Village Social structure and Labor Market Performance

Evidence from the Philippines*

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Abstract

This paper studies how social structure affects labor markets. We hypothesize that more fragmented social structures discourage network hiring, and hence improve the allocation of talent and investment in human capital. We test these hypotheses using data on marriage networks in 15,000 villages, combined with labor force survey data. Individuals living in more socially fragmented villages are less likely to work in family firms, more likely to use formal job search strategies, invest more in education and earn higher wages. These results survive 384 combinations of robustness checks and an instrumental variable strategy. We further provide direct evidence against reverse causality.

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1 Introduction

Social networks have a profound influence on the labor market (Granovetter, 2005; Beaman, 2016). Employers often hire using family networks and worker referrals (Heath, 2018; Chandrasekhar et al., 2020); jobseekers share information about job opportunities with their friends (Beaman and Magruder, 2012; Caria et al., 2020); migrants locate where their social connections are strongest (Munshi, 2020); and different types of peer effects can foster worker productivity and motivation (Mas and Moretti, 2009; Field et al., 2016). The way an individual's position in a social network determines their labor market outcomes has been studied both theoretically and in the field (Calvo-Armengol and Jackson, 2004; Bayer et al., 2008). On the other hand, the aggregate labor market implications of different network structures have rarely been documented empirically, and are generally not well understood.

In this paper, we explore how social network fragmentation — a key measure of network structure capturing the relative size of the clusters in which the network is divided — affects labor market performance. We hypothesise that fragmentation changes employers' incentives to hire from their cluster of the network. A natural possibility is that the social returns from network hiring decrease in cluster size, and hence employers in more fragmented societies have a weaker incentive to hire from their cluster of the network. Less network hiring, in turn, would lead to a better allocation of talent and skills (Chandrasekhar et al., 2020), and to stronger incentives for workers to invest in human capital.

Lack of data on social structure has so far prevented researchers from shedding light on these mechanisms. Our core contribution is thus to explore the influence of social fragmentation on labor market performance using unique social network data from the Philippines. We use data from 2008/2010 in 15,000 villages that includes information on all family names together with local naming conventions to map out marriage networks. We measure social fragmentation in two steps. First, in each village, we divide families into groups that have many connections with each other and limited connections to outsiders. For this purpose, we use some well-known community-detection algorithms (Girvan and Newman, 2002). Second, we compute the Herfindahl-Hirschman index of the clusters in each village, which gives us a measure of the relative size of the clusters. In socially fragmented villages, average relative cluster size is small.

Our main results show that in more fragmented villages individuals are less likely to access the labor market through social networks. Specifically, a one-standard-deviation increase in social fragmentation is associated with a 15 percent reduction in the probability of working for a family-firm and a 10 percent increase in the probability of work-

ing for a private firm not owned by a relative. This is consistent with the argument that fragmentation leads to a reduction in network hiring. We also show that individuals in more fragmented villages invest more in human capital. Then, we document that social fragmentation is associated with higher hourly wages and longer working hours. Importantly, poverty levels are also lower in more fragmented villages. A mediation analysis suggests that 64 percent of the boost in wages can be explained by changes in education while 25 percent can be explained by changes in the type of firm individuals work for. This supports the view that social fragmentation improves labor market performance through a combination of stronger human capital accumulation and a more efficient allocation of talent. Finally, in line with existing evidence that network hiring is detrimental to women, we find that both the human capital and the labor market effects of social fragmentation are stronger among women.

We implement a number of robustness checks that increase confidence in our findings. Importantly, we provide evidence against reverse causality — the hypothesis that economic outcomes change social fragmentation, e.g., by affecting migration or marriage patterns.[1] First, we show that social fragmentation is highly persistent and largely unrelated to a battery of municipal-level variables capturing education and assets in the 90s. To further reduce concerns related to migration, we include controls for how long individuals have lived in their villages, for the share of individuals who recently migrated into the village and the distance to the closest urban center. We also use an instrumental variable strategy that instruments current network links with old network links. Our results are unaffected. To reduce concerns related to changing marriage patterns, we show that an indicator of assortative matching in the marriage market has not changed over a 50-years time period. In addition, one may worry that fragmentation is correlated with urbanisation, population or other forms of social diversity. We show that our results are highly robust to including a rich set of controls capturing these potential confounders. Our specification curves show that our main results are robust to 384 combinations of our robustness checks.

Our results make three key contributions to the literature. First, we provide original empirical evidence on the effect of network structure on labor market performance. To our knowledge, we are the first to document the influence of a broad measure of network structure on labor market performance using data that directly measures social connections. As mentioned above, despite an abundance of theory, empirical analyses of network structure are surprisingly rare. To circumvent the lack of field data on net-

[1] Some of the interesting potential interactions between migration and social networks are explored in Munshi and Rosenzweig (2006) and Munshi and Rosenzweig (2016).

work structure, Dai et al. (2018) proxy network density with population density, Centola (2010) and Centola (2011) study online communities, and a number of researchers explore the effect of social structure in the lab (e.g. see Charness et al. (2014) and Gallo and Yan (2015)). Further, using the same data on family networks that we exploit in this paper, Cruz et al. (2020) investigate the effects of social structure on political outcomes.

Second, we show that social diversity can create economic dividends. Existing work has largely focused on the challenges posed by social diversity. For example, social rivalries can distort production (Hjort, 2014) and reduce support for redistribution (Alesina et al., 2018).[2] A smaller literature has documented an association between diversity and productivity, possibly due to skills complementarities (Ottaviano and Peri, 2006; Alesina et al., 2016). We advance this literature by proposing and providing evidence for a new channel through which an understudied dimension of diversity — social fragmentation — can affect economic performance.

Third, we highlight a novel mechanism that can distort the allocation of talent in labor markets. The recent literature in development economics has devoted much attention to factor misallocation (Hsieh and Klenow, 2009). Many of the proposed explanations revolve around standard economic forces such as credit constraints and asymmetric information (Abebe et al., 2021b; Bandiera et al., 2017; Bassi and Nansamba, 2017; Dillon and Barrett, 2017; Abebe et al., 2021a). In this paper, on the other hand, we show that misallocation can also have social origins. This finding has important policy implications. In particular, it suggests that policy makers may be able to target interventions on the basis of the social structure of communities. In socially fragmented communities, removing credit constraints or providing information may be a viable and effective policy option. Similar policies are unlikely to have the same effects in more socially concentrated communities.

2 A simple conceptual framework

In this section, we present a simple conceptual framework that clarifies how social structure can impact labor market outcomes. We assume that in each village there is large number of workers; a fixed, small number of homogeneous firms, each managed by a single manager; and a set of bilateral social connections between individuals. As is common in real-life networks, social connections are organised in 'clusters' — groups of individuals who share many social connections with each other and have only limited connections with individuals outside the cluster. The village economy works in the

[2] Alesina and Ferrara (2005) provide an early review of this literature.

following way. First, workers are randomly assigned a level of skills. Then, firms encounter random production opportunities over time. Once a production opportunity comes along, the firm manager hires an unemployed worker to produce output. 'Network hiring' occurs whenever the manager hires a worker who belongs to the same network cluster.

Firms have both a monetary and a social payoff. The social payoff is positive whenever the manager hires an individual who belongs to the same network cluster. If the manager hires outside of their network, the social payoff is zero. Naturally, we assume that larger clusters can offer larger social payoffs. This is because larger clusters are often better placed to offer insurance, future opportunities, and social prestige.[3] The monetary payoff, on the other hand, is determined by the level of skills of the worker, who is paid a wage that is a given by the value of their skills, minus some proportional rent for the firm. The higher the skills of the worker, the higher is the output they produce, and the absolute rent that the firm receives. Thus, whenever the most skilled unemployed worker belongs to a different social cluster, managers face a tradeoff between monetary and social payoffs. If they choose to hire from their network, output and wages are not maximised.

This framework highlights two key ways in which social structure can influence the workings of the labor market. First, the more fragmented the social structure, in the sense that average relative cluster size is small, the lower the average social payoff. This will induce managers to engage less frequently in network hiring. Second, the expected loss in monetary payoff from network hiring may also increase with social fragmentation, as the smaller is the manager's cluster, the lower is the expected ability of the best candidate in the cluster. This will give a further incentive for firms to refrain from network hiring. *Thus, our first prediction is that we will observe less network hiring in socially-fragmented villages.*

Importantly, a reduction in network hiring may in turn lead to a better allocation of talent. Firms in more socially-fragmented villages obtain a lower social payoff from network hiring and thus will be less willing to sacrifice worker talent for social rewards, which will lead to them making better hires. As a result, they will produce more output

[3]This assumption is supported by several pieces of empirical evidence. For example, Munshi (2003) shows that individuals with larger social networks have better labor market outcomes; Angelucci et al. (2018) find that individuals redistribute government transfers through their networks and that larger networks display a stronger overall consumption response to transfers; Ashraf et al. (2014) document that a prestige-based intervention has higher impacts among individuals who are part of a larger peer group.

and pay higher wages.[4] *Our second prediction is thus that wages and income will be higher in socially-fragmented villages.*

We can make an additional set of predictions by considering the possibility that individuals can acquire new skills. In this case, network hiring will have a second cost: it will reduce incentives to invest in skills. This is because workers rationally anticipate that the employment gains that accrue from having stronger skills are lower due to network hiring. Lower skills will in turn depress output and wages. *Our third prediction is that that individuals in socially-fragmented villages will invest more in human capital, and that higher human capital in turn will raise wages and income.*

Finally, if the social payoff also differs by demographic characteristics, we expect to see that social fragmentation has stronger positive impacts for groups that offer lower social payoffs, and are thus more likely to face reduced opportunities due to network hiring. This could be the case for women, who typically have lower access to labor market networks. *Our final prediction is that the impacts described above will be stronger for female workers.*

3 Network measures and data

In this section we introduce the algorithm we use to measure social fragmentation and present our various data sources.

3.1 Network data

We use data on marriage connections in Philippine villages from the non-anonymized version of the National Household Targeting System (NHTS) data collected between 2008 and 2010 by the Department of Social Welfare and Development (DSWD) to select beneficiaries for a large-scale conditional cash transfer (CCT) program (Fernandez, 2012). We limit our analysis to 20 million observations in the 709 municipalities in which full enumeration took place.

We use information on family names to measure family connections through marriage. This approach takes advantage of unique features of Filipino naming conven-

[4] The allocative implications of the monetary channel are, on the other hand, ambiguous. As discussed above, firms in socially-fragmented villages are less likely to hire from their network. However, when they do hire from their network, they suffer a larger expected loss of skills, which makes the allocative implications ambiguous. Here, we assume instead that allocative effects are driven by the first channel: firms in socially fragmented villages have a lower social payoff from network hiring and hence hire more efficiently.

tions:[5] (i) within a municipality, a shared family name implies family connections; (ii) each individual carries two family names, which establishes that a marriage took place between members of those two families; (iii) names are difficult to change.[6]

Names used in the Philippines were imposed by Spanish colonial officials in the mid-19th century. One of the stated objective was to distinguish families at the municipal-level to facilitate census-taking and tax collection. Last names were selected from the *Catalogo alfabetico de apellidos*, a list of Spanish names. They do not reflect pre-existing family ties. In each municipality a name was only given to one nuclear family. As a result, there is a lot of heterogeneity in names used at the local level, reducing concerns that names capture a similar ethnic background or other social grouping. Names are transmitted across generations according to well-established rules. Specifically, each individual has two family names: a last name and a middle name. A man's last name is his father's last name and his middle name is his mother's last name. Similar conventions apply to unmarried women. A married woman has her husband's last name and her middle name is her maiden name, *i.e.*, her father's last name.

The full names of all individuals in each village provides us with complete information on all marriages between families. We are thus able to reconstruct the full marriage network - with each name being a node - in each village and to implement the Girvan-Newman algorithm described below.

3.2 Measuring social fragmentation

Our main empirical challenge is to measure social fragmentation at the village-level. Following insights from Cruz et al. (2020), we measure how villages are divided into a number of clans. We rely on the notion of communities from social network analysis: groups of nodes with dense connections internally (i.e. within the group) and sparser connections between groups (Jackson, 2010). We identify clans using community detection algorithms. In particular, we rely on the Girvan and Newman (2002) algorithm which proceeds as follows:[7]

[5] It has been used by Fafchamps and Labonne (2017), Cruz et al. (2017), Fafchamps and Labonne (2020) and Cruz et al. (2020).

[6] As indicated by Fafchamps and Labonne (2017), there are strict legal constraints on name changes in the Philippines which reduce concerns about strategic name changes.

[7] We also implement the *walktrap* algorithm developed by Pons and Latapy (2006). Intuitively, the algorithm relies on the idea that random walks on a graph tend to get "trapped" into densely connected parts corresponding to communities. The algorithm thus generates a large number of random walks and groups together nodes that are tied together through those walks. See Pons and Latapy (2006) for more details.

1. Calculate the betweenness for all edges in the network[8]
2. Remove the edge with the highest betweenness
3. Recalculate betweenness for all edges affected by the removal
4. Repeat from step 2 until no edges remain
5. From resulting dendrogram, select the partition that maximizes network modularity

The algorithm delivers a partition of C communities (indexed by $c = 1, \ldots, C$), each containing a share s_c of nodes. Our main measure of fragmentation is a standard Herfindahl-Hirschman index:

$$\texttt{fragmentation} = 1 - \sum_{c=1}^{C} s_c^2$$

where s_c is the share of nodes in each community c. The total number of communities is C. As shown in Figure A.1, the levels of social fragmentation are high in our sample. To simplify interpretation we normalise the measure to be mean zero and standard deviation 1.

3.3 Labor market data

We use Labour Force Survey (LFS) data collected by the Philippine Statistics Authority (PSA). The surveys are conducted four times a year (January, April, July and October), and we have access to all 26 surveys in the period July 2003 to October 2009.[9] We only use working-age individuals (above 15) in the 1,110 villages for which the NHTS data is available. More details are available in Franklin and Labonne (2019).

Respondents provide three important pieces of data that allow us to compute the following outcomes: (i) Daily earnings; (ii) Average # hours worked per day during the past seven days and; (iii) Total # hours worked during the past seven days.[10] We combine them to compute hourly wage (Daily earnings / Average # hours worked per

[8]This centrality measure captures the extent to which the edge serves as a link between different groups. It is calculated using the number of shortest paths between nodes in the network that pass through that edge (Freeman, 1977).

[9]More information on the survey design is available at: http://www.census.gov.ph/data/technotes/notelfs_new.html visited on 26 March 2012.

[10]The measure of daily earnings is derived differently according to how someone is paid. For workers who are paid on an hourly basis, the daily rate is computed as their hourly rate multiplied by average working hours (per day) over the past week. For workers who are paid monthly, the daily rate is computed as their monthly wage divided by the number of working days per month.

day during the past 7 days) and weekly earnings (Hourly wage * Total # hours worked during the past 7 days).[11]

Respondents also provide information on the type of firm they work for (Family, private). In addition, for the sample of individuals who are looking for work, respondents provide information on how they look for jobs. We use this information to code whether they look for jobs through their networks (Approached Relatives or Friends, Approached Employer Directly) or through more formal strategies (Registered in Public Employment Agency, Registered in Private Employment Agency).

Finally, we use data from the 2010 Census of Population and Housing to generate measure of ethnic and religious diversity as well as measures of the availability of key public goods at the village-level for our robustness checks.

4 Results

In this Section, we present our empirical findings. First, we show that social fragmentation is associated with a more widespread use of formal job search methods, a higher likelihood of working for a non-family firm, and a stronger investment in formal education. Second, we document that social fragmentation is also associated with higher wages and lower village-level poverty. We use mediation analysis to show that a large part of these impacts could be explained by the changes in education and family-firm employment associated with social fragmentation. Finally, we discuss the robustness of our results.

We study the relationship between social fragmentation and individual outcomes of interest with models of the following form:

$$\texttt{outcome}_{ijm} = \alpha + \beta \cdot \texttt{fragmentation}_{jm} + \kappa \cdot X_{ijm} + \gamma \cdot W_{jm} + v_m + u_{im}. \qquad (1)$$

The unit of observation i is the individual in village j in municipality m. $\texttt{fragmentation}_{jm}$ is the Herfindahl-Hirschman index of social fragmentation discussed above, normalised to have mean zero and standard deviation one; X_{ijm} is a vector of individuals controls (usually age and gender); W_{jm} is a vector of village controls, including information on population, urbanisation, as well as information on the average length of stay in the village. We cluster standard errors at the village-level.

[11] Our main measures of earnings are at the weekly level because the reference period for earnings and hours worked in the survey is over the last seven days.

4.1 Job search, employment and human capital

Our first result is that individuals in more socially fragmented villages invest more in their human capital and are less likely to access the labor market through social networks. We show the headline specifications for these results in Table 1. We also report a more detailed analysis of the education variables in Table A.1 and look at the heterogeneity of the main effects by gender in Table 2.

We document that individuals in socially-fragmented villages are less likely to access the labor market through social networks in a number of ways. First, we show that, among those individuals who hold a job, a one-standard-deviation increase in social fragmentation is associated with a 15 percent reduction in the probability of working for a family-firm and a 10 percent increase in the probability of working for a private firm not owned by a relative. Second, among those individuals who are unemployed and are searching for work, we show that the likelihood of using formal job search methods (e.g., applying to formal vacancies by depositing a CV or registering to a public or private employment agency) is 4 percentage point higher when social fragmentation increases by one standard deviation, while the likelihood of approaching firms informally decreases by a similar amount. This evidence suggests that network hiring is less common in villages where social networks are more fragmented.

We also document sizable impacts on human capital accumulation, which hold both for high and low levels of education. In particular, a one-standard-deviation increase in social fragmentation is associated with a significant 5 percentage point increase in the probability of having some college (a 40% increase over the mean probability of having some college education in the sample). To put this in context, in our sample, individuals who live in urban areas are 14 percentage points more likely to have come college education compared to individuals who live in rural areas. Thus, the social-fragmentation effect corresponds to more than one third of the urban premium for college attendance. Similarly, we find that a gain of one standard-deviation of social fragmentation is associated with a 9 percent reduction in the probability of having no education and a 12 percent reduction in the probability of having only primary education.

Importantly, both the human capital and the labor market effects are significantly stronger among women (Table 2). In particular, the effect on working in a private firm is twice as large, and the reduction in the likelihood of working in a family firm is four times as large. Labor-market networks are widely thought to be disadvantageous for women (Beaman et al., 2018), so a strong move away from network hiring is likely to be particularly beneficial for this group.

Taken together, this evidence corroborates the hypothesis that social structure changes

the incentives to rely on social networks in the labor market. And, in particular, that the labor markets of villages where some large clusters dominate social life tend to rely more on social networks, while the labor markets of villages where social structure is more diverse and fragmented engage more robustly in formal, competitive hiring processes.

4.2 Wages, income and poverty

Our second result is that individuals in more socially-fragmented villages earn higher wages and have higher incomes. We illustrate these findings in a set of individual-level regressions in Table 1. Further, we report the results of village-level regressions that use income data from the NHTS dataset in Table 3.

The magnitudes of these effects are large. In the individual-level regressions, we find that a a one-standard-deviation increase in social fragmentation is associated with a 23 percent increase in the total wages individuals earn in a week. This effect is a combination of a 15 percent increase in hourly wages and an average gain of 1.6 hours worked per week (over a mean of 36 hours).[12]

The results on hourly wages are particularly important as hourly wages are typically thought to be a measure of worker productivity. In our setting, differential selection into employment complicates the interpretation of these regressions (e.g. there are more hours worked in more fragmented villages). However, we note that it is often assumed that marginal workers and marginal hours worked have lower latent wages. Thus, selection is likely to moderate the positive effects on hourly wages that we document and, if this is true, our results on hourly wages would offer a lower bound of the true effects of social fragmentation on productivity.

These wage effects translate into an increase in per-capita income of about 6 percent, or .18 of a standard deviation. Importantly, these gains are broadly distributed. Poverty rates decline significantly (by 3.7 percentage points, or 6 percent against a mean poverty rate of 61 percent). Similarly, females, who experience the largest changes in formal labor market participation in more socially fragmented villages, experience a 30 percent increase in weekly wages, driven both by significantly stronger effects on hourly wages and on hours worked.

[12]Not every employed survey respondent reports a wage. Hence, we run the wage regressions on a sample that is smaller than the sample of all individuals in employment.

4.3 Can the changes in education and formal labor market participation explain the wage effects?

Our theoretical framework posits that social fragmentation foster a more competitive, formalised labor market. This, in turn, increases worker productivity by enabling a better allocation of talent and by incentivising investment in human capital. The results we have just presented support both of these hypotheses. However, if this framework holds some truth, we should also expect that the changes in wages we documented are commensurate to the estimated changes in education and labor market participation. In this subsection, we provide evidence on this point by presenting the results of a mediation analysis.

We compute the average controlled direct effect (ACDE) of social fragmentation on wages, following the methods outlined in Acharya et al. (2016). The ACDE is the impact of a treatment when a given mediator is not allowed to respond to the intervention.[13] In our context, this amounts to estimating the effect of social fragmentation on wages if either education or the type of firm were not allowed to change as social fragmentation increases. A comparison of the original effect to the ACDE thus reveals the importance of a given mediator. We present the results of our analysis in Figure A.2. In this analysis, we proxy education with a set of dummies capturing different levels of education attainment, and we proxy the type of firm with a set of dummies capturing whether an individual works in a family firm, in a private non-family firm or in a government firm.

We find that both human capital and firm type appear to mediate a large share of the effect of social structure. In particular, changes in education mediate about 64 percent of the main treatment effect and changes in the type of type mediate about 24 percent of the effect of social fragmentation on wages. In other words, the magnitudes of the effects we document and their respective correlations are consistent with a causal interpretation of our findings in line with that proposed in our framework.

4.4 Robustness

In this Section, we present an extensive series of tests to address concerns about reverse causality and endogeneity, and to establish the robustness of our findings to a large number of sample and measurement checks. We start by focusing on our headline regression on weekly wages (Table 4 and Figure 1) but also show the results for all other outcomes variables (Appendix Figure A.3 - A.9.).

[13] Estimating this quantity requires the assumption of sequential unconfoundedness — we have to rule out the presence of unobservables correlated with both the mediator and the outcome of interest.

A key concern is related to reverse causality. Villages with strong labor markets might attract more migrants, which can in turn increase social fragmentation. Alternatively, labour markets conditions can potentially change marriage patterns, thereby affecting social fragmentation. We deal with these concern in three ways. First, we show that social fragmentation is highly persistent and that current social fragmentation is largely unrelated to economic outcomes in the 1990s. To show this, in Table A.2 we regress our measure of current fragmentation on (i) social fragmentation obtained on the networks of individuals aged 45 or older — a proxy for past social fragmentation — and (ii) municipal-level measures of education and assets from the 1990 Census. We find that past social fragmentation is highly predictive of current social fragmentation: the simple bivariate regression has an R^2 of 0.62. Province fixed effects and a battery of 14 regressors capturing education and assets in the 1990s do not offer any meaningful additional predictive power: the R^2 of the full model is 0.64, only marginally larger than the R^2 of the model that only includes past social fragmentation. Furthermore, none of the covariates capturing education in 1990 is significantly correlated with current fragmentation and, while some assets measures are significantly correlated with current fragmentation, the point estimates are very small. For example, a one standard deviation increase in the share of individuals with a car is associated with a 0.017 standard deviation units increase in fragmentation. Overall, these regressions provide empirical evidence against the hypothesis that the economic outcomes we consider in this paper have a meaningful impact on village social structure.

Second, to further reduce worries related to reverse causality driven by changes in marriage patterns, we investigate the stability of assortative matching on education — a key dimension of marriage patterns. Using the individual-level data, we compute the correlation between the spouses' education levels for different age groups (20-30, 30-40, 40-50, 50-60 and 70+), tracing marriage market patterns for a period of over 50 years. We find no evidence of any meaningful change in assortative matching over this time horizon: the correlations in the different cohorts are virtually identical, ranging between .68 and .70.

Third, to further reduce worries related to reverse causality driven by migration, we control for the average length of stay in the village (a measure of migration) in all regressions in the paper, and expand this in a number of ways in this section. We start by excluding areas that are classified as urban as they are the most likely migration destinations. Then, we use data from the Census to control for the share of recent migrants, specifically the share of individuals who lived in a different municipality 5 years ago. We are also worried that remoteness might be driving our results and control for

the distance to the closest urban center. Finally, we follow Cruz et al. (2020) and construct networks based on individuals aged 45 or older. These networks would mostly reflect marriage decisions made decades ago and thus the social fractionalisation measures based on these networks are less likely to reflect reverse causality. We use those measures as an instrument for current social fragmentation.

We also check robustness over alternative dimensions. First, there exist alternative algorithms to identify network clusters and we want to rule out that our results are specific to the algorithm that we selected. We thus also implement the walktrap algorithm developed by Pons and Latapy (2006). Second, while we control for population, we are concerned about potential non-linearity in the relationship between population and wages, which could be captured by our measure of fragmentation. We thus create dummies for each decile of the population distribution and check that our results are robust to adding those as controls. Third, our measure of fragmentation might be correlated with inequality as well as with ethnic and religious diversity and so we control for those variables as well. Finally, we test that are our results are robust to controlling for public goods provision (Cruz et al., 2020) and to dropping areas where naming conventions may apply more loosely.

In Table 4 we show the robustness of the coefficient of our headline regression on weekly wages changes when we separately implement the robustness checks above. The coefficient on social fragmentation remains positive, large and significant in all specifications. Most importantly, when we address selective migration by dropping urban areas or by using the IV estimator, we still estimate that a one-standard-deviation increase in fragmentation is associated with wages that are between 20 and 31 percent higher. The results are also robust to changing the algorithm used to identify communities, to controlling for population more flexibly and to adding other village-level controls. The point estimates are a bit smaller, which is expected as the algorithm relies on random walks and thus tends to identify communities less precisely.

In addition, we show that our results are robust to using 384 different combinations of the adjustments presented in Table 4.[14] We present the specification curve for the total wage effect in Figure 1 and the curves for the other effects on education, labor market participation, hourly wages, hours, poverty and income in appendix Figure A.3 - A.10. Importantly, we are able to show that the vast majority of specifications produces a significant coefficient and that the coefficients in our headline specification is

[14]We run our regressions with all possible combinations of: 3 samples (full, excluding urban, excluding ARMM), estimation (IV and OLS), two measures of fragmentation and 5 set of controls variables (recent migration, distance to urban centers population, public goods and diversity).

drawn from the middle of the distribution, and does not reflect a particularly favorable empirical specification. One exception is the regression on the likelihood of working in a private firm. Here, while the coefficient is consistently positive, it is often very noisy and insignificantly different from zero. We should thus interpret this result with a bit more caution that the other ones.

5 Conclusion

In this paper, we provide evidence that the structure of social networks affects the functioning of the labor market. Social fragmentation affects investment in human capital, job search behaviour and the type of firms individuals work for. This, in turn, affects proxies for productivity and income levels. To the best of our knowledge, this is the first evidence on the effects of social network structure on labor market outcomes using a large sample of villages.

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Tables for inclusion in the paper

Table 1: Social Fragmentation, Network Hiring, Education and Wages

Variable	Obs.	Mean	Point Estimate
Type of firm: Family firm	581,781	0.20	-0.03
		(0.40)	(0.01)
Type of firm: Private firm	581,781	0.21	0.02
		(0.41)	(0.01)
Job Search: Direct Approach	9,987	0.81	-0.04
		(0.39)	(0.01)
Job Search: Formal Approach	9,987	0.17	0.04
		(0.37)	(0.01)
Some College	1,318,552	0.13	0.05
		(0.34)	(0.01)
Report Wage	581,781	0.27	0.05
		(0.45)	(0.01)
Log(Weekly Wage)	161,169	6.59	0.23
		(0.95)	(0.02)
Log(Hourly Wage)	161,169	5.05	0.15
		(0.74)	(0.02)
Hours	591,429	36.25	1.61
		(19.30)	(0.31)
Hours (if wage)	161,169	41.60	2.45
		(16.65)	(0.32)

Notes: Each row reports the point estimate on our fragmentation measure from a different individual-level regressions with municipal fixed-effects. The dependent variable is a dummy equal to 1 if the individual works in a family firm (row 1), works in a private firm (row 2), looks for job through his/her network (row 3), looks for job through formal channels (row 4), has some College education (row 5), report a wage (row 6), the log of weekly wages (row 7), the log of hourly wages (row 8) and hours worked in the past 7 days (rows 9 and 10). In row 10, we restrict the sample to individuals who report a wage. Regressions control for village-level average length of stay in the village, village population, the number of distinct families in the village, whether the village is classified as rural, as well as variables from the LFS surveys: age, gender, survey month and survey year. Standard errors, clustered by village, in parentheses.

Table 2: Heterogeneity by Gender

	Some College	Family	Private	Log Weekly Wage	Log Hourly Wage	Hours
Frag.	0.047	-0.017	0.030	0.19	0.12	1.30
	(0.006)	(0.003)	(0.008)	(0.023)	(0.017)	(0.285)
Frag.*Female	0.0064	-0.047	-0.023	0.11	0.092	0.84**
	(0.002)	(0.010)	(0.006)	(0.027)	(0.020)	(0.333)
Mean (male)	0.12	0.14	0.26	6.60	5.07	36.7
Std. Dev (male)	0.32	0.35	0.44	0.89	0.65	17.6
Mean (female)	0.15	0.31	0.13	6.57	5.04	35.5
Std. Dev (female)	0.35	0.46	0.34	1.06	0.89	21.9
Obs	1318552	581781	581781	161169	164461	591429
R2	0.092	0.22	0.15	0.19	0.22	0.11

Notes: Results from individual-level regressions with municipal fixed-effects. The dependent variable is a dummy equal to 1 if the individual has some College education (Column 1), works in a family firm (Column 2), works in a private firm (Column 3), the log of weekly wages (Column 4), the log of hourly wages (Column 5) and hours works in the past 7 days (Column 6). Regressions control for village-level average length of stay in the village, village population, the number of distinct families in the village, whether the village is classified as rural, as well as variables from the LFS surveys: age, gender, survey month and survey year. All variables are interacted with gender. Standard errors, clustered by village, in parentheses.

Table 3: Social Fragmentation and Household Welfare

	Poverty Rate	per capita income
Frag.	-0.037	908.9
	(0.007)	(163.395)
Mean	0.61	15359.1
StdDev	0.21	5127.5
Obs	15853	15853
R2	0.62	0.63

Notes: Results from village-level regressions with municipal fixed-effects. The dependent variable is the village-level poverty rate (Column 1) and average (predicted) per capita income (Column 2). Regressions control for village-level average length of stay in the village, village population, the number of distinct families in the village, whether the village is classified as rural. Standard errors, clustered by municipality, in parentheses.

Table 4: Social Fragmentation and Log(Weekly Wage): Robustness Checks

	Exc. Urban	Recent Migration	Distance to Urban Center	IV	Flexible Pop.	Alt. Alg.	Other Frag	Facilities	Exc. ARMM
Frag.	0.20	0.22	0.18	0.31	0.23		0.21	0.22	0.24
	(0.029)	(0.025)	(0.026)	(0.046)	(0.027)		(0.026)	(0.025)	(0.026)
Frag. (alt)						0.10			
						(0.021)			
Observations	107564	161169	134799	161169	161169	161169	161169	161156	153860
R^2	0.17	0.18	0.17		0.18	0.18	0.18	0.18	0.17

Notes: Results from individual-level regressions with municipal fixed-effects. The dependent variable is the log of weekly wages. In Column 1, all areas classified as urban are excluded from the sample. In Column 2, regressions control for the share of the population that moved to the municipality between 2005 and 2010. In Column 3, regressions control for the distance to the closest urban center. In Column 4, we instrument the fragmentation measure with the fragmentation obtained on the sample of individuals older than 45. In Column 5, regressions control for population flexibly (a different dummy for each population decile). In Column 6, the measure of fragmentation is computed using communities identified with the Latapy/Pons algorithm. In Column 7, regressions control for gini as well as ethnic and religious fragmentation. In Column 8, regressions control for the availability of key public goods in the village. In Column 9, all villages in ARMM are excluded from the sample.

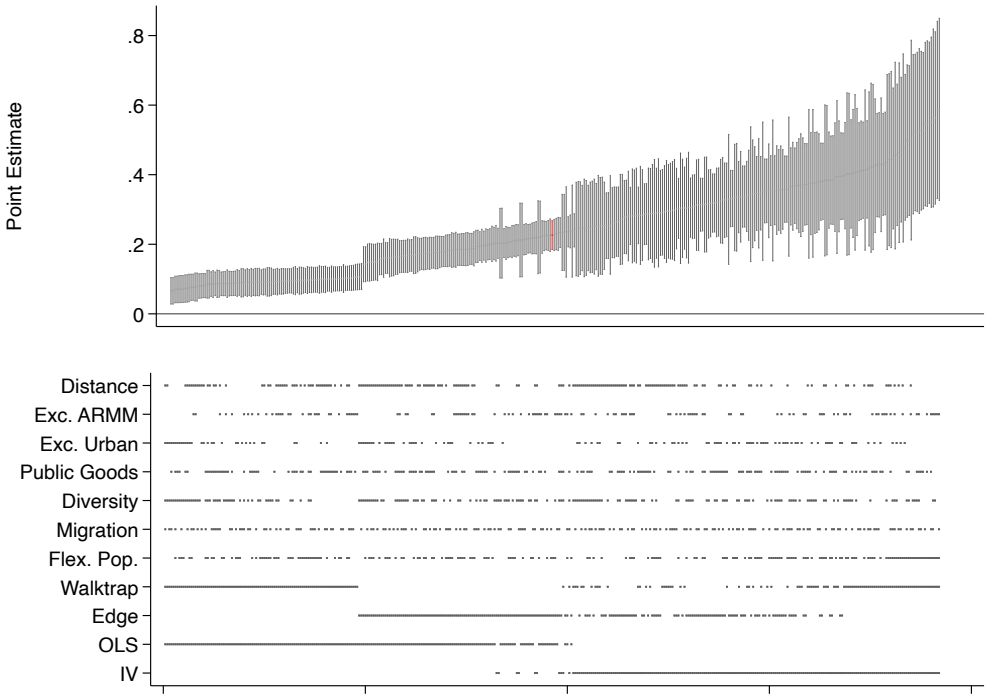

Figure 1: Specification Curve for Log(Weekly Wage)

Appendix
For Online Publication

Table A.1: Social Fragmentation and Schooling Investment

	No Schooling	Some Primary	Primary Grad	Some HS	HS Grad.	Some College
Frag.	-0.0097	-0.041	-0.017	0.0071	0.011	0.050
	(0.004)	(0.006)	(0.003)	(0.003)	(0.003)	(0.006)
Mean	0.11	0.34	0.14	0.16	0.11	0.13
StdDev	0.32	0.47	0.35	0.37	0.31	0.34
Obs	1318552	1318552	1318552	1318552	1318552	1318552
R2	0.071	0.044	0.044	0.012	0.026	0.091

Notes: Results from individual-level regressions with municipal fixed-effects. The dependent variable is a dummy equal to one capture the highest level of schooling : none (Column 1), some primary school grades (Column 2), graduated from primary school (Column 3), some high school grades (Column 4), graduate from high school (Column 5) and some college (Column 6). Regressions control for village-level average length of stay in the village, village population, the number of distinct families in the village, whether the village is classified as rural, as well as variables from the LFS surveys: age, gender, survey month and survey year. Standard errors, clustered by village, in parentheses.

Table A.2: Predicting Fragmentation

	(1)	(2)	(3)	(4)
Fragmentation (over 45)	0.74***	0.70***	0.69***	0.69***
	(0.028)	(0.033)	(0.034)	(0.034)
No Schooling (Male)			0.048	0.61
			(1.007)	(1.046)
Some Primary (Male)			-0.027	0.68
			(0.933)	(0.967)
Primary Grad (Male)			-0.43	0.26
			(0.991)	(1.021)
Some High School (Male)			0.31	1.02
			(1.310)	(1.330)
High School Grad (Male)			0.039	0.30
			(2.904)	(2.849)
Some Primary (Female)			-1.10	-1.07
			(0.680)	(0.671)
No Schooling (Female)			-1.02	-0.85
			(0.735)	(0.723)
Primary Grad (Female)			0.30	0.22
			(0.818)	(0.785)
Some High School (Female)			-1.66*	-1.78*
			(0.988)	(0.982)
High School Grad (Female)			-0.31	-0.76
			(2.414)	(2.461)
Radio				0.17*
				(0.098)
TV				0.23
				(0.174)
Vehicle				0.64*
				(0.390)
Phone				0.70
				(1.728)
Province FE	No	Yes	Yes	Yes
Observations	14720	14720	14720	14720
R^2	0.62	0.63	0.64	0.64

Notes: Results from village-level regressions. The dependent variable is our main fragmentation measure Standard errors, clustered by municipality, in parentheses.

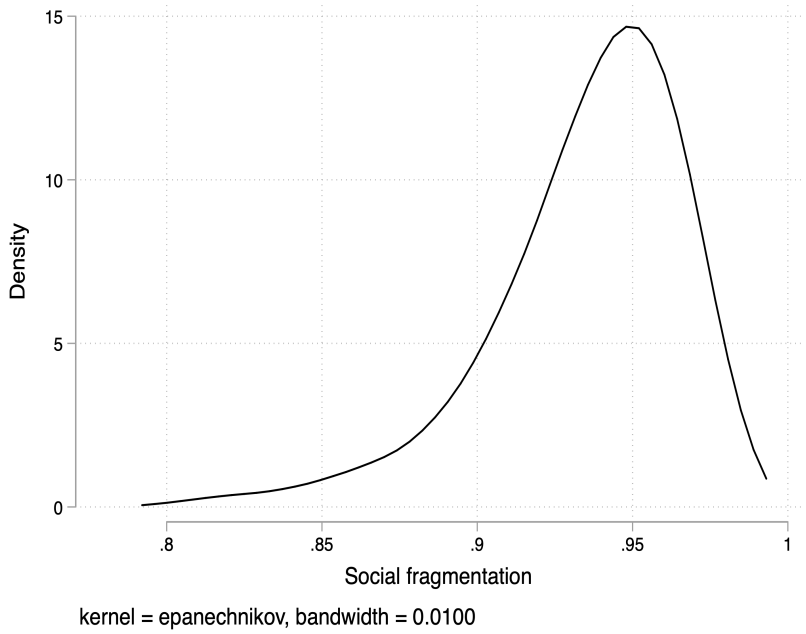

Figure A.1: Distribution of Social Fragmentation

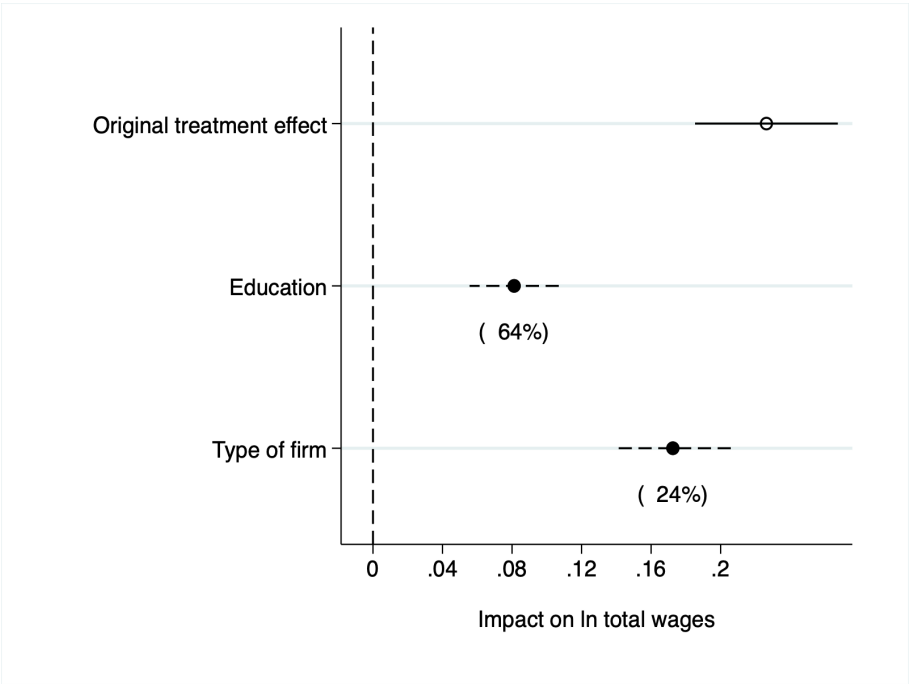

Figure A.2: Mediation Analysis

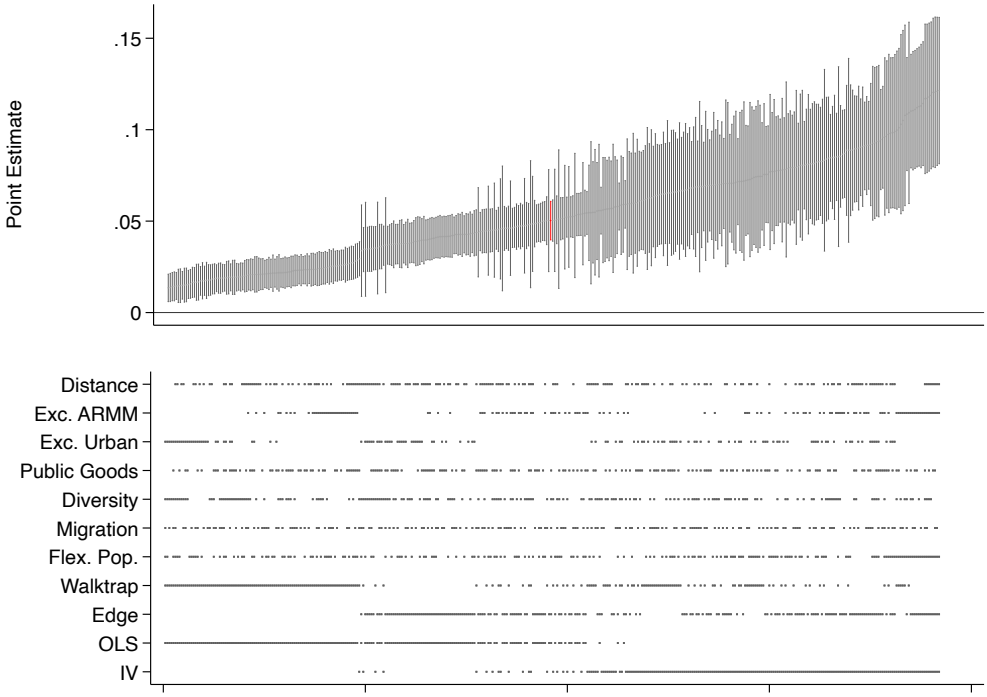

Figure A.3: Specification Curve for College

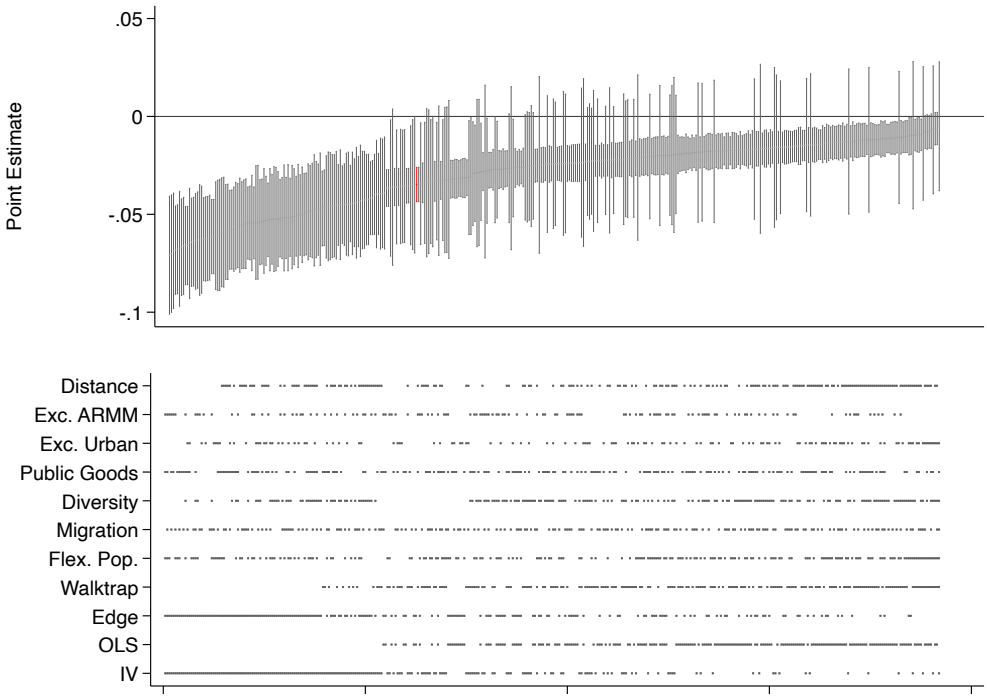

Figure A.4: Specification Curve for Family

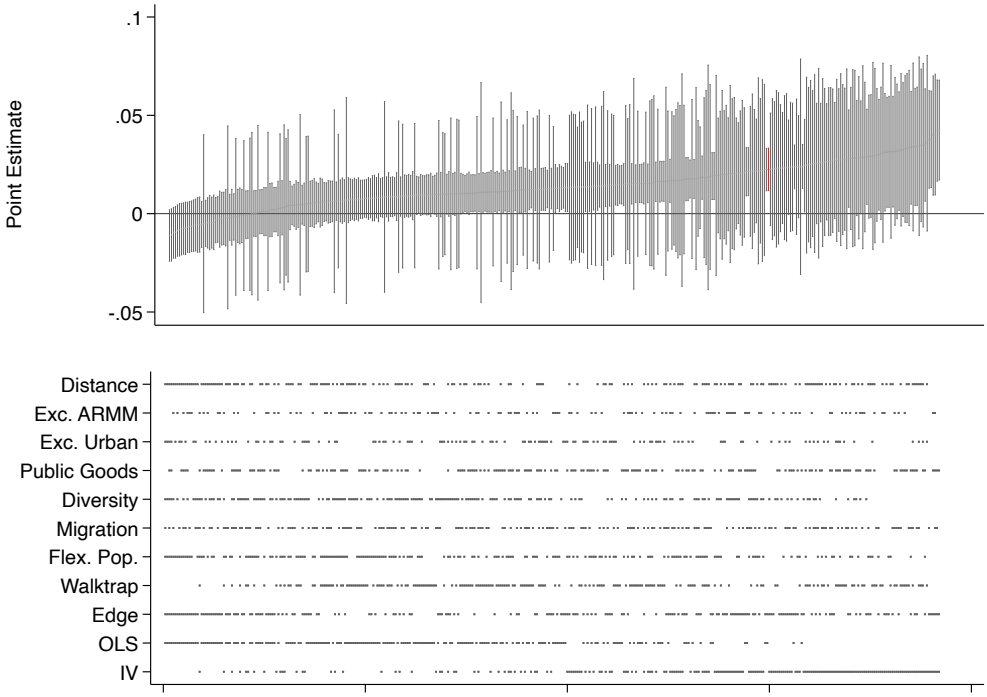

Figure A.5: Specification Curve for Private

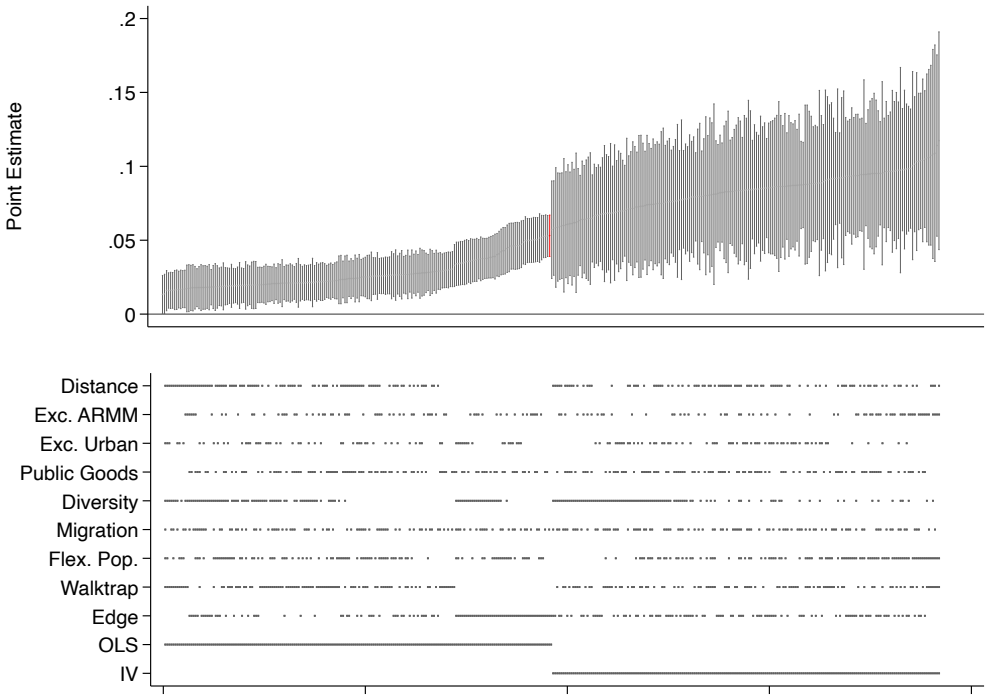

Figure A.6: Specification Curve for Report a Wage

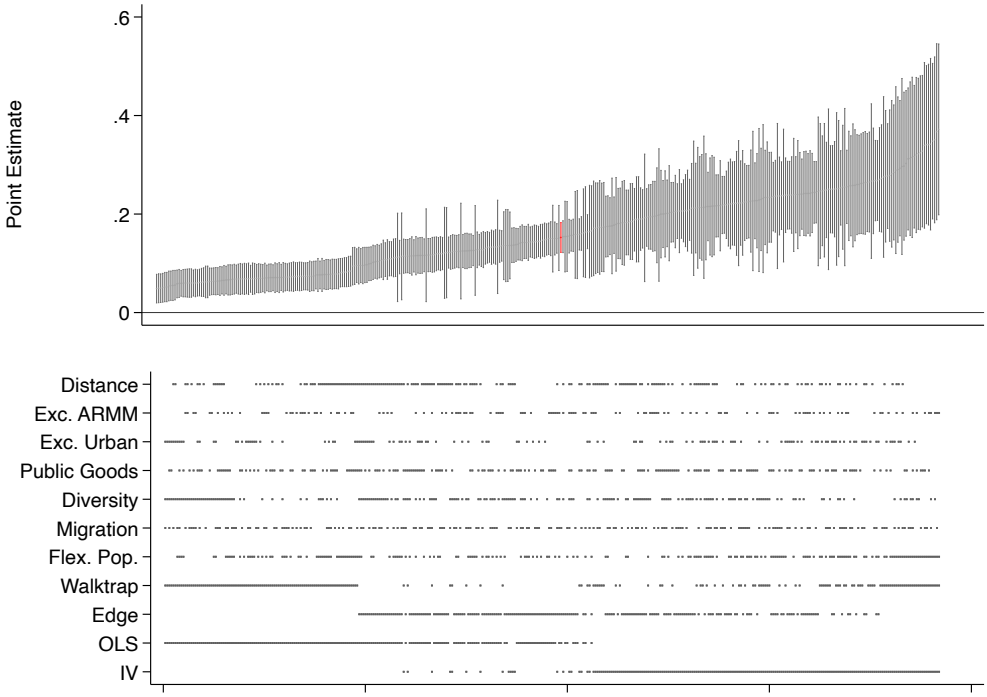

Figure A.7: Specification Curve for Log(Hourly Wage)

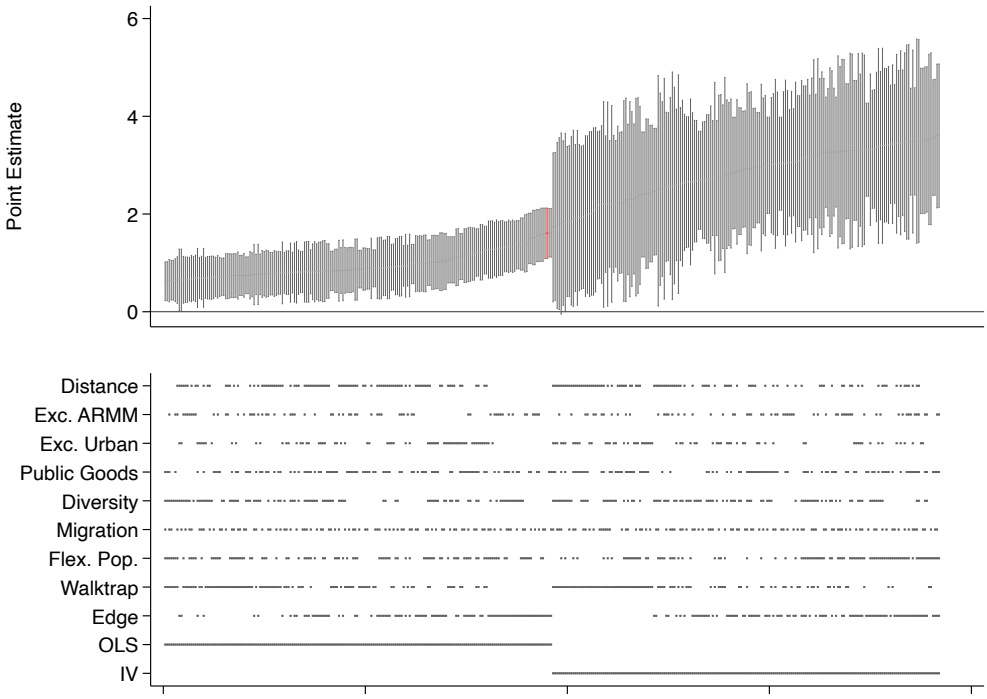

Figure A.8: Specification Curve for Hours

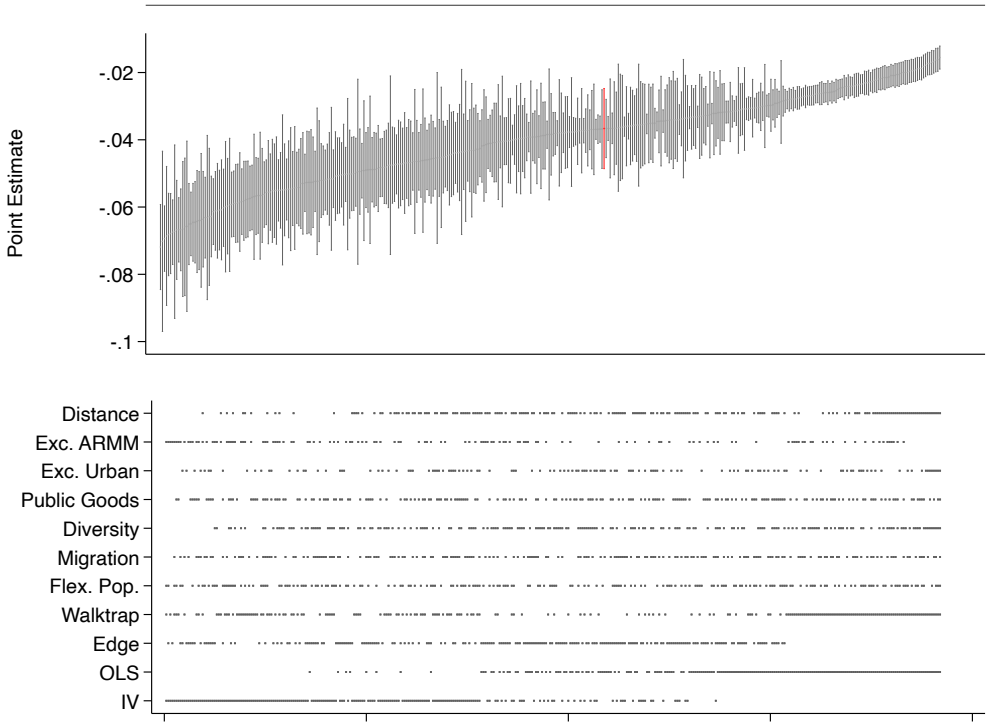

Figure A.9: Specification Curve for Poverty

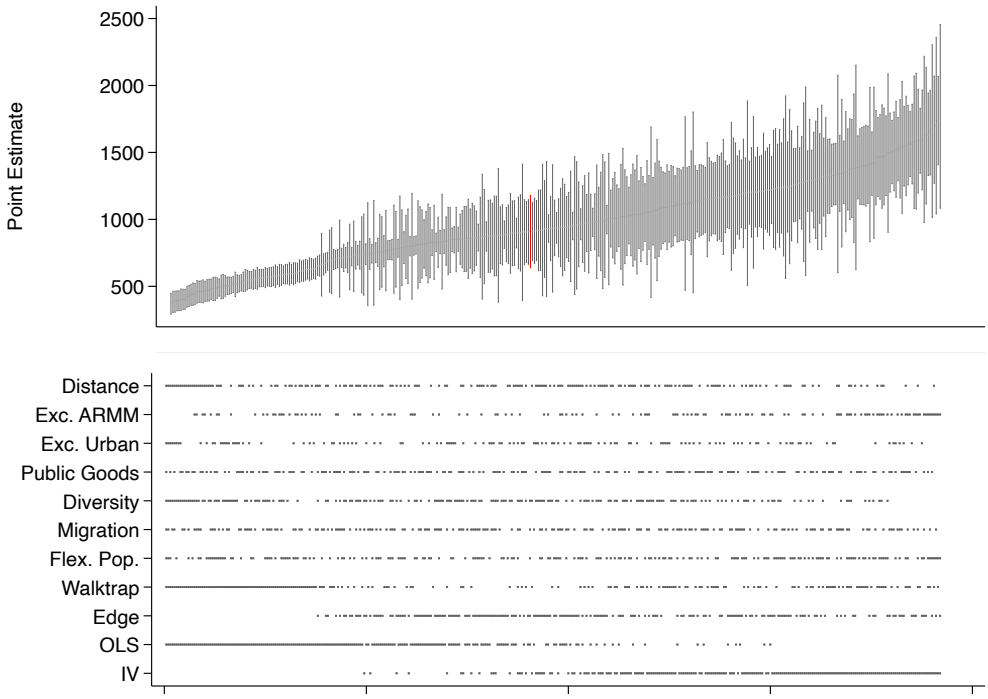

Figure A.10: Specification Curve for (predicted) per capita income