized, thorough, and planful.
Neuroticism	Includes traits like tense, moody, and anxious.
Openness	Includes traits like having wide interests, and being imaginative and insightful.

We conduct regression tests for each of the five traits with every interaction measure in Table I. Accordingly, we ended up with 30 pairs of regressions to analyze.

A. *Correlation between Personality and Social Behavior*

We describe all significant correlations revealed in our experiment here. Overall, we found that 'agreeableness' significantly correlates with the number of unique phone call contacts positively ($r = 0.38, p = 0.001$) and the number of unique Bluetooth contacts ($r = 0.25, p = 0.04$) positively. This is intuitive as more sympathetic and kind individuals do attract more friends by our own life experience.

For the amount of time spending in calls and face-to-face meetings, we found that 'agreeableness' significantly correlates with the number of all phone calls ($r = 0.28, p = 0.02$), while 'neuroticism' weakly correlates with the number of phone calls negatively ($r = -0.20, p = 0.10$). We suspect that people with higher 'neuroticism' measure are more difficult to interact with, thus they have less acquaintances. 'Agreeableness' also significantly correlates with overall face-to-face Bluetooth interaction time positively ($r = 0.22, p = 0.07$).

We discover that none of the five traits can explain the call diversity measures $D_{\text{call}}(i)$. However, we find that among all five traits, 'neuroticism' correlates with face-to-face interaction diversity $D_{\text{Bluetooth}}(i)$ negatively ($r = -0.28, p = 0.02$).

We also compute the overall happiness score and stress score from daily surveys deployed during the second phase. We notice no significant correlation between interaction diversity and those scores. Therefore, the overall mood of the participants is not correlated with their social diversity.

To conclude, we find that personality does explain time spent in social interactions and the number of of contacts in social networks. However, we find that except the correlation between 'neuroticism' and the Bluetooth interaction diversity, none of the other personality traits correlates significantly with the interaction diversity measures analyzed in this paper.

B. *The Moderator Effect*

Since we found that the 'neuroticism' personality trait is correlated with face-to-face interaction diversity, which is also connected to income, we here continue to investigate whether any personality trait is a moderator [14] for the relationship between income and interaction diversity measures, i.e. whether one's income influences one's interaction patterns via personality change. In the same manner, we also test if income is a moderator for the relationship between personality and interaction diversity to rule out the hypothesis that personality influences income which continues to influence social interaction diversity.

To do so, we adopt the Sobel test [15], a statistical tool to test the moderator effect. We discover that none of the personality trait plays any moderator role (with significance threshold at 0.10) to influence the interaction diversity measures $D_{\text{call}}(i)$ and $D_{\text{Bluetooth}}(i)$, which suggests that income does not influence social diversity via personality change. This result matches previous findings that dramatic personality change at any stage of life is very rare [16]. The dramatic income change for all participants do not necessarily leads to dramatic personality change, and eventually social behavior change.

Similarly, we do not notice any significant moderator role played by income for the weak correlation between 'neuroticism' and interaction diversity. Therefore, personality does not change interaction diversity via its influence over income.

C. *Discretionary Spending and Personality*

We have already discovered that discretionary spending is related to current household income. We now ask whether it might also be related to personality variance. To investigate this possibility, we run regressions with all five traits as independent variables and discretionary spending as the dependent variable, and discover no significant correlation between any of one's personality trait and one's discretionary spending. Therefore, we argue that personality variance can not explain variance in discretionary spending at all.

VI. DISCUSSION

A. *Individual-level Correlation between Social Interaction Diversity and Financial Status*

Although we have a relatively small participant pool ($N = 55$ for the pilot phase, 85 people for the second phase), we are still able to observe evidence suggesting the connection between one's financial status (i.e. discretionary spending and income) and one's interaction diversity. Our results are well aligned with previous finding [1].

Widely used social measures such as time spent on social interactions and number of unique friends are not related to one's financial status. Our study shows that counter-intuitively, wealthier individuals do not necessarily spend more or less time on meetings and calls, and they also do not necessarily have more friends or contacts. These two measures of social interaction can be explained by one's personality traits to some extent.

However, it seems that the diversity measure (Eq. 1) is superior to other simpler measures such as number of phone calls and number of unique contacts in revealing one's financial status. The diversity measure is also robust to individual personality variance as described in the previous section. Our finding can benefit the mobile industry to leverage mobile data and adopt this particular diversity measure to better understand and serve their customers.

B. Causality

The prevailing social theories argue that diversity brings wealth [2] [3] [4] [7] [5]. This class of causality explanations implies the following reasoning: If successful or experienced individuals are suddenly deprived of their income like many participants in this study, naturally they will continue to keep their diverse interaction behavior. Their previous experiences and success suggests that they understand and benefit from their social diversity, and their future success still relies on their continuous diversity interaction.

However, the most surprising fact unveiled in this study is that social interaction diversity is not related to their immediate previous household income at all, even though most participants just left their previous life condition and moved to the university for a new life. On the contrary, we observe the connection between current income and interaction diversity patterns. To further demonstrate our findings, we compute the change between previous and current household income, and we now show the difference in interaction diversity for both individuals with sudden significant loss of income (defined as a loss of $50,000$ or more over previous income) and individuals with sudden significant gain of income (defined as a gain of $30,000$ or more over previous income) in Fig. 6. While our sample size is small ($N = 6$ and 8 respectively), we discover from Fig. 6 that individuals with sudden income gain are more likely to show higher interaction diversity compared with individuals with sudden income loss.

As most participants are newly arrived students and partners, we emphasize that their current income is largely independent of opportunities from their diverse social contacts, but rather external factors that are not controllable by the individuals such as fixed stipend and limited employment opportunities for student families. Therefore, our evidence seems again to point us in the opposite direction: Individuals' social diversity is influenced by their current financial status.

Our study is very related to a recent project by Krumme et al. [17], in which researchers are investigating a large

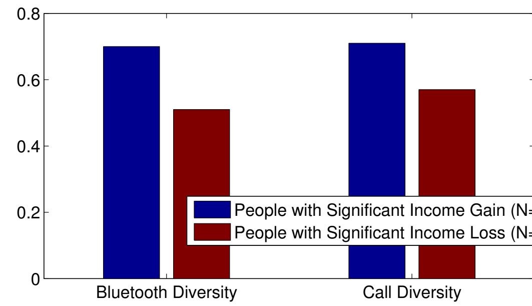

Figure 6. We examine individuals with self-reported significant income loss ($> 50,000$) and significant income gain ($> 30,000$) here, and we illustrate the mean Bluetooth and call diversity for both groups. K-S test confirms the difference for Bluetooth diversity ($p = 0.07$) but cannot confirm the difference for call diversity ($p = 0.25$) due to the small sample size.

financial credit card transaction dataset to study shopping patterns of individuals. They observe that shopping diversity correlates with individuals' current financial status. By tracing users' checking accounts to establish their financial status, researchers have found that the shopping diversity (measured by entropy) for rich people is significantly higher than poor people ($p = 10^{-4}$). Krumme et al. also made use of data from the period of the recent financial downturn, and studied users who suddenly lost 20k–30k income between the year 2007 and the year 2009. It turns out that these people suddenly lost their shopping diversity by 0.05 on average, while they have not reduced their trips to shops. Their results suggest that shopping diversity is more related to current financial status and sensitive to changes in income, but overall shopping times are not sensitive to income at all.

Their observation surprisingly matches our observations on individuals who left well paid jobs to attend graduate schools. This coincidence leads us to believe that while prevailing theories are still sound, the causality mechanism is more complicated than we previously thought.

In addition to the weak effects of personality variance in interaction diversity as described in Section V, we suspect that a more behavioral and psychologically oriented mechanism plays an important role in the other direction of causality: Individuals' social diversity patterns are influenced by their financial status. We believe that as good financial status ensures people with safer and more satisfied living conditions [18], they naturally feel more confident [19] and secure in exploring new social potential [20] [21].

VII. Conclusion and Future Work

With the advancement of mobile technology, we have conducted this study by deploying smart phones to measure people's social interaction behavior. To our knowledge, this work is the first result that establishes the existence of individual-level correlation between financial status and interaction patterns, and their connection to personality traits.

Compared with other simple social interaction measures such as number of contacts and sum of interactions, we find that the diversity measure based on entropy in Eq. 1 performs better in inferring users' financial status. The diversity measure is also insensitive to personality variance unlike other interaction metrics investigated in this paper.

Prevailing social theories argue that social diversity leads to individual success. Based on our findings, we propose an alternative theory suggesting that behavioral and psychological effects from income level play important roles in influencing social behaviors. We show this by examining the relationship between one's interaction behavior and both one's immediate previous income and one's current income, and connecting our results with another study [17] and other previous psychological and behavioral research.

However, while in this work we provide a new perspective and some supporting evidence for this complicated causality problem, we still think that more evidence such as a more general group of subjects and a controlled long-term study is necessary to further cross examine our theory as well as other related social theories. We leave it as a future work.

VIII. Acknowledgements

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