UZBEKISTAN

DYNAMICALLY IDENTIFYING COMMUNITY-LEVEL COVID-19 IMPACT RISKS

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Abstract

We build a new database of highly spatially disaggregated indicators related to risk and resilience to the social and economic impacts of the COVID-19 pandemic in Uzbekistan. The outbreak disproportionately affects particular groups – the elderly, the poor, those living in areas under lockdown, and families who rely on remittance income are all examples of groups that are especially vulnerable to effects of the crisis in Uzbekistan. We assemble indicators summarizing concentrations of these and other risk factors at the lowest administrative level in the country, neighborhood-sized units called *mahallas*. Local official administrative statistics (published for the first time in this study) are combined with monthly panel survey data from the ongoing Listening to the Citizens of Uzbekistan project to produce an overall risk index, which is decomposable by dimension or risk factor to inform targeted and issue-specific responses. We then demonstrate a process for updating key indicators (such as employment or remittance flows) on a monthly basis using linked survey data combined with small area estimation techniques. These neighborhood-level results are intended to improve resource allocation decisions and are particularly relevant in Uzbekistan where local representatives are responsible for implementing key social and economic programs to respond to the outbreak.

Keywords: COVID-19, Risk factors, Panel survey; Economic shocks, Poverty, Small area estimation

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I - Introduction

The impacts of the coronavirus pandemic on health and economic wellbeing are unprecedented. As of this writing, the disease has claimed more than 540 thousand lives around the world, World Bank estimates suggest that extreme poverty has increased more than at any other time since the Second World War, and per capita incomes have suffered the largest decline since 1870.[6]

It is also the most severe crisis Uzbekistan has faced in generations, with expected annual GDP growth for 2020 reaching its lowest point since independence from the Soviet Union. Although the outbreak in Uzbekistan has remained moderate thus far – the official case count is currently about 14 thousand and the death toll of 68, for a country with a population of more than 34 million – Uzbekistan has not been spared the economic impacts of the crisis. In April 2020, the authorities introduced lockdown measures of all non-essential work and travel to protect public health. As the health situation permitted, restrictions were gradually relaxed in May and June. However, national lockdowns were reintroduced on July 10th due to a resurgence in the rate of infection. These lockdowns have caused similar collateral economic damage that has been seen elsewhere in the world, leading to sharp declines in employment, income, and other measures of economic wellbeing.

A national monthly household panel survey focused on social and economic wellbeing called Listening to the Citizens of Uzbekistan (L2CU) was in the field leading up to and following the COVID-19 outbreak in Uzbekistan. Data collected in the survey are used in this study to measure the impacts of the crisis and extrapolate lessons to individual communities throughout the country that can be used to guide anti-poverty and recovery efforts. Following the outbreak, the core survey instruments were expanded to cover focus areas relevant to COVID-19 and the economic impacts of the unfolding global recession. Analysis of the ongoing survey modules that monitor employment, migration, and similar themes gained added urgency as a result of the crisis, especially as traditional surveys in the country use in-person interview methods and were partially disrupted during lockdowns. Fortunately, data collection activities conducted in the L2CU project have thus far been unaffected.

Results from L2CU reveal dramatic declines in employment and incomes beginning in April 2020, as well as very high levels of concern about the health and economic impacts of the pandemic among the population. World Bank projections find that between .5 and .8 million additional people will likely fall into poverty in 2020 – with high risks of further deterioration in the event of a more extended emergency. Considering the widespread impact of COVID-19 globally, there are also likely to be both large reductions in remittances and increased domestic unemployment, as the lingering pandemic severely affects both domestic and international businesses. Production and import disruptions increase the risk of inflation. Together, these factors are likely to have a profound and long-lasting impact on the overall wellbeing of the population, increase the poverty levels in the country, and create deep hardship for those who are directly affected.

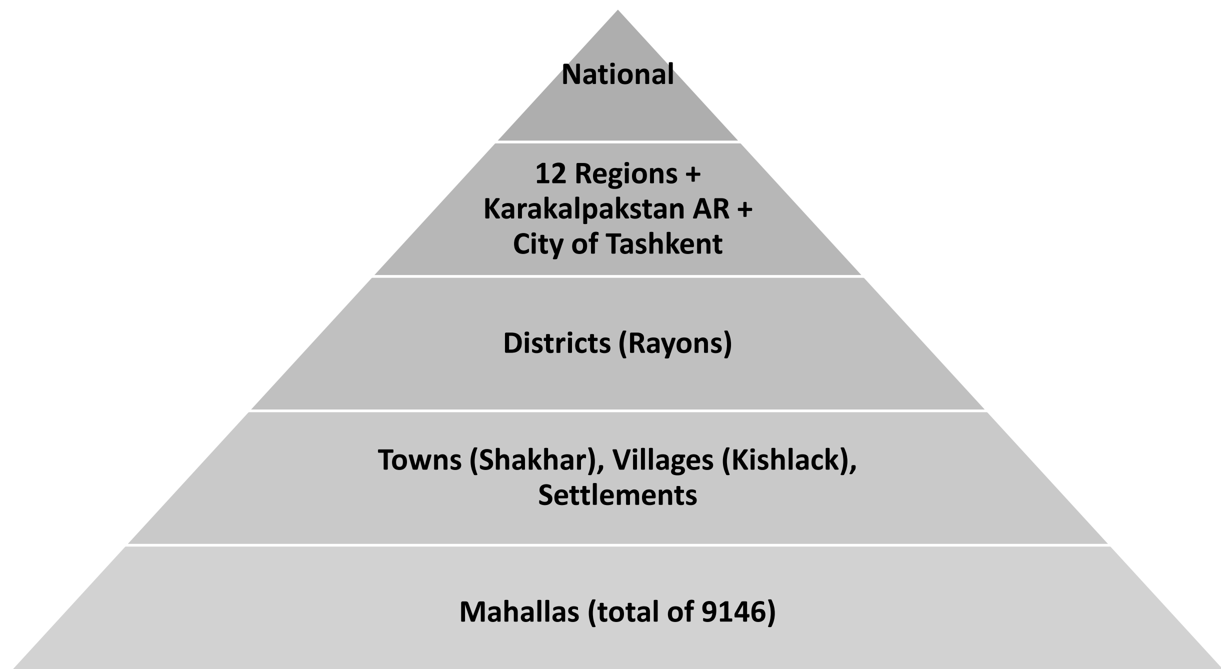
The aim of the analysis described in this paper is to identify risk factors of COVID-19 impacts at the level of small communities, such that policy makers can prioritize actions and support those in greatest need. The smallest administrative unit in Uzbekistan is called the *mahalla* (Figure 1). The leaders of these communities collect administrative data on an annual basis, and these statistics are also used in this study. The databases generated by local authorities are conventionally aggregated to the district-

[6] https://www.worldbank.org/en/news/press-release/2020/06/08/covid-19-to-plunge-global-economy-into-worst-recession-since-world-war-ii

level in Uzbekistan (including 200 districts and urban areas in total) and primarily used for implementing local policies. We are aware of no previous instances when these data have been systematically gathered into a single database and harmonized at the national level. These data are published together with the results of this paper for use by policymakers and other partners responding to the impact of COVID-19.

Uzbekistan is subdivided into 9145 mahalla neighborhoods in both rural and urban areas (the precise number frequently changes when small mahallas are merged and large mahallas are split). Mahallas usually range in size from between 500 to 10,000 families. The mahalla is a formal institution, and each has a defined geography, though the cartography of the units is not digitized at this time. All maps presented in this paper report aggregate statistics at the district level. However, the data file including mahalla-specific results is published together with this paper for direct use at the level of mahalla.

Figure 1: Administrative Units in Uzbekistan



The official activities of a mahalla are organized and carried out by an executive committee (Mahalla fuqarolar yig'ini) under the leadership of a chairperson (Raiis). Though mahallas are grounded in local tradition, today, mahalla officials implement many state functions including data collection, implementing public information campaigns, and administrative duties related to the social assistance system. The role of the mahalla has been is a state of flux in recent years due to policy and regulatory developments in Uzbekistan since 2017; however, the core social assistance related activities of mahalla leadership are particularly relevant as policy makers expand the provision of benefits to combat the impact of the COVID-19 pandemic.

The results of this study are intended to support efforts to prioritize local interventions in response to the impact of COVID-19. A growing body of evidence from Uzbekistan and elsewhere in the world finds that individual and community level risk profiles from the effects and aftereffects of the pandemic are highly variable. Membership in particular age groups, employment in particular sectors, and access to sources of resilience all play a role in how the crisis will affect a person, family, or village. For instance, work published by the Furman Center found[7] that the both the direct and indirect effects of the pandemic have been highly localized in particular populations in the city of New York, in the United States. Neighborhoods with higher rates of confirmed COVID-19 cases were shown to have much lower median incomes, higher shares of residents from Black or Hispanic minority groups, and higher shares of residents under the age of 18 relative to less affected neighborhoods. Residents of disproportionately affected neighborhoods were also shown to be less likely to be able to work from home, disproportionately reliant on public transit during the crisis, and less likely to have internet access. Finally, neighborhood level analysis found that areas with higher numbers of confirmed COVID-19 cases had lower population density, yet higher rates of overcrowding at the household level.

Chetty, et. al. (2020) similarly show that neighborhood-level impacts are highly specific and variable. Using high frequency private sector data, the authors demonstrate the heterogeneity of outcomes with respect to incomes and local economic factors. Due to data limitations, the full approach adopted in that study is not possible in all countries, and the range of data available for Uzbekistan is more limited. However, the intuition and objective of the analysis that follows are quite similar to those of Chetty, et. al. (2020) and the Furman Center, if considerably less ambitious in terms of spatial, temporal, and topic granularity.

To summarize, we assemble the data from the highly disaggregated survey and administrative sources described above. The resulting database allows us to develop a variety of measures related to the impacts of COVID-19 at the local level. We then use these indicators to construct a community-level COVID-19 risk index for Uzbekistan. The ultimate aim of the study is to prepare a database of relevant indicators to aid in the design of response and recovery programs. In some cases, these indicators can be updated over time using linked survey data and small area estimation techniques. The summary index includes six dimensions – related to age and ability risk factors, economic conditions, access to social assistance, local services infrastructure, reliance on remittances from migrants, and local measures of monetary poverty – and is comprised of a total of 26 individual mahalla-level indicators. The dimensions and indicators can be decomposed as needed for targeted interventions.

The remainder of this introductory section describes the index dimensions in more detail, as well as their relevance to the outbreak and related economic consequences. Section (II) describes the data used, and section (III) the methods of analysis applied (with additional details provided in annexes). Section (IV) reports the results of small area imputations at the mahalla level (for those high-priory indicators that are not observed in administrative statistics). Section (V) describes the results of the index, both overall, and by dimension. Finally, section (VI) provides examples of dynamic updates of key indicators using linked panel survey data and small area imputation techniques.

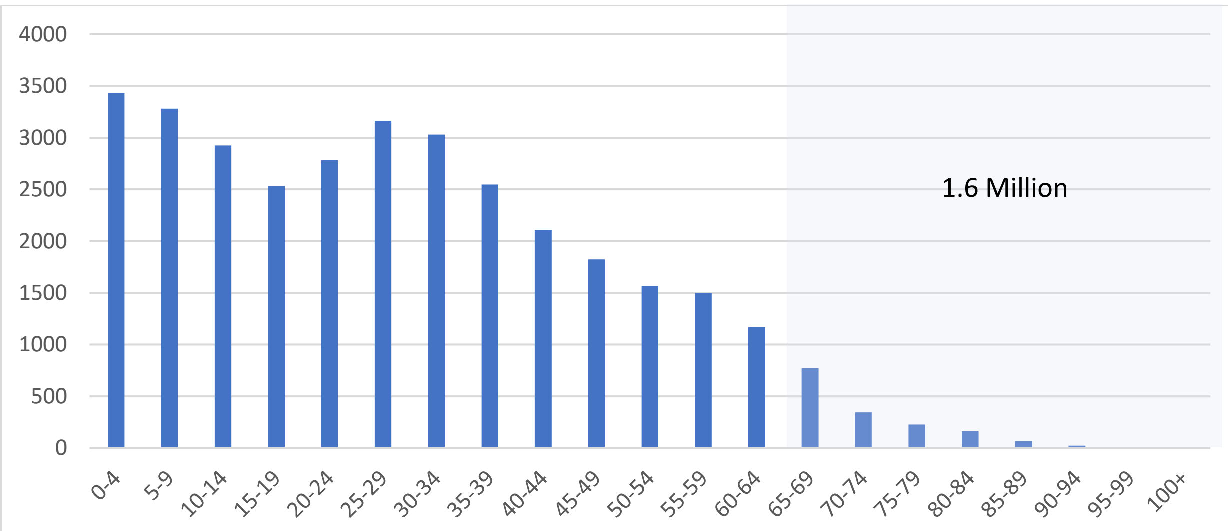
Elderly and Disabled Populations

Uzbekistan has a relatively young population and the elderly represent a comparatively small share of the total – only about 4.8 percent of citizens are age 65 or older (figure 2). However, the wellbeing of this population is of particular concern. Older people are at much higher risk of health compilations

[7] https://furmancenter.org/thestoop/entry/covid-19-cases-in-new-york-city-a-neighborhood-level-analysis

and are more reliant on services that may be impacted by the pandemic. Evidence in many counties has highlighted the greater severity of the disease among older people, and especially high rates of mortality have been concentrated in communities of older people, care centers, and in nursing homes. Goldstein and Lee (2020) find that about 75 percent of all US Covid-19 deaths to be among people aged 70 or above, somewhat above the 64 percent for normal mortality. In China (Hubei), South Korea, Italy, France, and Spain, virus-attributed mortality rates rise by about 11 percent per year (a bit slower in Hubei, where the rate is 9.5 percent), close to the 10 percent that would be expected for all-cause mortality. A national analysis of comorbidities in China found strong associations with chronic obstructive pulmonary disease, diabetes, hypertension, and malignancy (Guan, Wei-jie, et. al., 2020). These illnesses are also more prevalent among older populations. In the analysis that follows the elderly and disabled are identified as particularly vulnerable groups.

Figure 2: Population by Age Group (Thousands of People)

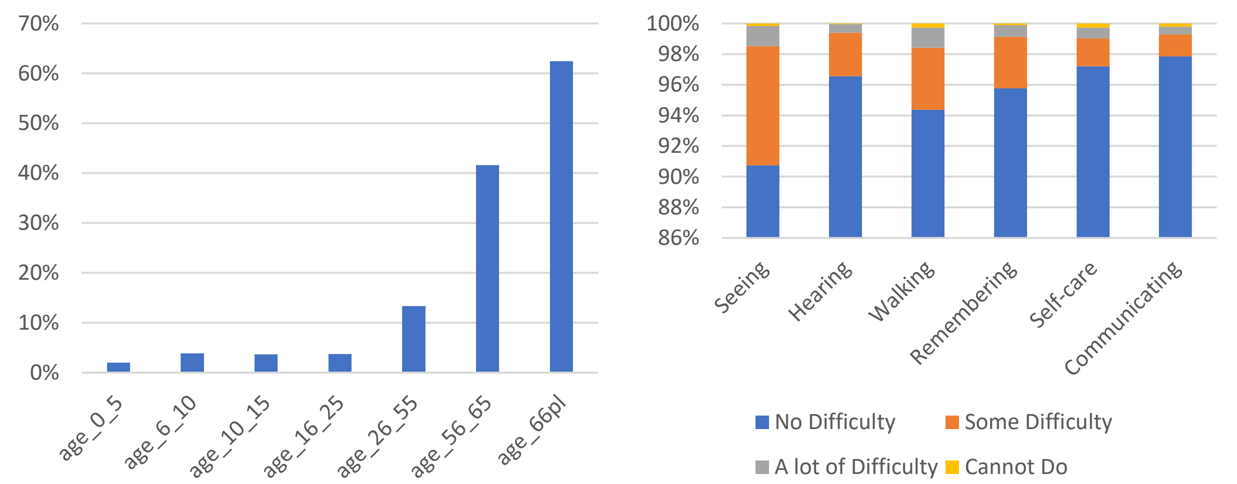


Source: UN Population Statistics

Beyond infection and mortality risks, older people are also expected to have more difficulty adapting to lockdowns and other disruptions of normal life. Older people have more limited information communication technology (ICT) skills on average, which may prevent them from accessing internet-based services or for leveraging other communications needs. Many older people also rely on help from relatives and others who may be prevented from visiting during the pandemic. To address this challenge, there is presently some COVID-19 related support for the elderly provided by government beyond standard pensions. This includes eligibility to receive a package of food from local officials (largely targeting single seniors through the Sponsor Coordination Center). However, there are some concerns as to the adequacy of these measures: wait times have been reportedly quite long (often 3-4 days), and some have reported that care packages are insufficient. Elderly people commonly are also more reliant on the health system, which is strained by the extraordinary demands of responding to COVID-19.

Likewise, people with disabilities often require specialized services that are reduced or unavailable during lockdowns and related disruptions. Health facilities and other buildings are not disability friendly (lacking, for example, accessible toilets and handwashing facilities). UNFPA in Uzbekistan has reported concerns that information dissemination on COVID-19 related issues are not always disabled-friendly. Many people with disabilities struggle with accessing markets, especially while navigating lockdowns and quarantines and while personal support networks are reduced in their functioning. The L2CU baseline survey collected information on disability using the standard Washington Group questions regarding vision, hearing, walking, remembering, ability to provide self-care, and communication, reported in Figure (3). These results highlight that disability and age are not completely separate considerations: there is large overlap of age risks and disability status.

Figure 3: Measures of Washington Group Questions on Disability



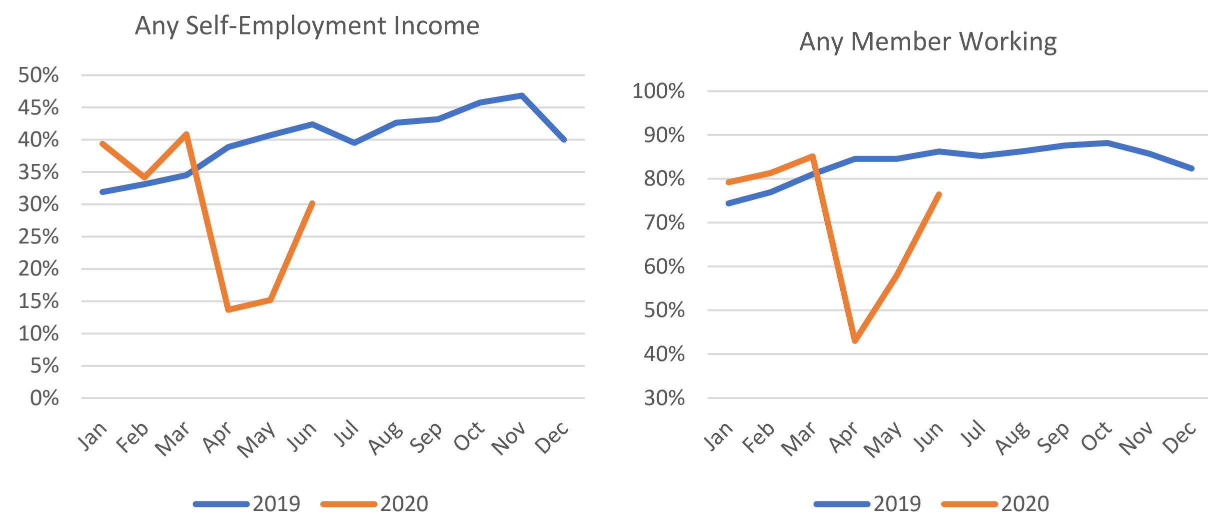
Source: Listening to the Citizens of Uzbekistan Baseline

Economic Factors

Data from April 2020 show that the economic impacts of the outbreak on livelihoods – including through reduced employment and income – has been severe. According to L2CU, the share of households with at least one member actively working fell more than 40 percentage points (from 85 to 43 percent) between March and April in 2020 when lockdowns were instituted to prevent the spread of the disease. But while incomes fell for a large share of the population (median per capita income combined from all sources fell by 38 percent in comparison to the previous month), there were also clear concentrations among particular populations. Individuals with stable formal employment in large firms, SOEs, or government, as well as those relying largely on predictable government transfers (e.g. old-age pensions) were relatively more protected than those with less certainty in their employment and activities. In contrast, those working in sectors particularly reliant on in-person interaction, including retail and other services, construction, transportation, and small-scale business were at much greater risk to the economic consequences.

When lockdown measures were phased out in stages during May and June 2020, a labor-market recovery quickly asserted itself (figure 4). The share of households with at least one working member rebounded by 33 pp in May. Reporting that someone "lost a job or stopped work" in the household jumped from 1 to 19 percent in April, before falling back to 3 percent in June. Nearly all respondents to the survey stated that they believe work disruptions are temporary. However, at the time of this writing, employment remains far below both 2019 levels and the pre-COVID trend. In addition, these statistics do not reflect the reintroduction of stricter lockdown measures effective from July 10, which will likely reimpose economic costs and disruptions of the labor market.

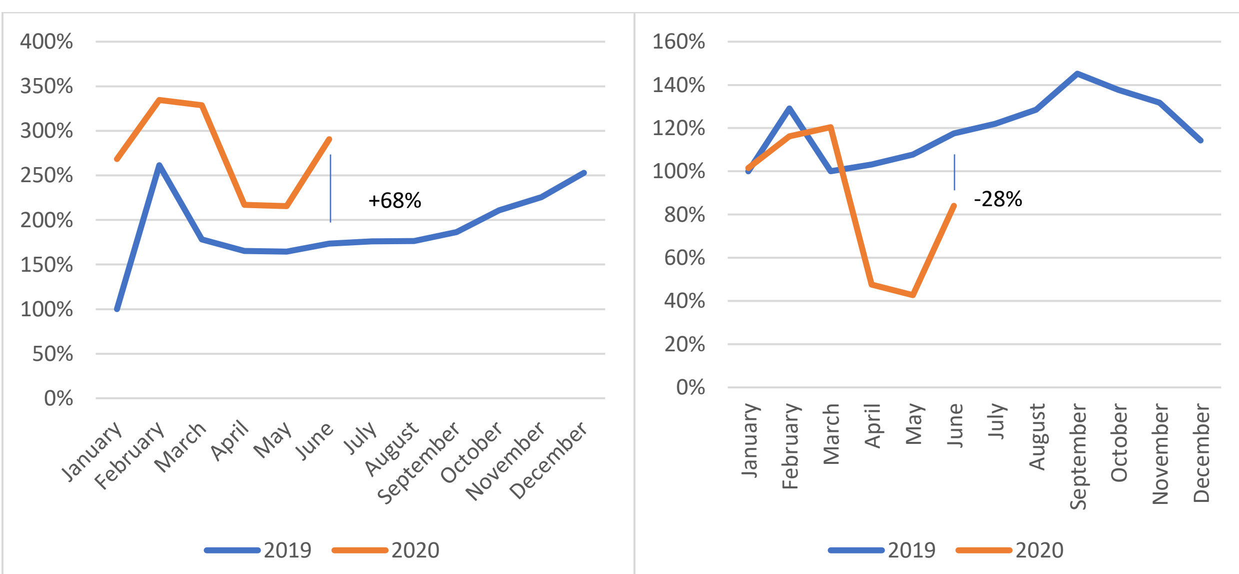
Figure 4: Large Declines in Employment Concentrated among the Self -Employed



Source: Listening to the Citizens of Uzbekistan Panel

The declines in employment and incomes were largest among the self-employed. In April, the share reporting any self-employment income fell by 67 percent in comparison to the previous month and remained down 26 percent in June. In contrast, the share reporting any wage income declined by 16 percent., but on average re-attained its 2019 level in June, crossing that threshold more quickly among men than among women. Urban incomes started higher and fell faster than in rural areas, due in part to the start of the agricultural season and the relatively limited impact of the lockdown measures on the sector. Thus, declines were larger in urban areas – falling 46 percent in a single month – but were also high in rural and semi-urban areas (37 percent).

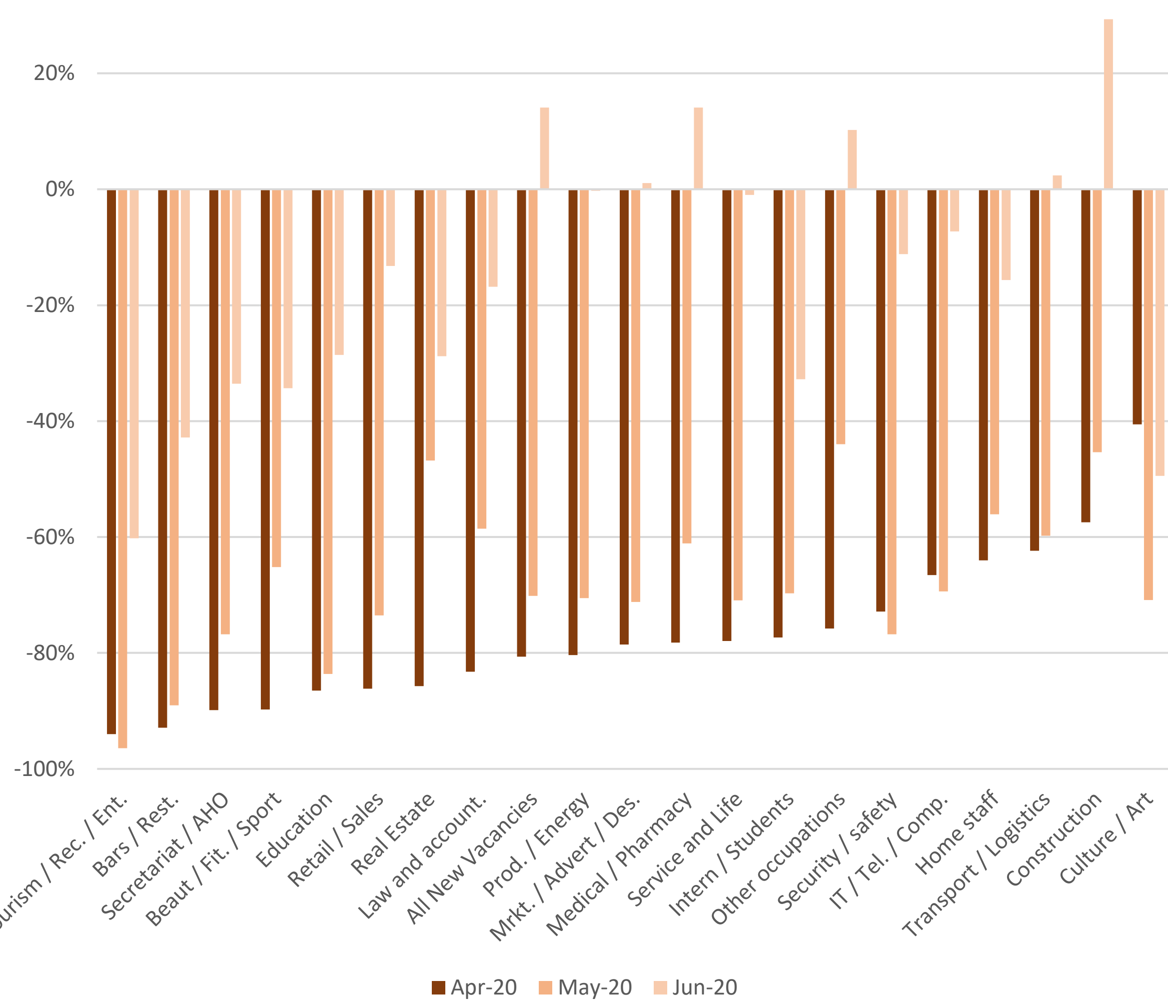
Figure 5: Total Job Seekers (Left), Total Job Offers (Right)



Source: Data courtesy of olx.uz

Data on new online job listings also showed signs of recovery in May and June, after new listings fell by 80 percent following the outbreak (figures 5 and 6). Sectors with particularly large declines compared to the same period in 2019 included tourism, recreation and entertainment (-95 percent), bars and restaurants, (-91 percent), and education (-85 percent). Even the least affected occupations, declined by 50 percent or more compared to the same period last year, though in June there was a quick recovery in medical and construction sectors (Figure 6).

Figure 6: Year-Over-Year Change in Newly Posted Vacancies



Source: Data courtesy of olx.uz

The challenges posed by recovery will exacerbate difficulties in the labor market that were present pre-COVID-19. While the working age population has been increasing over time in Uzbekistan, formal job creation has not kept pace, resulting in high informality, inactivity rates and growing outmigration. The working age population increased by some 50 percent since 2000, from 14 million to 22 million today. Unemployment and inactivity rates are higher especially for youth, women and people in the poorest two quintiles. Job quality and inclusiveness remain a concern, as average wages are low

(US$218, average monthly nominal wage in 2018) and almost half of the Uzbek workers are in the informal sector. More than half of the agricultural workers are subsistence farmers (World Bank 2017). Based on the recent L2CU data (2018), the lack of jobs as well as the low salaries are main concerns especially among the poorest and the beneficiaries of social assistance.

Social Assistance and Transfers

Uzbekistan has several targeted cash assistance programs to support low-income people (Table 1). These include social assistance (noncontributory), social insurance schemes (contributory), and labor market programs. Entitlement to social insurance programs is conditional on contributions that people make when they work and are supposed to protect people during old age or maternity, or in case of accidents and sickness. Social assistance benefits include four types of programs:

- cash allowances provided to low-income households (means-tested benefits);
- cash allowances provided to the elderly, persons with disabilities (PWD), and survivors (breadwinner loss);
- allowances in case of special events or shocks;
- allowances, discounts, and in-kind support to vulnerable groups.

The first type of allowances is means tested, i.e., conditional on household income being below a fixed eligibility threshold (expressed in per capita terms and equal to 1.5 times the minimum wage).

Table 1: Beneficiary Families of Targeted Social Assistance Programs

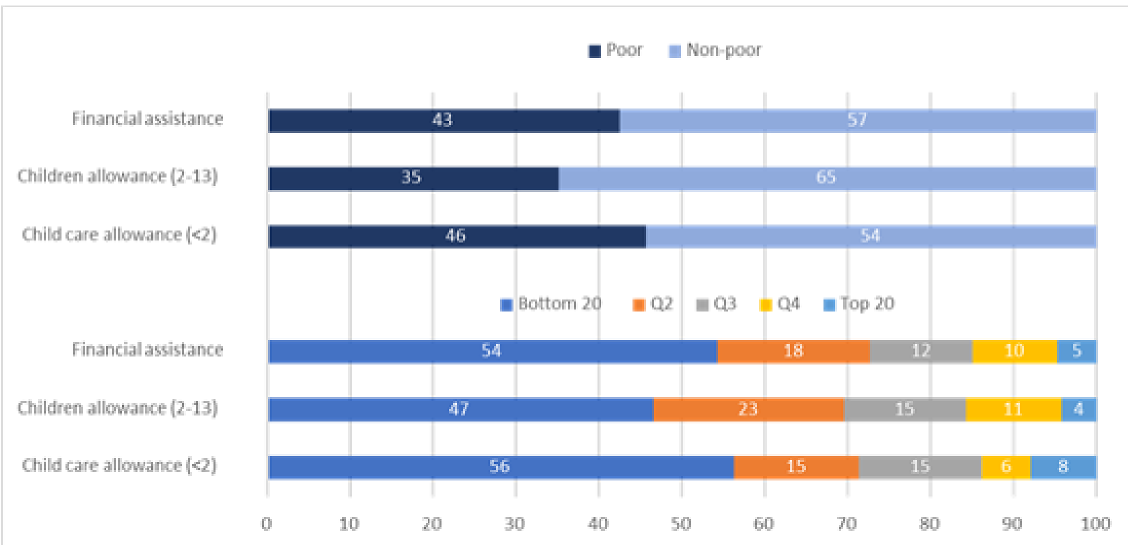
	2015	2016	2017	2018	UZS Share
Republic of Karakalpakstan	4375	3331	5191	10443	17%
Andijan	3544	2591	1922	3781	6%
Bukhara	2090	1238	1170	2553	4%
Jizzakh	2198	1747	1785	3640	6%
Kashkadarya	4594	3612	3859	7987	13%
Navoi	1334	1020	932	1784	3%
Namangan	3945	2902	2964	5758	10%
Samarkand	4969	3706	3283	6963	11%
Surkhandarya	2452	1647	1664	3523	6%
Syrdarya	1522	921	966	1758	3%
Tashkent (region)	1604	927	979	2002	3%
Ferghana	3907	2657	2364	4907	8%
Khorezm	2972	2184	3385	5928	8%
Tashkent (city)	230	137	179	465	1%
Total	39736	28620	30643	61492	100%

Source: Ministry of Finance and Ministry of Employment and Labor Relations of Uzbekistan

Social assistance is provided through two distinctive administrative channels: mahalla and khokimiyats (regional governorates) are responsible for the administration of the low-income family allowances. Means-tested benefits rely on identification processes administered by local community (mahalla) officials. Almost all other social allowances are administered through the national pension fund, which has an office in each district. Employment Services Centers are responsible not only for labor market programs, but also perform a monitoring function for the low-income family allowances.

Existing targeted social assistance programs have modest inclusion error, but substantial exclusion error due to budget-related caps on the number of beneficiaries (Figure 7). A World Bank assessment of the three main targeted cash assistance programs found more than 70 percent of beneficiaries were members of the bottom 40 (modest inclusion error), but that 63 percent of the poor were not reached by low-income allowances (relatively high exclusion error). The assessment further found that one of the main reasons for exclusion errors is the use of caps in budgeting and in the number of beneficiaries at the local level. The cap results in a rationing behavior, whereby limited resources are spread across eligible households, assigning allowances at a lower amount, or trigger a rotating approach, whereby applications are the facto postponed or payments of eligible applications are delayed.

Figure 7: Consumption Per Capita among Beneficiaries of Targeted Assistance Programs



Source: Analysis of Listening to the Citizens of Uzbekistan survey, 2018. Poor are defined using the international poverty line of 3.2 US$ PPP. Eligibility criteria do not use the international poverty definition, and as such, poverty status alone does not indicate errors of either inclusion or exclusion.

The system also struggled with suboptimal transfer amounts. This imbalance means that among the poor receiving support, only one-half are pushed above the poverty line commonly used by the World Bank for lower middle-income countries.

Local Health Services and Density

Uzbekistan has a network of public health centers represented at every regional and district level. The public health centers include virology laboratories, rapid response teams, epidemiological staff, units responsible for infection prevention and control. Uzbekistan also has an extensive network of state health facilities, including primary care facilities, district and regional general and pediatric hospitals, emergency care hospitals, and specialized inpatient care centers. Throughout the healthcare system, there is a relatively large hospital bed capacity, which is likely to be able to absorb initial surge needs in hospital overall, and specifically in intensive care units if repurposed and complemented by the necessary equipment and human resources. There are 334 acute beds per 100,000 population in Uzbekistan, compared to 290 beds in United States and 275 beds in Italy.

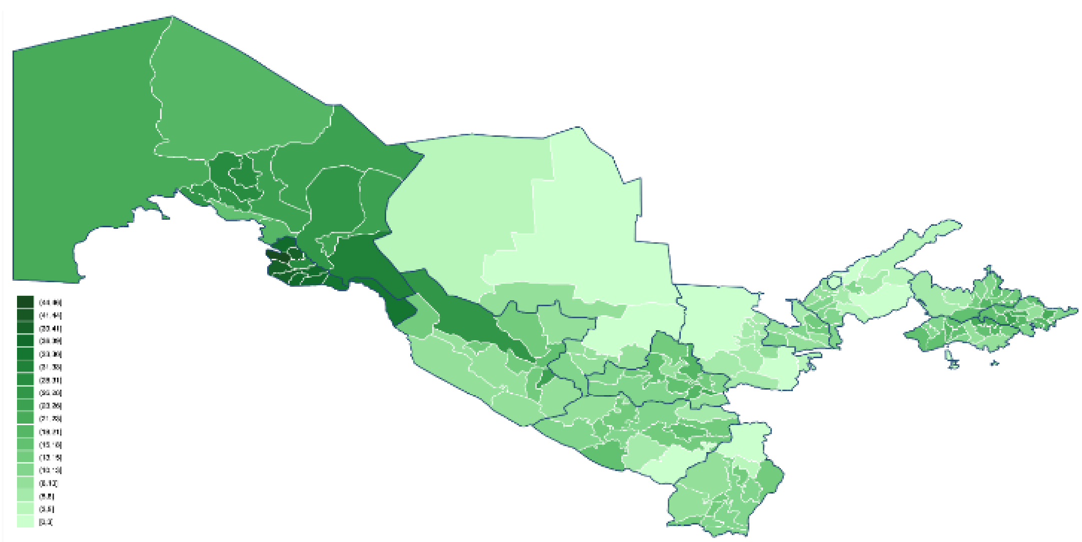
However, the Uzbek health system still faces many challenges in mounting effective prevention and control measures against COVID-19. Public health staffing levels have seen significant cuts over the last several years, which will pose challenges in meeting rapidly increasing needs in case detection, contact tracing, and laboratory testing. There are also challenges regarding the availability of resources in public health facilities to carry out essential functions. In May and June, an elevated number of people reported not being able to get medical care according to L2CU results. Since the outbreak, about 6-8 percent of respondents reported a member requiring medical treatment per month. Beginning in May and continuing in June, about 16 percent reported as being unsuccessful in obtaining treatment, though this estimate is based on a small absolute number of cases.

The population of Uzbekistan is also relatively dispersed (officially about half of the population lives in rural areas), simultaneously reducing some risk of transmission while also leading to high average travel times to local service providers (including clinics, hospitals, and pharmacies). As a proxy for local risk factors in the analysis that follows, those locations are identified that lack a local health clinic (within the mahalla) and/or local hospital, as well as the presence of a local pharmacy within the mahalla. In addition, measures of local density (apartments/families) are included at the mahalla to highlight risks specific to many people living in close proximity.

Migration

Remittance income is falling rapidly in Uzbekistan. In April 2020, the share of households receiving any remittances fell by 54 percent over the same period the previous year. Among those that did receive remittances, the value of the median transfer fell by 21 percent (in terms of inflation adjusted So'm). The share of households with members currently abroad fell by 22 percent in comparison the same period in 2019 (from 17 to 13 percent), and among those still abroad, active employment fell 18 percent in a single month (from 88 to about 73 percent of migrants). Future migration expectations have fully collapsed, as the number of respondents with household members considering seasonal migration fell by more than 95 percent over the previous year (Figures 8 and 9).

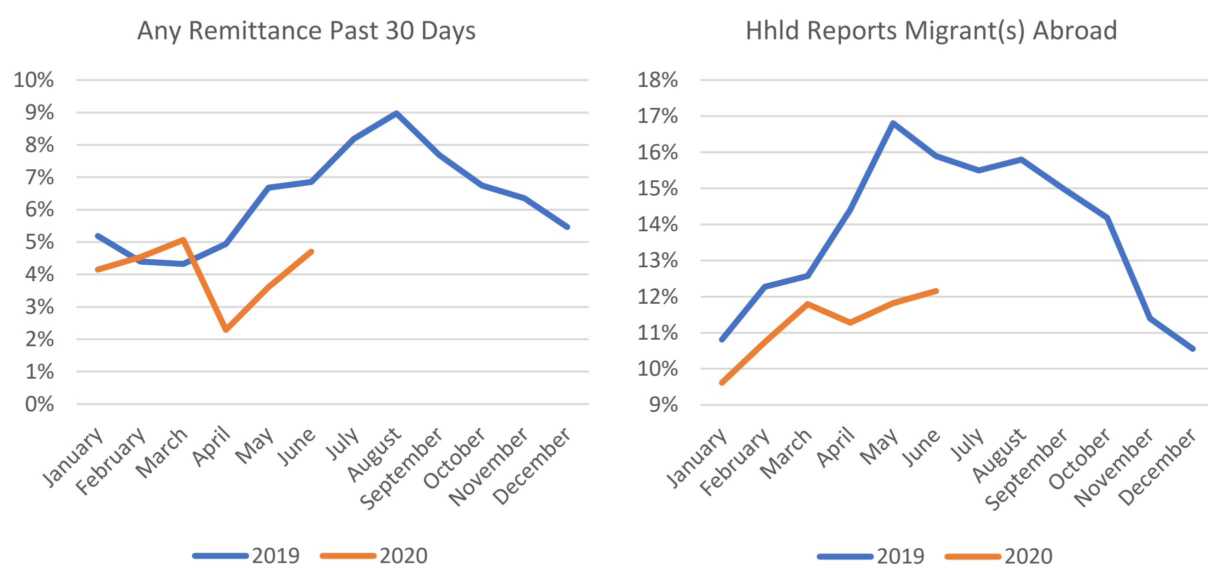
Figure 8: Share of Households with at Least One Member Currently Abroad (2018)



Source: Small Area Estimates from Listening to the Citizens of Uzbekistan baseline

Related previous analysis from the L2CU study (Seitz, 2019) found that remittances are very well targeted to depressed regions of the country, and transfers from abroad thus represent a crucial driver of poverty reduction in Uzbekistan. Findings show that weak local labor markets drive labor migration. Beginning to consider migration is associated with low life satisfaction, job loss, and unemployment. In contrast, actually migrating is associated with a remarkable improvement in labor market outcomes, alongside strong recovery in subjective and monetary measures of household welfare. The results further show that current migrants are more likely to send remittance payments when household members have deteriorating life satisfaction and/or subjective reports of worsening economic conditions at home.

Figure 9: Households Reporting Remittances and a Member Currently Abroad



Source: Listening to the Citizens of Uzbekistan Panel

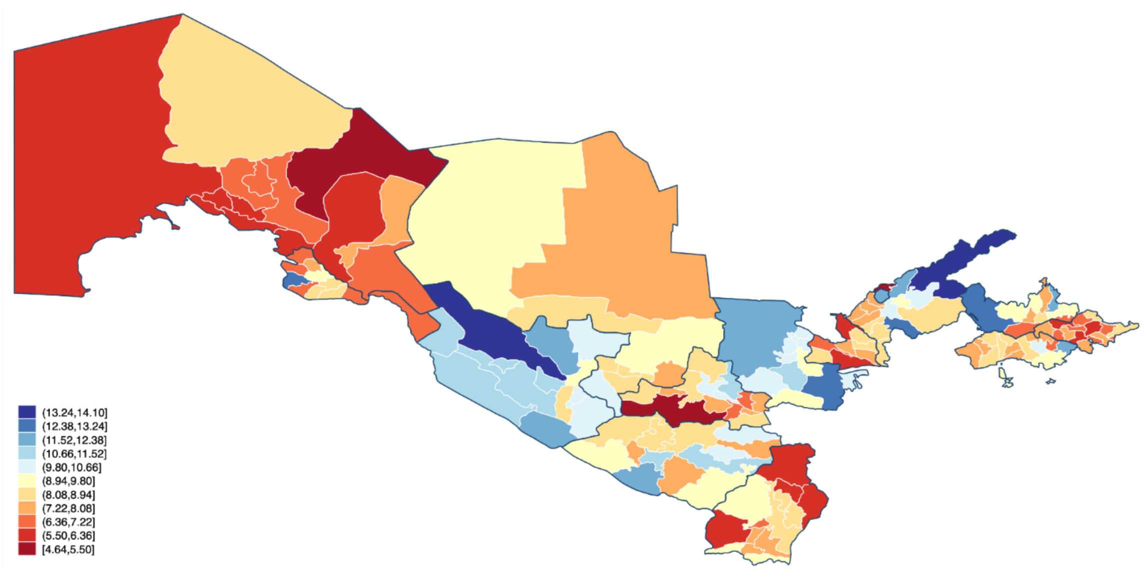
That study estimated that in the absence of remittance income, the poverty rate in Uzbekistan (measured at $3.2 per day purchasing power parity) would have been expected to rise from 9.6 (at that time) to 16.8 percent, or to about 12.2 percent assuming (implausibly) that all current migrants were to find formal employment at the local prevailing median wage. In the current context and the near absence of the opportunity to migrate for employment abroad for an extended period, it is likely that many dimensions of wellbeing in areas that were already economically struggling pre-COVID-19 will face deteriorating conditions.

Dimensions of Monetary Wellbeing

As of this writing, the World Bank projects that the poverty rate is quickly increasing. The poverty rate likely rose to between 8.7 and 10 percent following the outbreak, compared to pre-COVID estimates of 7.4 percent – equivalent to between .45 and .88 million additional people in poverty. This is a remarkable reversal for a country that has seen sustained poverty reduction for decades. Using the

Government's official national definition[8] of the low-income population, the poverty rate in Uzbekistan fell from nearly 28 percent in 2000 to 11 percent in 2019, though the pace of progress has gradually slowed over time. Both official and L2CU-based consumption measures are consistent with subjective self-classifications of households believing they are "poor."[9]

Figure 10: Average Per Capita Daily Consumption in 2011 $PPP for Uzbekistan (2018)



From Seitz (2019a)

During lockdowns, household spending diverged between those with higher and lower incomes. In April, about 55 percent of respondents report significant changes in their household spending. Of the reported changes, about 60 percent report spending more than usual (split evenly between "moderately" and "substantially") over the preceding 30 days. About 40 percent report reducing their spending (23 percent moderately, and 77 percent substantially). Respondents with higher incomes were significantly more likely to report increased spending, compared to those with lower incomes, who report reduced spending on average. There were reports of shortages in April and May as well. About 16 percent of those who responded reported that items were out-of-stock in their local area. Of them, food items were most commonly cited by far (90 percent) and particularly flour. About 5 percent of those reporting out-of-stock items listed an inability to buy medicines, and 5 percent an inability to buy masks. However, shortages were large resolved by May, and by June a negligible number of households reported any remarkable local shortages of essential goods.

High shares of people reported that they were unable to afford basic needs and were without savings. Those reporting an inability to afford food rose from less than 9 percent to more than 12 percent of the population in April. Pre-COVID-19, most respondents already reported that they did not have any financial savings, and the measure spiked 21 percent in April (up from 59 to 71 percent). In April, the share of people who "completely agree" that the prices of bread and flour increased also spiked from 6 percent to 19 percent. A rising share reported that they were worse off financially than the previous month, from 2 to 10 percent, with similar expectations for the coming month. The share of

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[8] The Ministry of Economy measures poverty in terms of income requires for minimum food consumption of 2,100 kilocalories per person per day. This approach is currently under revision.

[9] In 2018, about 10 percent of L2CU respondents described their household as poor.

respondents reporting that their financial situation "improved over the past month" fell by 60 percent, again with expectations for the next month falling by a similar amount.

Responding to the Crisis

In the absence of a "quick recovery," the COVID-19 health crisis is likely to be most severe for poor and vulnerable households, limiting their ability to abide by directives to contain the spread of disease. Labor market impacts in particular are expected to have knock-on effects on vulnerable households and are very likely to increase the prevalence and depth of poverty.

In this context, the President of Uzbekistan signed a US$1 billion economic relief plan to aid the economy and vulnerable population groups. The plan establishes the Anti-Crisis Fund and National Anti-Crisis Commission headed by the Prime-Minister. The Anti-Crisis Fund will finance COVID-19 prevention and control activities, social support to low-income families, support to strategic economic areas and small businesses. The plan also introduces time-limited tax rate reductions to support individuals and enterprises. As part of the relief plan, the Government announced salary top-ups for healthcare workers involved in the care of COVID-19 patients. Physicians can receive up to US$ 2,500 per month, nurses – up to US$ 1,500, and ancillary staff – up to US$ 500 per month.

The Government is expanding targeted social assistance programs to respond to the outbreak. Components of many of these will be implemented by local officials and there will be local variation in resource needs. Existing national cash allowances to low-income households currently cover (as of 2019) 249,341 families with children under the age of two, 411,422 families with children between the ages of 2 and 14, and 106,696 families received low-income allowances. However, due to cycling and re-application requirements, many of these families only received benefits for a six-month period, limiting the impact of such assistance. In March 2020, officials announced the expansion of social assistance programs to an additional 60 thousand families in response to the COVID-19 outbreak. In addition, as of April 3, 2020, the Government announced that they would waive the re-registration requirements for existing beneficiaries and automatically extend the payment of benefits to families with children, child care benefits and material assistance (currently slated to expire in March-June 2020) from six months to one year without the need for applying and submitting documents.

In addition, the authorities describe several locally administered initiatives to address the impacts of the crisis. The Centers for Coordination of Sponsorships that operate in all regions and in Tashkent City reported distributing food products worth 49.91 bln UZS, 3,201 drugs and medical items worth 137.9 bln UZS, among 413,072 families in need of social assistance. These benefits were provided according to lists compiled by over 5,200 volunteers together with the Mahalla chairs at citizen's assemblies.[10] The food packages distributed to the population included items mostly needed by the families (flour, potatoes, rice, onions, pasta, oil, sugar, carrots, eggs, meat products, poultry meet, etc.)

With the aim of provide direct support to the population, the Cabinet of Ministers of Uzbekistan issued an order[11] on the provision of financial assistance from the proceeds of "Sakhovat va Kumak" Funds established under the Mahalla Public Charity Foundation and its regional branches. Material assistance totaling 147 billion UZS was distributed to 346,292 families in accordance with the resolutions of the district (or city) level assemblies (Kengashes) of peoples' deputies. This included

[10] According to Protocol 14 issued by the Special Republican Committee, between 2 April and 20 May
[11] 213F

daily consumer goods worth 47.8 billion UZS for 242,347 families, monetary financial assistance of 74.5 billion UZS to 72,588 families, medicine worth 819 million UZS to 3,125 families and other goods worth 22.2 billion UZS distributed to 26,250 families. From national funds, an additional amount totaling 153,368 billion UZS was distributed to 201,900 families in the period from 30 July to 12 August this year.[12] Poor households and families in need of assistance received up to 1.0 million UZS each on the eve of Eid holiday.[13]

As of this writing, work is underway to provide an additional 380 billion UZS to support 400,000 needy families through a new initiative called the "Iron Book" system. Lists of 101,980 families to be supported by the regional departments of the Ministry have been developed including 49,961 poor families, 52,019 families that lost incomes during lockdowns, as well as 106,439 families with elderly people aged over 65 that are identified as in-need of social assistance. Starting 14 July, the reinstated Centers for Coordination of Sponsorships and Volunteering began distributing daily in-kind assistance to needy families in accordance with the lists put together by the Ministry for Support to Mahallas and Families.

Finally, a national hotline connecting to the regional call centers operated by support centers, as well as the hot line operated by the Ministry of Mahalla and Family Affairs, are in continuous operation. Authorities report that a total of 151,600 calls were received from 14 July to 12 August 2020. Grievances are registered and forwarded to the sponsorship centers. As of this writing, the authorities report that a total of 317,282 families have received food packages after contacting call centers.

[12] According to the Decree of the Cabinet of Ministers Nr 346 dated 29 July 2020

[13] As provided in the Presidential Decree PD-6038 dated 30 July 2020 "On additional measures aimed at supporting population groups in need of social protection and assistance during Coronavirus pandemics"

II – Data

Data reported in this paper are combined from four primary sources: i) mahalla passport data (local administrative statistics), ii) baseline survey data from the L2CU study, iii) data from the monthly household panel survey in L2CU, and iv) regional price statistics from the Central Bank of Uzbekistan. Spatial details and classifications from the national statistical agency of Uzbekistan are also used.

Mahalla Passport Data

Mahalla officials are responsible for maintaining up-to-date administrative details on people registered to their local area, and regarding the programs they administer. These details include information on demographics, community infrastructure, local services, characteristics, and other data required for implementing social assistance programs. Regional authorities assemble these data on an annual basis within their jurisdictions. For this study, a subset[14] of these mahalla-level statistics were combined into a single national mahalla passport data file, covering the full universe of mahallas in Uzbekistan. Table (2) lists the regions of Uzbekistan along with their number districts, mahallas, population, and families.

Table 2: Regional Composition

Region name	Districts	Mahallas	Population	Families
Andijan	16	881	3,025,716	794,641
Bukhara	13	544	1,892,003	495,625
Fergana	19	1041	3,664,590	990,239
Jizzakh	13	294	1,328,268	297,718
Karakalpakstan	16	413	1,897,213	419,730
Kashkadarya	15	770	3,040,710	737,091
Khorezm	12	519	1,860,577	505,982
Namangan	12	775	2,700,061	714,937
Navoi	10	307	995,311	263,430
Samarkand	16	1095	3,860,467	948,380
Surkhandarya	14	719	2,573,314	608,605
Syrdarya	11	222	826,933	207,398
Tashkent-City	11	512	2,538,857	802,342
Tashkent-Region	22	1028	3,078,095	836,089
Total	200	9120	33,282,115	8,622,207

Source: Mahalla Passport Database and Authors' calculations

Tables (3) and (4) present summary statistics of the key variables used in this study from the mahalla passport database. The data include information for 200 districts and cities that consist of 9120 mahallas, though in the interim, the final list of mahallas has been consolidated due to splits and mergers of mahallas. These passport data were treated as the most authoritative source at the mahalla level, and additional information available from other sources was linked to address missingness or dimensions of wellbeing that were not covered in the Mahalla passport database.

[14] Some details that are collected were withheld, including statistics on the number and destination of international migrants.

Table 3: Descriptive Statistics of Residents from Mahalla Passport Dataset

Variable description	N	Mean	St. Dev.	Min	Med	Max
Total number of families	9119	1154.3	1286.8	14	952	22807
Total population	9119	4535.4	5318.5	60	3888	96592
Total number of men	9116	2205.5	2606.4	0	1887	47185
Total number of women	9114	2289.9	2699.6	26	1966	49093
Number of young children (up to 7 years)	9109	563.4	799.9	0	425	33214
Number of children and adolescents (7-16 years)	9106	689.7	4067.3	0	531	517045
Number of minors (16-18 years old)	9090	258.6	360.3	0	167	4654
Number of adults (18-30 years old)	9094	893.4	1200.3	0	697	19995
Number of families who have lost a breadwinner	9012	16.5	37.8	0	10	1560
The number of single seniors	8739	2.3	6.4	0	1	152
Number of disabled people	9035	53.7	68.2	0	42	1042
Number of war veterans	8395	0.8	13.7	0	0	716
Number of retirees	9032	411.2	596.6	0	344	24088
Number of people over 100 years old	8527	0.3	7.7	0	0	586
Number of college graduates (2019-2020)	9024	32.7	66.7	0	21	1048
Number of lyceum graduates (2019-2020)	8966	5.9	10.7	0	3	301
Number of people engaged in entrepreneurship	9071	83.6	193.5	0	28	3000
Number of people engaged in trade	9064	55.3	134.2	0	18	1752
Number of people engaged in home-based work	8918	12.5	107.3	0	2	5525
Number of people engaged in handicrafts	8936	11.4	44.9	0	2	974
Number of people engaged in animal husbandry	8983	133.2	397.4	0	15	10014
Number of able-bodied unemployed people	8992	42.7	133.8	0	11	3025
Number of families engaged in family business	8973	23.7	81.7	0	5	1571
Number of families in need of social protection	8989	26.5	58.1	0	10	1188
Number of families received financial assistance	9012	7.7	11.7	0	5	302
Number of retirees aged 2-14	9022	34.3	50.4	0	23	995
Number of pensioners under 2 years of age	9043	31.7	62.7	0	25	2418
Number of people receiving disability benefits	8972	49.5	67.9	0	36	968
Number of able-bodied unemployed people	8941	150.1	590.6	0	22	10936
Number of unemployed college graduates	8927	19.3	60.3	0	7	2125

Source: Mahalla Passport Database and Authors' calculations

Table 4: Descriptive Statistics of Mahalla Amenities from Mahalla Passport Dataset

Variable description	N	Mean	St. Dev.	Min	Med	Max
Number of retail stores	8985	10.8	20.8	0	7	709
Number of weddings	8562	3.4	37.9	0	0	1900
Number of public catering outlets	8899	2.3	5.5	0	1	120
Number of teahouses	8878	0.9	2.9	0	0	78
Number of internet clubs	8674	0.2	1.2	0	0	65
Number of computer service providers	8821	0.5	1.4	0	0	66
Number of training centers	8658	0.4	1	0	0	20
Number of hospitals	8615	0.3	0.8	0	0	8
Number of family clinics	8751	1.2	8.5	0	0	147
Number of farms	8832	6.7	13.8	0	2	153
Number of playgrounds	8681	1.1	3.4	0	0	74
Number of sports fields	8740	0.8	1.5	0	0	54
Number of mosques	8379	0.4	2.1	0	0	61
Number of other religious temples	8569	0	0.3	0	0	16
Number of shrines	8563	0.4	3.4	0	0	59
Number of cemeteries	8808	1.2	1.7	0	1	34
Number of markets	8444	0.2	1.2	0	0	25
Number of bakery enterprises	8598	0.8	2.3	0	0	57
Number of beauty salons	8797	1.2	3.1	0	0	46
Number of repair and defect facilities	8867	1.2	2.2	0	1	72
Number of attractions	8575	0.2	7.2	0	0	681
Number of libraries	8670	0.5	1.5	0	0	32
Number of pharmacies	8880	1.1	2.7	0	0	60
Number of bathrooms	8739	2.6	25.6	0	0	1021
Number of streets	8968	110.7	975.8	0	8.11	17735
Total number of apartments	9110	851.8	1039.9	0	690	18024
Number of apartments (yard)	8955	600.3	443.5	0	598	7898
Number of multi-story houses	8579	26.1	151	0	0	2484
Number of apartments in buildings	7592	174.9	473.9	0	0	4215

Source: Mahalla Passport Database and Authors' calculations

Listening to the Citizens of Uzbekistan

The survey component of the L2CU project is conducted by a private firm (Nazar Business and Technology, based in Tashkent) under the supervision of World Bank staff, the Development Strategy Center, the Center for Economic Research and Reforms, and in cooperation with government Ministries and the Statistical Agency. The study included a comprehensive baseline survey that can be matched at the mahalla level with passport data.

The L2CU survey design closely followed that of conventional Living Standards Measurement Study (LSMS) surveys and was conducted using a standard two-stage sampling design, in which 200 mahalla were randomly selected with probability proportionate to (population) size. The national sample was stratified by region and by urban areas. The data were re-weighted based on observed population totals within the each mahalla at the time of the survey fieldwork. The second stage procedure was conducted using simple random selection with equal probability within selected mahalla. A separate stratification level for households that receive social assistance was included, totaling 4 households per mahalla. The final sample included 4,000 households in total (20 households per mahalla), 800 of which were social protection recipients by design.

The baseline survey included a full consumption and expenditure module using a list/recall approach. The resulting estimates are representative for 12 regions, 1 autonomous republic, and 1 independent city (Tashkent), crossed with their urban areas (except for the City of Tashkent, which is entirely urban). The survey was conducted entirely on tablet devices (CAPI), enabling validation using cross-referencing and other techniques to ensure accuracy. The survey was conducted over the course of a 1.5-month period in May/June 2018.

Listening to the Citizens of Uzbekistan Panel

After completion of the face-to-face baseline, interviewers began regularly calling a randomly selected panel of 1,503 households over the phone to conduct short interviews, following a set monthly schedule agreed with the participating household. The questionnaire for these phone interviews was designed to monitor trends in migration, subjective well-being, measures of income, employment, service disruptions, and related indicators. Phone-based interviews began on September 5, 2018, and the first 22 rounds of the survey are used in the analysis that follows, covering the entire period to the end of June 2020. A total of 33,443 unique observations are available for analysis.

Attrition is one potential concern using panel data of this type. To ensure that non-take-up in the first round (and attrition in subsequent rounds) did not seriously affect the required sample size for survey representativeness, households that refused to participate were replaced with other households drawn from the same sample cluster. However, any systematic difference in the household characteristics due to refusal to participate could lead to bias if the replacement households were different on average (with respect to observable characteristics) from the households that refused. Among the random sample of 1,503 households originally drawn from the baseline, about 25% refused to participate in the first round (i.e. initial take-up in the first phone round totaled 1,122 randomly sampled households, and 381 randomly selected replacement households to make up for those that refused or could not be contacted). Comparing those who agreed and those who refused to participate shows that in general, relevant household characteristics such as total household consumption, migration status, and household size do not differ significantly between the two groups. The exception is that rural households are substantially less likely to drop out of the sample and require replacement. However, random selection of replacements from the same PSU results in near perfect balance when comparing to baseline summary statistics.

Attrition rates (or nonresponse rates) have tended to be low and stable across rounds of the L2CU panel survey, ranging from 1 to 3 percent, and about 66 percent of the sample completed every round between September 2018 and June 2020 (and many of those that missed one or more interviews were successfully re-contacted later in the panel). These results are particularly encouraging if compared to similar high-frequency surveys, in which attrition rates are generally higher. For instance, the World Bank project "Listening-to-LAC" registered attrition rates for Peru of around 67 percent for the first follow-up survey, increasing by about 3 percent with each round and reaching 75 percent in round six (Ballivian et al. 2015). Both the initial and final attrition rate for the Listening-to-LAC survey in Honduras was lower than for the survey in Peru (41 and 50 percent, respectively), but still consistently higher than for L2CU. Other examples World Bank high-frequency surveys in Africa have resulted in similar rates of attrition, or higher (Demombynes et al. 2013; Croke et al. 2012). However, a similar study in Tajikistan (Listening to Tajikistan) that began in 2015 met with similarly high rates of compliance.

To take non-take-up and attrition into account, the participating sample is reweighted by developing a model using observable and relatively time-invariant characteristics from the baseline to predict the probability of dropping out for each household. Responses are then weighted to account not only for the sampling design but are also reweighted in each round to partially account for any bias introduced due to households dropping out (if it is unaccounted for by randomly sampling replacement households from the same PSUs).

Regional Price Statistics

The Central Bank of Uzbekistan monitors regional price changes over time for a core basket of goods, including food and a small number of health supplies. These data are aggregated by group, and regions with the highest average price increases are identified. The resulting measure is included in the analysis that follows.

III – Methods

Derived Small Area Estimates

Many relevant indicators to identify important COVID-19 risk factors are not included in the mahalla passport database. This is due in part to measurement challenges (especially for indicators such as poverty rates, consumption, and rates of migration) but also due to the fact that the system was originally intended for other purposes aside from crisis response and recovery.

The data required to estimate poverty rates, average per capita consumption and other welfare indicators is traditionally collected conducted using surveys. To allow for frequent monitoring and to contain the costs of gathering detailed information, such surveys usually visit only a small sample of the population. When this sample of the population is representative, welfare surveys provide reliable estimates of poverty incidence for the entire population at a small fraction of the cost that would be required to survey each person in the country. However, this approach necessarily leads to sampling errors, and consequently, a typical household income or expenditure survey cannot produce statistically reliable welfare estimates for small geographic units. To address this issue, the approach adopted here begins with nationally representative survey data for measures of consumption per capita and other measures of interest from survey sources. The analysis then proceeds to sharpen the reliability of the survey estimates using small area estimation techniques to allow reporting at a level below what is traditionally reported (moving from oblast-level estimates, to either district or mahalla-level estimates). Using statistical models, these approaches provide estimates of indicators for small areas that would not be possible to reliably construct with traditional survey data alone. In such studies, the results are often used to target policies and assign resources to have greater poverty-reducing impact or are intended to address the concerns of specific welfare groups at the local level.

A variety of small area estimation methods have been devised to overcome the increasing imprecision of welfare estimates as they are disaggregated. The standard approach used by the World Bank to small area estimation, provided that the required data are available, is described in Elbers, Lanjouw, and Lanjouw (2003) and is often referred to as the "ELL" poverty mapping method. The assumptions and data employed for ELL maps are further elaborated upon in Bedi, Coudouel, and Simler (2007). However, a pre-requisite for using the ELL approach is access to micro-level census data, and no census has been conducted in Uzbekistan since independence in 1991. In such cases, a common alternative approach is the Fay-Herriot (FH) method (Fay & Herriot, 1979), which is adopted to generate the imputed estimates described in this report.

The FH method allows estimation of indicators and rates using a combination of survey data and mahalla-level indicators from available sources that are less subject to imprecision, such as administrative data or remote sensing. In this report, most of the publicly available sources used are administrative, while a small number are derived from satellite imagery. The FH approach proceeds by matching accurate area-based information with indicators that are aggregated to the level of interest in the survey (the mahalla, in this case). Starting from the relatively imprecise estimates from the survey, a statistical model is developed, which attempts to explain the variation of the welfare indicator at the mahalla level (in this case, focusing on average consumption per capita, per capita income, and rates of migration).

Once the model is estimated, the direct survey estimates also enter into the final area-level results: the final estimated area-level level of consumption is a weighted average of the observed and model-based estimates for cases in which both estimates are present. For areas that do not appear in the survey data (accounting for the large majority of cases as only 200 are directly observed out of more than 9000 mahallas), the results rely entirely on estimates derived from the statistical model.

Constructing a Summary Risk Index

The summary index described in this note follows the Alkire and Foster (2011) method to developing multidimensional measures of deprivation. Though usually conducted at the household level, in this case the index is calculated at the community (mahalla) level. There are several properties of this approach that are particularly useful in this case. In the context of the COVID-19 outbreak and recovery planning, officials and development partners will engage at several levels to support vulnerable communities. Many response initiatives will likely target particular at-risk populations, and in such cases, issue-specific information is critical. However, broad resource allocation decisions will also be required for recovery programs and anti-poverty initiatives. In this respect, a summary of the overlapping nature risk factors is also useful in understanding local needs. The Alkire-Foster approach is a strong option in such a situation as it is decomposable by indicator, and both by subgroups and dimensions. With this feature, users can thus make comparisons of need between mahallas, by demographic groups, or by vulnerability status. Moreover, dimensional decomposability allows comparisons within specific dimensions across subgroups of mahalla.

A list of the variables used to create the index is included in Table (5), alongside details of the weight placed on each indicator. The inclusion of indicators from the list available indicators in the database was conducted on the basis of literature review and the direct analysis of risk factors using the L2CU survey. In the first stage, the weights for each indicator and dimension were set to be first equal across dimensions, and then equally across indicators. In a second stage, views on the importance of each indicator (measured on a scale of 1-5) were collected through a stakeholder consultation survey, conducted online in Uzbekistan in June 2020. The summary statistics of the stakeholder survey are included in Annex (C). The indicator weights were then adjusted by the difference from the average value across all indicators for each indicator, such that indicators viewed on average as more important receive greater weight, and those viewed as less important receive less weight. Data on the importance of dimensions was also collected, however, these varied so little on average that the final index did left the weights of dimensions unchanged.

Table 5: Summary of the COVID Needs Index

Dimension	Indicator	Start Weight	Adjust Weight
Elderly and Health	Top two quintiles of single seniors per capita	3.3%	3.4%
	Top two quintiles of people with disabilities per capita	3.3%	3.8%
	Top two quintiles of retirees per capita	3.3%	3.2%
	Top two quintiles of people aged 100 or more per capita	3.3%	3.2%
	Top two quintiles of disabled and no support per capita	3.3%	3.9%
Economic	Top two quintiles of entrepreneurs per capita	2.8%	2.7%
	Top two quintiles of trade sector workers per capita	2.8%	2.5%
	Top two quintiles of not employed people per capita	2.8%	2.5%
	Top two quintiles of retail sector workers per capita	2.8%	2.4%
	Top two quintiles of workers in family businesses per capita	2.8%	2.6%
	Top two quintiles of young children per capita	2.8%	3.0%
Social Assistance	Top two quintiles of lost breadwinner per family	4.2%	4.6%
	Top two quintiles of families receiving SA per family	4.2%	4.3%
	Top two quintiles of families in need of SA per family	4.2%	4.6%
	Top two quintiles of difference between 2 and 3 per family	4.2%	4.5%
Services and Density	No local hospital	2.8%	2.3%
	No local clinic	2.8%	2.5%
	No local pharmacy	2.8%	2.6%
	No public bathrooms	2.8%	2.4%
	Top two quintiles of density (apartments/families)	2.8%	2.6%
	Medium-sized urban mahalla	2.8%	2.5%
Migration	District in top half of migrant sending	8.3%	8.5%
	Top two quintiles of women as a share of total	8.3%	8.8%
Poverty	District with $3.2 poverty rate over 10 percent	5.6%	6.6%
	Mahalla in Bottom 40 average per capita consumption	5.6%	6.2%
	Region of above average increase food/medicine prices	5.6%	5.8%
Total		100%	102%

In the results and following discussion, we defined a mahalla as being "high need" when it is in the top quintile of the index value, at "substantial need" in the next highest quintile, at "medium need" in the middle quintile, at "modest need" for the next highest quintile, and at "lowest need" in the bottom quintile. However, such an index is not intended to suggest that the lowest need mahalla will not require substantial official support in responding to the impacts of the COVID-19 pandemic. Rather, the index highlights the variation in risk factors to efficiently deploy limited resources to those areas that are expected to have the greatest (often overlapping) needs and the lowest resilience to these impacts.

IV – Small Area Estimate Results

Mahalla-level small area estimates of consumption were derived according to the procedure described in Section (III). This only derived indicator estimated directly in this analysis and used in the index (though additional small-area indicators that change over time are discussed in Section VI). Automated model construction using stepwise variable selection and including dummy variables for regions resulted in a model with an adjusted R^2 of .63, after excluding variables with measured variance inflation factors of 10 or more. Modeling of the mahalla-level average consumption was relatively successful, though for some individual mahallas the estimate can be relatively imprecise. The median coefficient of variation was about 10 (average about 11) with only about 2.7 percent of mahallas with coefficients of variation greater than 20 (a rough threshold used in some cases to assess sufficient precision). Out of 200 districts and urban areas, 129 had no mahalla for which the coefficients of variation greater than 20. However, imprecision was particularly concentrated in the city of Navoi, the urban settlement of Nurabad, and the town of Akkurgan, suggesting estimates for these should be treated with additional caution. Annex D includes additional diagnostics regarding precision. Rather than directly using the relatively imprecise average consumption estimated in this procedure, these estimates are grouped into quintiles, and only the lowest two quintiles of average consumption per capita are included as being "at risk" on this indicator included in the overall index, lessening the risk of overly relying on a single imprecise indicator.

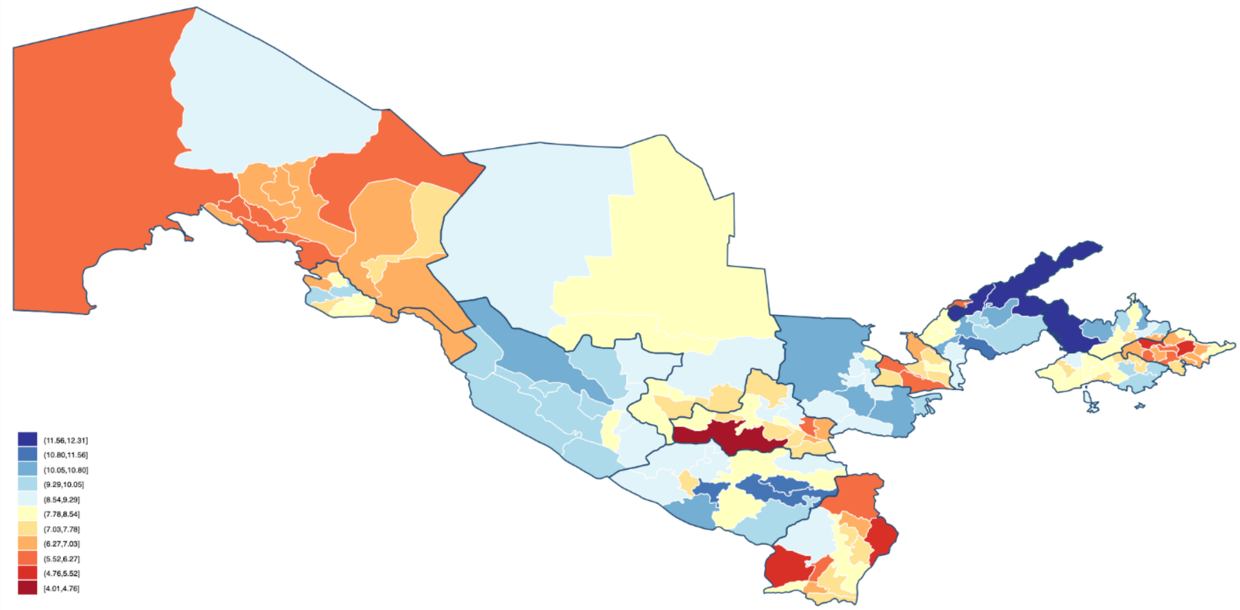
Table 6: Descriptive of Average Daily Consumption (per capita) in 2011 $PPP

	Average	Median	Lowest	Quint2	Quint3	Quint4	Highest
Andijan	6.45	6.47	70.3%	17.3%	12.4%	0.0%	0.0%
Bukhara	9.22	9.26	0.5%	2.7%	19.3%	63.3%	14.2%
Fergana	8.67	8.42	0.7%	23.4%	33.5%	25.2%	17.2%
Jizzakh	9.69	9.61	1.0%	0.5%	9.3%	45.5%	43.6%
Karakalpakstan	6.41	6.29	77.9%	15.9%	4.5%	1.5%	0.2%
Kashkadarya	9.39	9.20	2.9%	15.2%	18.9%	26.3%	36.7%
Khorezm	8.05	7.94	19.6%	26.4%	24.2%	24.3%	5.5%
Namangan	8.84	8.74	9.3%	15.0%	24.6%	27.8%	23.3%
Navoi	8.18	8.29	6.9%	24.2%	38.1%	28.4%	2.3%
Samarkand	7.59	7.42	20.4%	43.4%	19.7%	15.3%	1.1%
Surkhandarya	6.90	7.07	46.3%	33.6%	15.3%	4.4%	0.3%
Syrdarya	7.14	7.33	36.8%	35.9%	24.4%	1.5%	1.3%
Tashkent-City	11.85	11.82	0.2%	0.0%	0.0%	1.3%	98.5%
Tashkent-Region	10.28	9.23	7.2%	9.5%	20.6%	24.1%	38.7%

Notes: The table reports summary statistics from the small area imputation of average per capita consumption in 2018 based on the L2CU baseline survey. Administrative estimates of mahalla population are applied as weights.

Small area estimation in this case highlight significant within district variation that would otherwise go unmeasured. At the district level, the mahalla average income per capita is about $6 in the bottom quintile, and 11 in the top quintile. In addition, the extreme concentration in the city of Tashkent of high per capita consumption at the mahalla level is striking, with only 2 percent of mahallas projected to fall below the top quintile on average. Figure (11) reports these estimates aggregated to the district level and weighted by population.

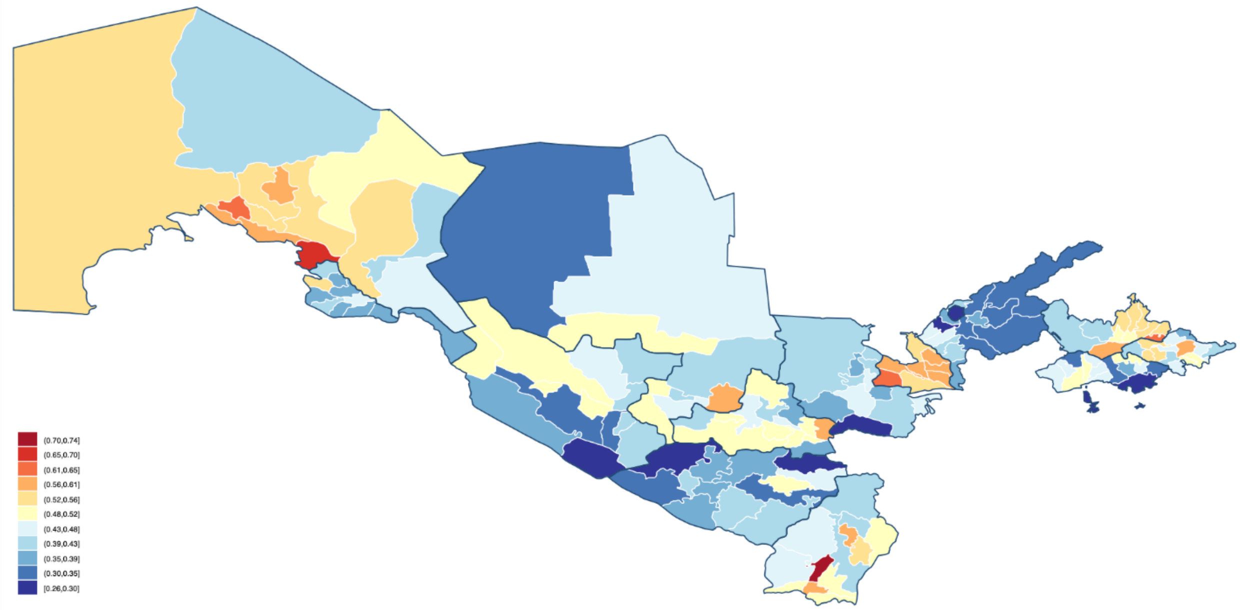
Figure 11: Map of Average Mahalla-level per capita Consumption



V – Index Results

Figure (12) reports the summary index value aggregated to the district level and weighted by population. This analysis of the local risk factors highlights substantial spatial variability, both between and within larger territorial units of Uzbekistan. The results thus enable much more granular and targeted interventions than would be possible using solely the aggregated information available at the district or regional level. Further, the resulting values can be decomposed to suit a variety of purposes, and expressed in either a summary index, by dimension, or by individual indicator. The results further identify clusters of need within regions and at times across provincial borders.

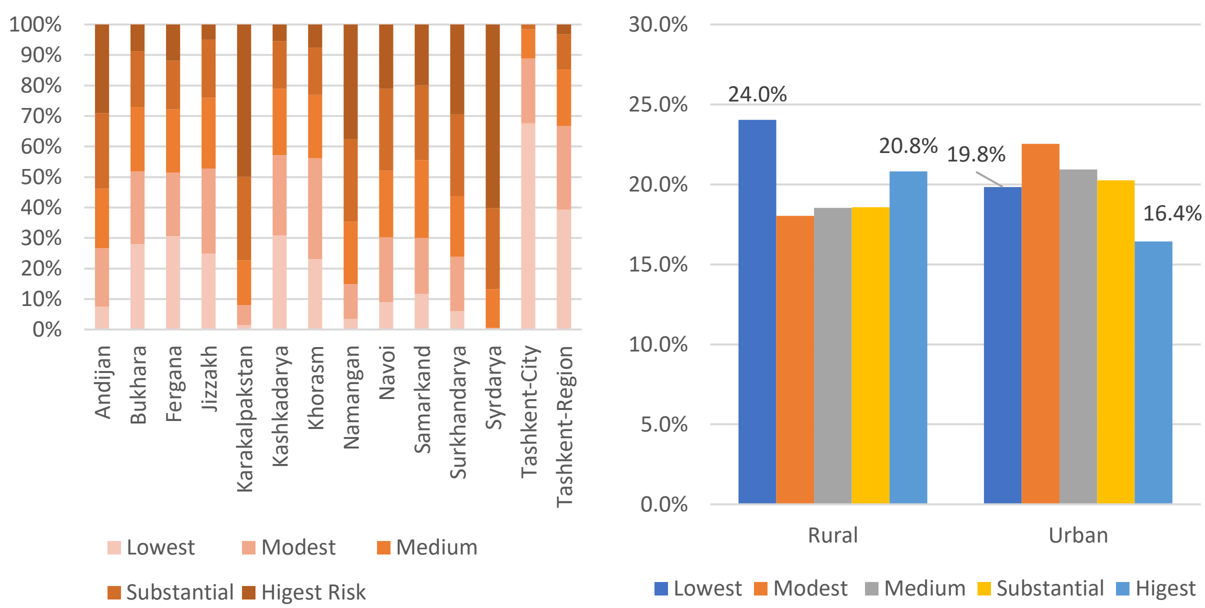
Figure 12: Map of District-Average Index Values, Population Weighted



Source: Authors' estimates

The results show that a large share of mahallas in the regions Syrdarya, Karakalpakstan, and Namangan face many overlapping risk factors. These regions have relative more mahallas with low estimated consumption per capita (pre-COVID-19), relatively less stable employment, higher levels of unemployment (pre-COVID-19), and much higher reliance on remittances. These regions have a high share of mahalla categized into the "highest needs" group in the overall summary index as a consequence (Figure 13).

Figure 13: Descriptive Statistics of Index



Source: Authors' estimates

At the other extreme, no mahalla in the city of Tashkent is identified in the "highest need" category, with most mahallas clustered at the bottom of the need scale. The region of Tashkent (which is a distinct administrative unit from the city) is also found to have a relatively small share of mahallas in the "highest need" category (Table 7 and Figure 14). This underscores that while several types of impacts are localized in the largest agglomeration in Uzbekistan, there are fewer overlapping risk factors there than in other areas (such as regional capitals, medium-sized cities, and those areas highly reliant on remittance income). This does not minimize the considerable direct impact of COVID-19 in urban areas, and particularly Tashkent, which is the densest location in the country, and has suffered the highest rates of infection at the time of this writing.

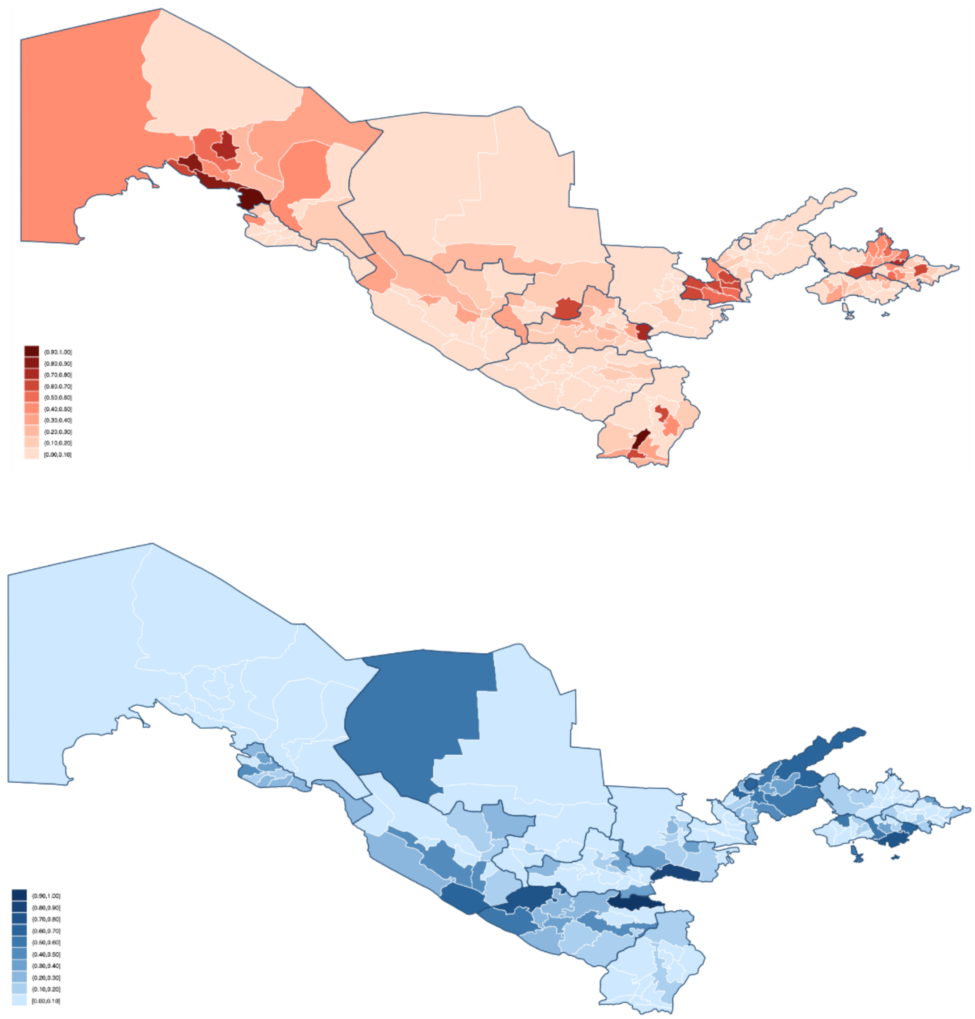
Table 7: Summary Statistics of Needs Index by Region

	Average Index	Average Quintile	Lowest	Modest	Medium	Substantial	Highest
Andijan	0.48	3.49	7.5%	19.1%	19.5%	24.8%	29.0%
Bukhara	0.39	2.56	28.0%	23.8%	21.1%	18.4%	8.7%
Fergana	0.40	2.58	30.6%	20.8%	20.7%	16.0%	11.8%
Jizzakh	0.40	2.52	24.8%	27.9%	23.2%	18.9%	5.1%
Karakalpakstan	0.55	4.18	1.5%	6.6%	14.6%	27.4%	49.9%
Kashkadarya	0.38	2.39	30.9%	26.3%	21.7%	15.7%	5.4%
Khorezm	0.40	2.51	23.1%	33.1%	20.8%	15.5%	7.6%
Namangan	0.51	3.84	3.5%	11.4%	20.5%	27.0%	37.6%
Navoi	0.46	3.30	8.9%	21.3%	21.8%	26.9%	21.1%
Samarkand	0.46	3.23	11.6%	18.4%	25.5%	24.5%	20.0%
Surkhandarya	0.49	3.56	6.0%	17.9%	19.9%	26.8%	29.4%
Syrdarya	0.58	4.46	0.0%	0.5%	12.7%	26.5%	60.2%
Tashkent-City	0.29	1.45	67.6%	21.3%	9.6%	1.5%	0.0%
Tashkent-Region	0.36	2.12	39.3%	27.4%	18.4%	11.7%	3.1%

Source: Authors' calculations

Indeed, urban areas also face disproportionate economic impacts due to a greater share of employment in services sectors such as retail and transportation. However, the most prosperous urban areas of the country can also rely on many sources of resilience that are unavailable in less dense areas. Urban areas in Uzbekistan have more formal labor markets, and a higher share of (stable) government and state-owned enterprise-based employment. The densest urban areas also have greater access to health facilities, have modest numbers of vulnerable elderly people, faced low initial levels of poverty and unemployment pre-COVID, had a low reliance on social assistance, and send relatively few migrants. As a result, proxies of these factors measured in mahalla data lead to a lower ranking of need in the summary index.

Figure 14: Highest (red) and Lowest (blue) Overlapping Factors



Source: Authors' calculations

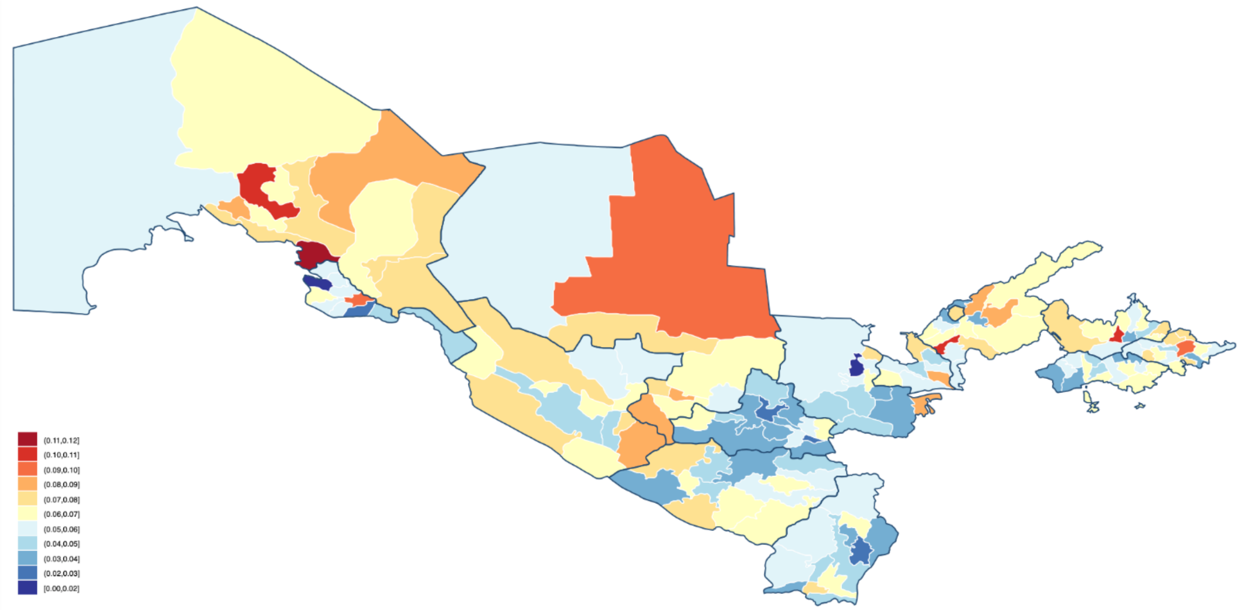
Elderly and Disabled

The mahalla data reveal relatively high concentrations of elderly and disabled people in at least some mahallas in all regions of the country. Single seniors are found to be a larger share of the population in Karakalpakstan, Namangan, and Andijan. Karakalpakstan also struggles with the highest shares of the population who are registered as disabled. In terms of population shares, the city of Tashkent is the oldest regional unit, with 72 percent of people there living mahallas in the top two quintiles of that measure. Kashkadarya has an abnormally high number of people over the age of 100. Andijan and Jizzakh have relatively high rates of people who are disabled but did not receive disability benefits in 2019. Across all measures in this dimension, Karakalpakstan have the largest number of mahallas with overlapping risk factors overall, followed by the city of Tashkent, and the region of Andijan.

In contrast, mahallas in Surkhandarya, Khorezm, and Bukhara are found to have relatively fewer single seniors. Mahallas in Jizzakh and Samarkand have relatively few disabled people per capita in comparison to other regions, while Jizzakh and Surkhandarya have relatively few retirees overall.

Kashkadarya and Syrdarya have relatively few mahallas with many disabled people who lack financial support. Across all measures in this dimension, mahallas in Jizzakh, Samarkand, and Surkhandarya have the lowest share of overlapping risks (Figure 15 and Table 8).

Figure 15: Elderly and Disabled Dimension



Source: Authors' calculations

Table 8: Average by Region of Indicators Related to Elderly Population and Disability

	ElderHealth1	ElderHealth2	ElderHealth3	ElderHealth4	ElderHealth5
	Top 2Q of single seniors	Top 2Q of people with disabilities	Top 2Q of retirees	Top 2Q of people aged 100+	Top 2Q of disabled and no support
Andijan	57.0%	33.6%	47.9%	7.5%	42.7%
Bukhara	18.1%	56.4%	39.7%	9.5%	35.1%
Fergana	43.9%	23.6%	47.6%	7.0%	34.5%
Jizzakh	25.9%	24.6%	11.1%	17.3%	40.1%
Karakalpakstan	62.7%	81.9%	26.1%	4.3%	36.5%
Kashkadarya	32.0%	35.2%	28.3%	30.0%	14.8%
Khorezm	14.3%	54.7%	38.2%	4.3%	28.6%
Namangan	57.6%	40.7%	32.1%	6.8%	22.7%
Navoi	45.2%	67.5%	39.9%	7.5%	27.2%
Samarkand	34.3%	18.4%	26.4%	7.4%	29.4%
Surkhandarya	14.3%	43.1%	12.3%	23.1%	34.7%
Syrdarya	37.7%	57.4%	31.4%	21.8%	20.7%
Tashkent-City	40.6%	30.8%	72.2%	7.3%	49.9%
Tashkent-Region	39.2%	31.1%	47.4%	19.6%	39.3%

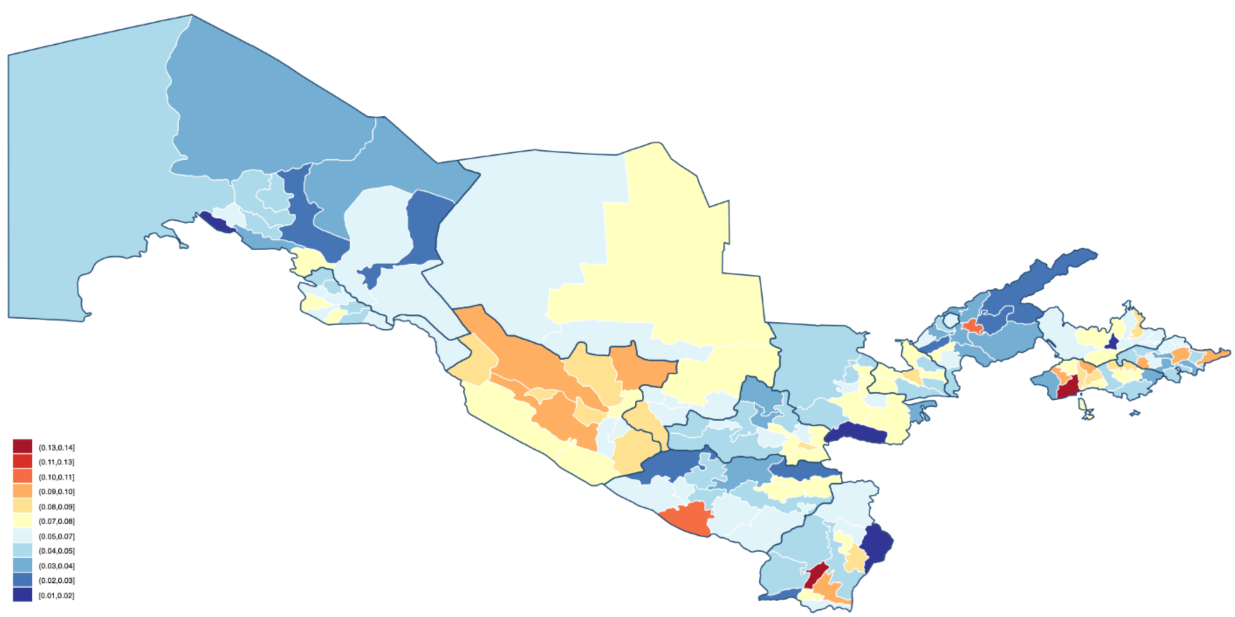
Source: Authors' calculations

Economic Factors

The passport data show that mahallas in the regions of Tashkent and Bukhara have relatively high shares of entrepreneurs and trade workers (measured in two separate indicators). The regions of Fergana, Surkhandarya, Tashkent city and Navoi all have higher recorded "able bodied people not working." This result should be interpreted with caution, however, as it contrasts with official unemployment rates which find much lower joblessness in the city of Tashkent (and other urban areas) than in rural parts of the country. Rather than simply indicating higher deprivation, this indicator may partially reflect a larger share of the population enrolled in education programs in urban areas. Mahallas in Navoi, Samarkand, Bukhara, and Andijan all have higher than average shares of the population working in family businesses, which is assumed here to correlate strongly with informality in this analysis. Finally, mahallas in Karakalpakstan, Namangan and Khorezm all have higher shares of children than the national average, highlighting the difficulties expected for workers and others during the closure of schools, and related care responsibilities. Across all measures in this dimension, mahalla in Bukhara, Ferghana and Syrdarya had the most overlapping deprivations on average.

In contrast, mahallas in Tashkent region (excluding the city) and Karakalpakstan have relatively few concentrations of entrepreneurs according to the mahalla passport data. Trade sectors are a smaller share of workers on average in predominantly rural areas in Karakalpakstan, Kashkadarya, and Navoi. Mahallas in the region of Tashkent, Karakalpakstan, and Khorezm are able bodied but not working. Relatively few people in Tashkent region work in retail jobs, contrasting with the city of Tashkent. Fewer residents in the city or region of Tashkent work in family businesses, on average. Tashkent city and Navoi have relatively few young children, in comparison to other regions (Figure 16 and Table 9).

Figure 16: Economic Factors Dimension



Source: Authors' calculations

Table 9: Average by Region of Indicators Related to Economic Factors

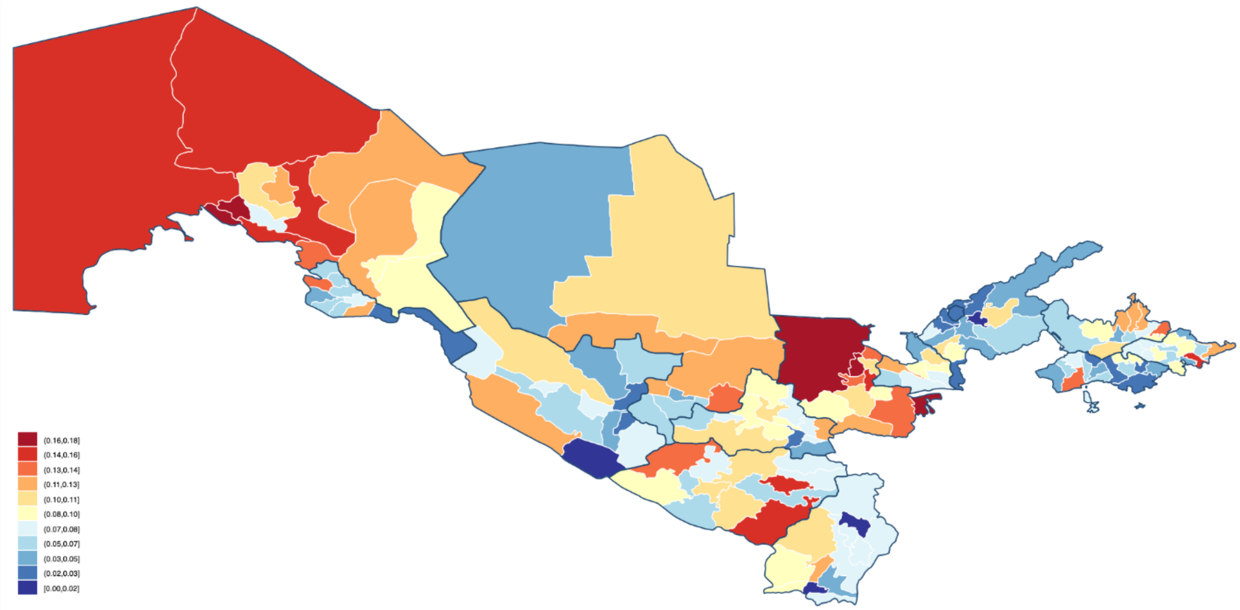
	Econ1	Econ2	Econ3	Econ4	Econ5	Econ6
	Top 2Q of entrepreneurs	Top 2Q of trade sector workers	Top 2Q of not employed people	Top 2Q of retail sector workers	Top2 quintiles of family businesses	Top 2Q of young children
Andijan	35.4%	44.9%	41.8%	37.7%	54.2%	38.1%
Bukhara	53.2%	53.9%	36.0%	61.5%	65.8%	32.2%
Fergana	40.5%	45.9%	55.5%	53.4%	49.4%	34.9%
Jizzakh	38.0%	35.4%	29.7%	41.4%	43.0%	34.8%
Karakalpakstan	31.5%	24.6%	25.7%	22.5%	23.2%	58.0%
Kashkadarya	34.4%	27.4%	33.6%	34.0%	36.7%	40.8%
Khorezm	34.5%	33.7%	27.8%	38.3%	45.5%	45.7%
Namangan	36.9%	30.0%	38.3%	36.8%	49.5%	50.0%
Navoi	42.8%	30.1%	45.8%	72.1%	39.6%	24.3%
Samarkand	43.5%	36.5%	37.6%	47.2%	29.8%	38.8%
Surkhandarya	39.6%	41.2%	51.6%	34.4%	33.1%	50.6%
Syrdarya	45.2%	37.9%	38.0%	62.3%	18.9%	45.4%
Tashkent-City	52.9%	63.6%	44.6%	29.8%	24.1%	11.9%
Tashkent-Region	28.5%	40.9%	25.0%	0.0%	28.9%	41.7%

Source: Authors' calculations

Social Assistance

Social assistance (SA) provision is concentrated in several clusters in Uzbekistan. In particular, mahallas in Karakalpakstan and Jizzakh on average have many more assistance beneficiaries than mahallas in other regions. This relationship is clear across measures in the relevant indicators in the mahalla passport data, as both regions are above average with respect to loss of breadwinner benefits, other SA benefits, overall need of SA, and unmet need of SA. The region of Navoi, in contrast, has relatively low provision, but relatively high unmet need according to passport data. Across all measures in this dimension, mahalla in Karakalpakstan, Jizzakh, and to a lesser extent in Kashkadarya have a larger number of overlapping deprivations in this dimension. In contrast, the city of Tashkent has relatively few people eligible or receiving social assistance, which is also consistent with estimates of average per capita consumption and income. Mahallas in the region of Tashkent are somewhat more often among those with a large number of recipients of lost breadwinner allowances, but among other types of benefits there are similarly low levels as in the City of Tashkent. Across all measures in this dimension, mahallas in and around Tashkent are substantially less likely to be receiving (or identified as in need of) social assistance benefits, followed by mahalla in Bukhara and Ferghana (Figure 17 and Table 10).

Figure 17: Social Assistance Dimension



Source: Authors' calculations

Table 10: Average by Region of Indicators Related to Social Assistance

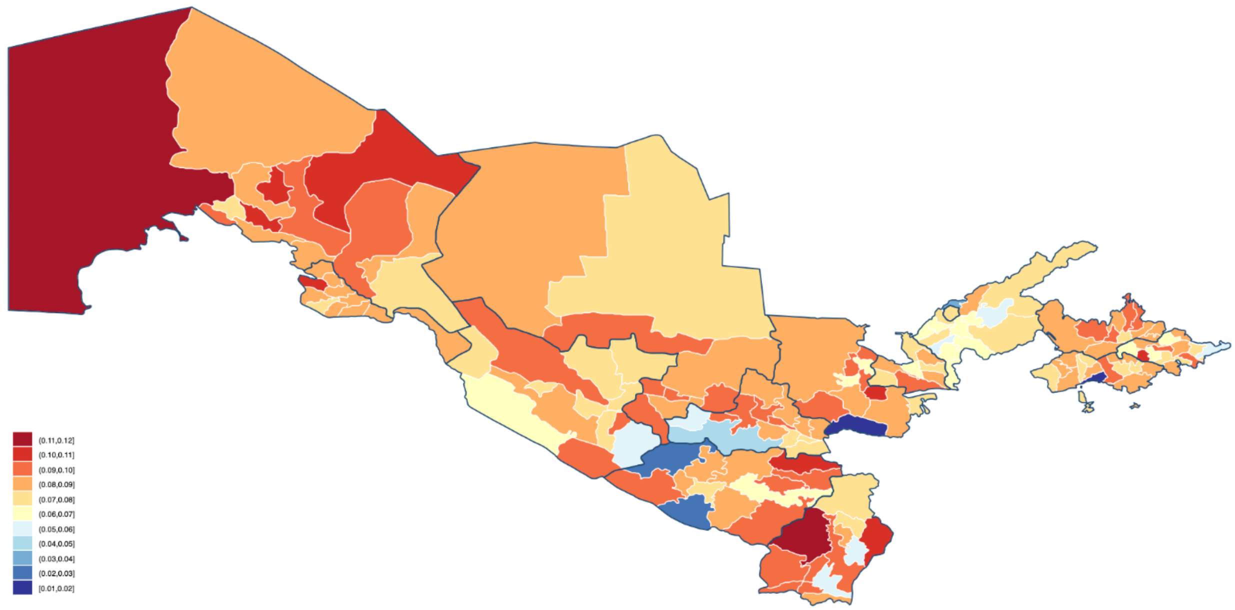
	SocialAssist1 Top 2Q lost breadwinner	SocialAssist2 Top 2Q receiving SA	SocialAssist3 Top 2Q in need of SA	SocialAssist4 Top 2Q unmet need
Andijan	46.9%	38.6%	43.8%	44.8%
Bukhara	25.8%	34.4%	31.4%	30.2%
Fergana	29.3%	21.0%	31.7%	37.1%
Jizzakh	61.8%	84.2%	72.1%	56.6%
Karakalpakstan	75.0%	77.8%	62.4%	44.6%
Kashkadarya	47.7%	81.4%	47.5%	36.9%
Khorasm	28.1%	17.5%	47.9%	52.0%
Namangan	33.8%	67.7%	46.0%	43.1%
Navoi	34.9%	21.6%	56.6%	60.9%
Samarkand	39.2%	51.8%	36.5%	29.8%
Surkhandarya	59.0%	28.1%	26.7%	26.3%
Syrdarya	49.1%	39.6%	45.9%	44.1%
Tashkent-City	8.8%	0.1%	13.8%	37.7%
Tashkent-Region	35.6%	4.0%	23.5%	34.6%

Source: Authors' calculations

Services and Local Infrastructure

Very few mahalla in Uzbekistan have immediate (within mahalla) access to hospitals, clinics, pharmacies and other health facilities. Those that do, are concentrated largely in urban areas. Tashkent has high numbers of local hospitals, and fewer mahalla with local clinics. The region of Tashkent is an outlier with respect to a very low number of mahallas registered as having a local pharmacy. Across all measures in this dimension, mahalla in Karakalpakstan, Navoi and Namangan are more likely to have overlapping risk factors, while the mahallas located in the city of and region of Tashkent have disproportionately low overlapping risk factors across the indicators in this dimension (Figure 18 and Table 11).

Figure 18: Local Services and infrastructure Dimension



Source: Authors' calculations

Table 11: Average by Region of Indicators Related to Local Service and Infrastructure

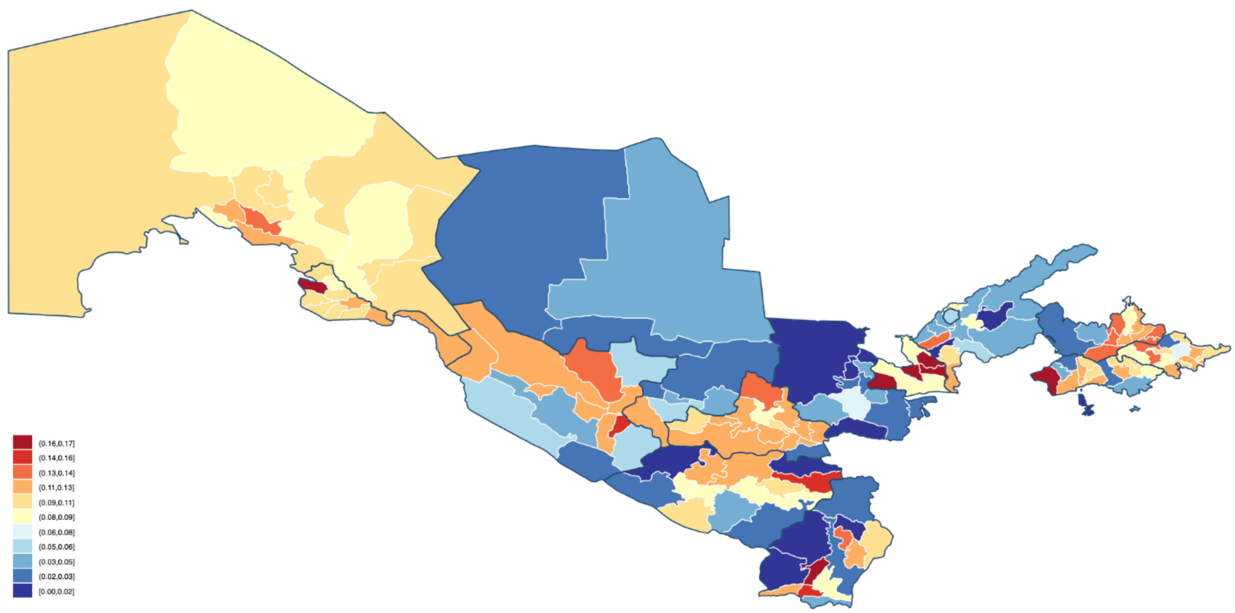
	Infra1	Infra2	Infra3	Infra4	Infra5	Infra6
	No local hospital	No local clinic	No local pharmacy	No public bathrooms	Density (apt/family)	Mid-sized urban mahalla
Andijan	82.4%	78.6%	53.9%	67.8%	21.3%	21.0%
Bukhara	80.3%	57.6%	38.4%	93.9%	47.1%	7.5%
Fergana	75.1%	66.8%	45.3%	80.2%	34.3%	14.8%
Jizzakh	80.4%	58.9%	43.2%	72.1%	44.5%	25.7%
Karakalpakstan	86.0%	60.7%	66.6%	80.8%	65.4%	18.3%
Kashkadarya	75.7%	49.1%	56.5%	77.5%	61.6%	19.2%
Khorezm	91.1%	76.6%	53.7%	89.0%	17.7%	18.1%
Namangan	81.1%	76.2%	54.7%	86.3%	30.5%	26.2%
Navoi	71.8%	70.8%	45.8%	90.3%	68.2%	20.3%
Samarkand	81.9%	65.7%	64.5%	78.8%	37.8%	9.1%
Surkhandarya	72.6%	64.6%	65.1%	86.8%	34.8%	19.5%
Syrdarya	78.1%	51.6%	45.7%	89.7%	38.9%	22.1%
Tashkent-City	69.3%	80.4%	22.3%	97.0%	47.4%	0.2%
Tashkent-Region	72.3%	40.8%	95.9%	2.8%	46.8%	12.9%

Source: Authors' calculations

Migration

International out-migration is much more common in rural areas and highly associated with low levels of labor income. Mahallas in Khorezm and Namangan all send high numbers of migrants abroad. However, many districts and mahallas struggle to accurately record migration patterns, and survey estimates are relatively rough. An additional proxy indicator is therefore included in this dimension: having a large gender imbalance in the mahalla, as a large majority of out-migrants in Uzbekistan are young men. By this measure, Syrdarya has an abnormally high number of such mahallas. Across all measures in this dimension, mahallas in Syrdarya, Karakalpakstan, and Khorezm are most commonly identified as most reliant on migration and remittances with many overlapping concentrations on both indicators in this dimension. In contrast, Jizzakh, Navoi, and Tashkent region or Tashkent city have relatively few mahallas with concentrations of these indicators and cases on which they overlap (Figure 19 and Table 12).

Figure 19: Migration Dimension



Source: Authors' calculations

Table 12: Average by Region of Indicators Related to Migration

	Mig1	Mig2
	District in top half of migrant sending	Top 2Q women as a share of total
Andijan	72%	38%
Bukhara	60%	49%
Fergana	69%	35%
Jizzakh	0%	42%
Karakalpakstan	100%	25%
Kashkadarya	74%	26%
Khorezm	100%	30%
Namangan	83%	39%

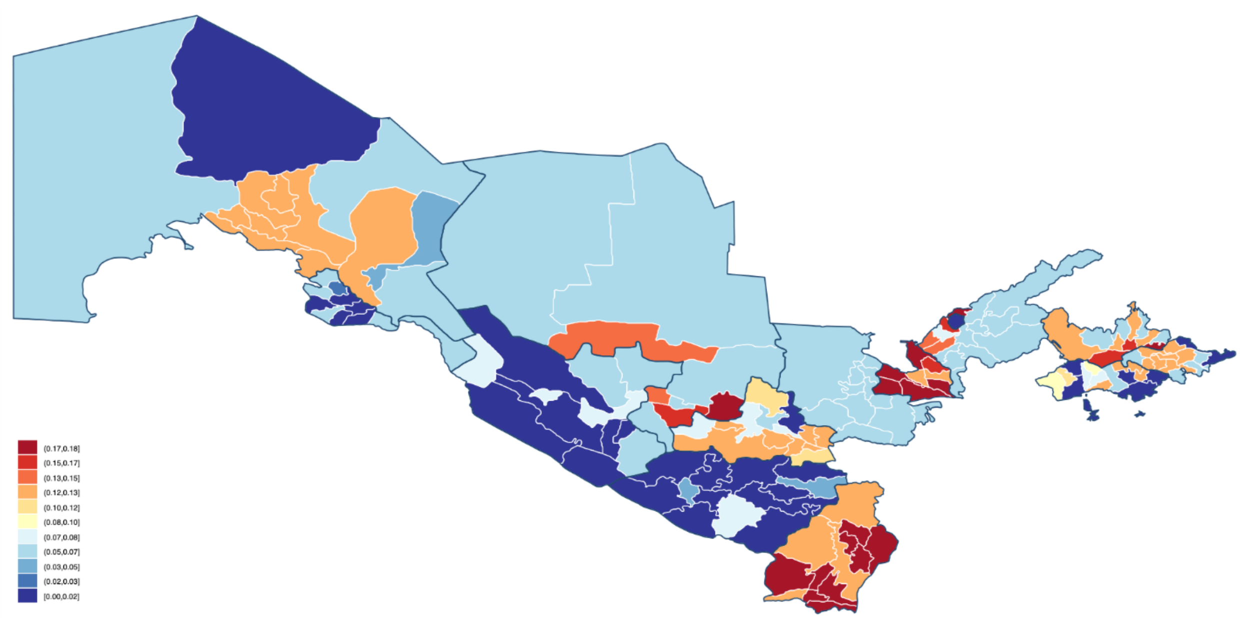
Navoi	14%	42%
Samarkand	81%	40%
Surkhandarya	46%	31%
Syrdarya	52%	100%
Tashkent-City	0%	67%
Tashkent-Region	20%	42%

Source: Authors' calculations

Dimensions of Monetary Poverty

The regions of Samarkand, Surkhandarya, and Syrdarya all have an above average number of districts with a poverty rate of over 10 percent. Karakalpakstan has a large number of mahallas at risk by this measure and is also an outlier with respect to mahalla in the bottom 40 percent of average consumption per capita. Food and medicine price increases were found to be highest in Jizzakh, Namangan, Navoi, Surkhandarya, Syrdarya and the Region of Tashkent. Across all measures in this dimension, mahallas in Surkhandarya and Syrdarya had a large share of mahallas with overlapping risk factors across all three. In contrast, the city of Tashkent, and the regions Kashkadarya and Khorezm had relatively few mahallas with overlapping risks in this dimension (Figure 20 and Table 13).

Figure 20: Monetary Dimensions of Wellbeing



Source: Authors' calculations

Table 13: Average by Region of Indicators Related to Monetary Poverty

	Pov1	Pov2	Pov3
	District in bottom40 poverty rate	bottom40 average per capita	Reg. increase food/medicine prices
Andijan	68%	88%	0%
Bukhara	41%	3%	0%
Fergana	53%	24%	0%
Jizzakh	0%	2%	100%
Karakalpakstan	70%	94%	0%
Kashkadarya	7%	18%	0%
Khorasm	0%	46%	0%
Namangan	69%	24%	100%
Navoi	53%	31%	100%
Samarkand	91%	64%	0%
Surkhandarya	92%	80%	100%
Syrdarya	91%	73%	100%
Tashkent-City	0%	0%	0%
Tashkent-Region	23%	17%	100%

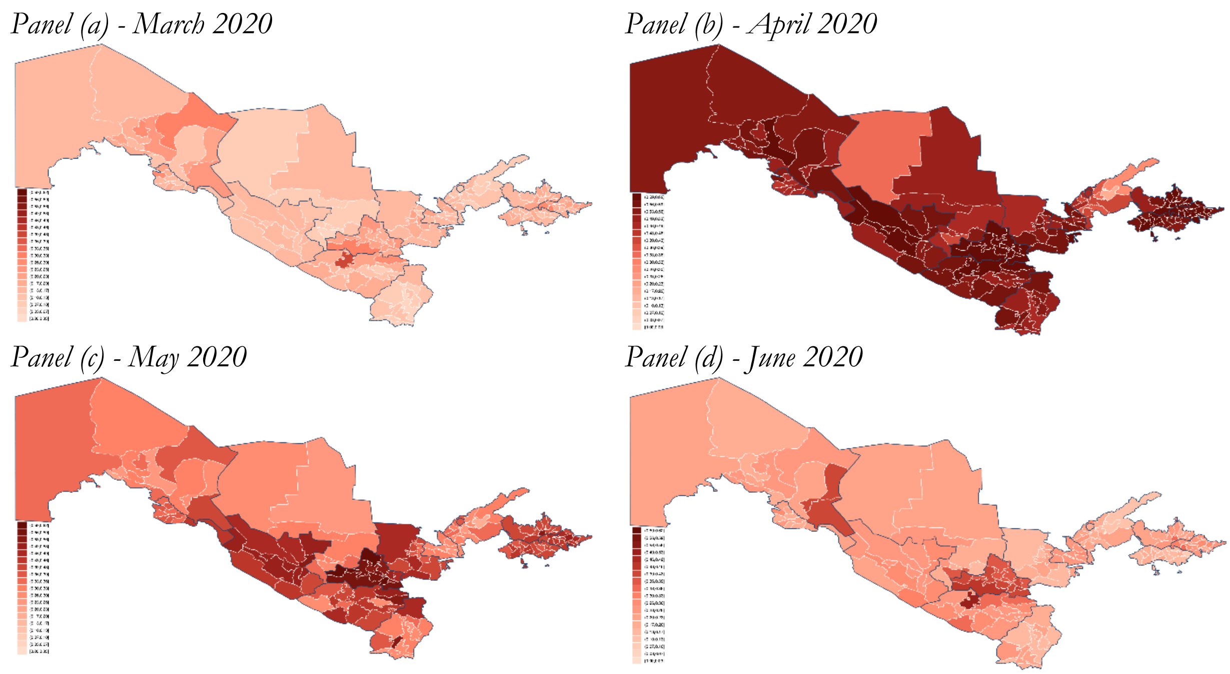
Source: Authors' calculations

VI – Dynamic Updates of Critical Indicators

The primary risk index described above is set using data that are collected infrequently, leading to challenges in updating responses in light of a rapidly changing situation. To address this, estimates from higher frequency sources of information can be linked with the database and used to impute small area estimates of critical measures over time. Users should bear in mind however that these estimates come with greater uncertainty than is often the case with official data. Nonetheless, patterns of the magnitude observed during lockdowns in April, and the gradual relaxation of these measures in May and June, are clearly discernable and provide much greater nuance to monitoring of national-level trends using the panel survey data.

Figure (21) reports the results of small area estimation performed at the level of the mahalla (and aggregated to the district level for the purposes of mapping). Strict lockdown began with the reinstatement of interregional police posts on March 23 to restrict the movement of cars. On March 25, Uzbekistan made mandatory the wearing of face masks in public. On March 27, the movement of people and personal vehicles was restricted to grocery shopping and pharmacy visits. The impact of these measures on reported employment was very large, with a decline of households reporting "any member working" falling by more than 40 percentage points in April (Figure 21 -Panel (b)). During this time, employment fell dramatically throughout the country, however areas with more resilient labor markets (in particular those with a greater share of wage workers) saw milder declines than those with higher shares of self-employed workers. This is especially clear with respect to the region and city of Tashkent, where disruptions were severe, but less so than in areas with a larger share of people who were unable to work remotely and saw a full suspension of activity. In May and continuing through June, the labor market recovery is also clearly present, however, progress has proceeded unevenly across the country.

Figure 21: Monthly Percentage of "No household member working in the past 7 days"

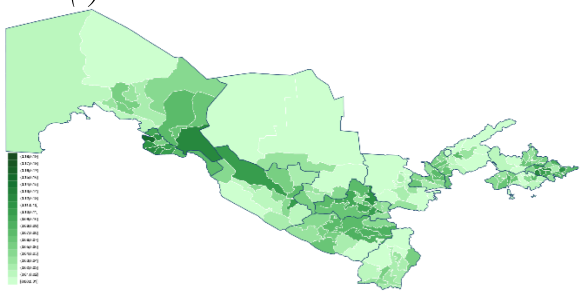


Notes: The maps report the results of small area imputation using the Fay-Herriot method of the share of households reporting no members having worked in the preceding 7 days. Estimates are performed at the mahalla level and aggregated to the district level using mahalla population weights.

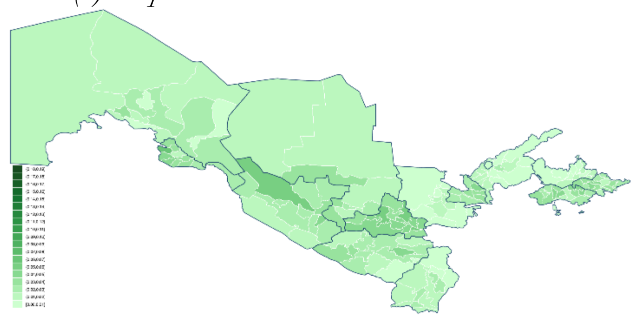
As reported in figure (22), migration and remittance income declined rapidly following the outbreak. About 70 percent of labor migrants from Uzbekistan live and work in the Russian Federation, and a rapid decline in the value of the Russian Ruble in April substantially decreased the value of sent remittances, before the So'm weakened in parallel somewhat offsetting this effect. Since May, the ruble has been recovering against a USD benchmark, which means that the value of remittances has started to climb following April's large decline. But this is only relevant for those migrants who remain actively employed and are able to send money: lockdowns in Russia have also been severe, which disrupts the ability of workers to earn any income to send home, and the share sending any remittances is presently a much smaller share than is usually the case for Uzbekistan (see figure 9). In addition, travel restrictions mean that many fewer migrants have been able to leave for Russia (and other places) in comparison to last year. Remittance income is one of the most important drivers of poverty reduction in recent years (Seitz, 2019) and poorer, rural households much more commonly rely on remittance income.

Figure 22: Monthly Percentage of "Household Received Remittances in Past 30 Days"

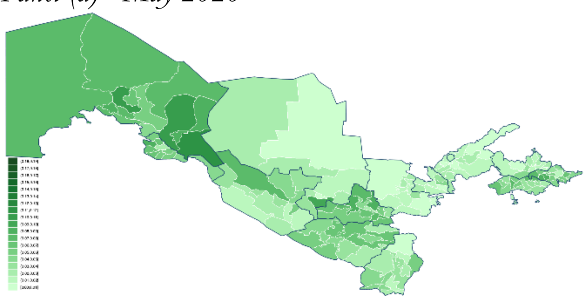
Panel (a) - March 2020



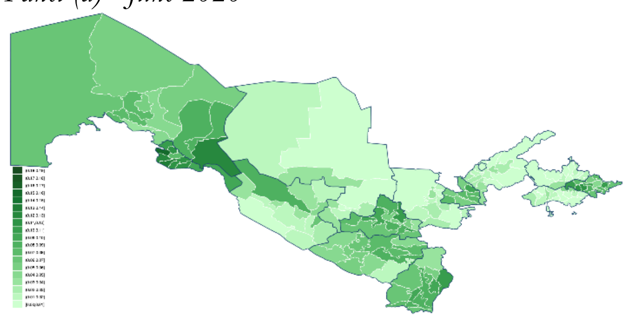
Panel (a) - April 2020



Panel (a) - May 2020



Panel (a) - June 2020

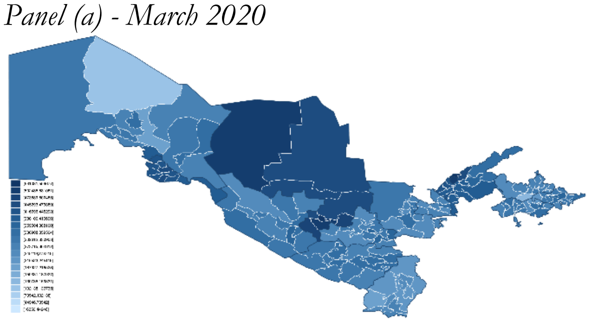


Notes: The maps report the results of small area imputation using the Fay-Herriot method of the share of households reporting having received any remittance income in the past 30 days. Estimates are performed at the mahalla level and aggregated to the district level using mahalla population weights.

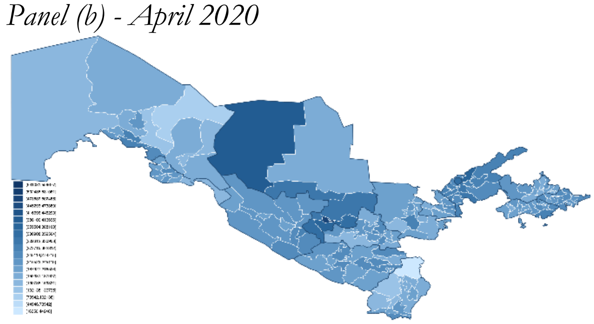
Small area estimates of per-capita income from all sources (including income from wages, remittances, pensions, agriculture, social assistance, and other sources) is reported in figure (23). The results highlight the link between income from work and per-capita income (by a large margin the most important component of total income in Uzbekistan, accounting for more than half even among the poorest quintile). With the disruption in employment caused by the pandemic, average incomes fell across the country, though some areas much more deeply than others.

Figure 23: Mahalla Monthly Income Per Capita from All Sources

Panel (a) - March 2020

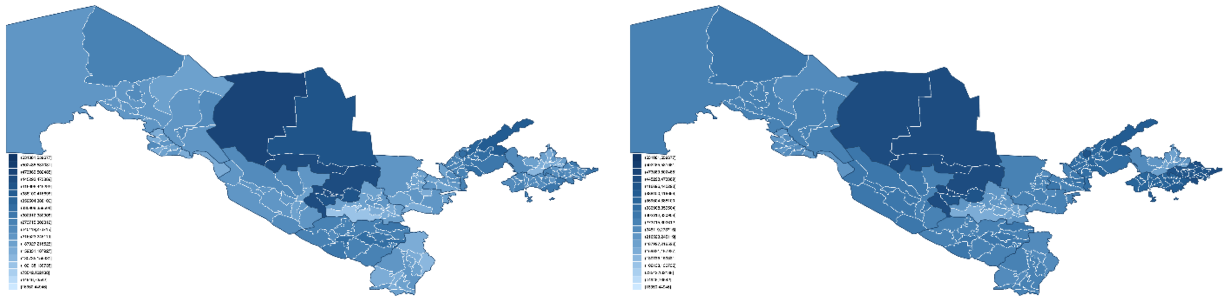


Panel (b) - April 2020



Panel (c) - May 2020

Panel (d) - June 2020



Notes: The maps report the results of small area imputation using the Fay-Herriot method of the share of households reporting having received any remittance income in the past 30 days. Estimates are performed at the mahalla level and aggregated to the district level using mahalla population weights.

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Annex A: Other Data Sources

Mahalla list provided by the National Statistical Office (NSO Data): In addition to the mahalla passport data set, the second data set on mahalla characteristics was provided by the National statistical office (NSO). The main reason for using this data set is that it contains a detailed information of settlement type (urban or rural) of each mahalla. According to the NSO, there are three types of settlements: city (urban/shakhar), small city (urban/shakharcha), and village (rural/kishlak). Table 14 shows distribution of mahalla and population by the settlement types. While over 52% of the population are living in rural areas, 16% and 32% of population reside in regular cities and small cities respectively. It is important to note that in this data set, there are 190 districts consisting of 8933 mahallas. Although we are able to match the two data sets (the mahalla passport list and the NSO list) at district level, there are significant mismatch at mahalla level. Table 5 documents the differences between the two data set in terms of number of mahalla, population, and number of families. A fuzzy matching method based on mahalla names within a district was used to merge the two data set at mahalla level. With this method, we are able to match 8700 mahallas whereas 475 mahallas from the passport data and 255 mahallas from the NSO data are not matched given the information provided in the data set.

Table 14: Number of Mahallas by Settlement Type and Region

	Number of Mahallas				**Number of People**			
Region	**Urban (City)**	**Urban (Small City)**	**Rural (Village)**	**Total**	**Urban (City)**	**Urban (Small City)**	**Rural (Village)**	**Total**
Andijan	195	188	493	876	629,920	766,005	1615032	3,010,957
Bukhara	41	164	335	540	142,735	555,067	1176732	1,874,534
Fergana	170	283	540	993	546,865	1,038,432	1936790	3,522,087
Jizzakh	75	63	149	287	353,747	297,087	679004	1,329,838
Karakalpakstan	77	163	172	412	325,441	729,797	818391	1,873,629
Kashkadarya	136	193	397	726	627,805	719,605	1782812	3,130,222
Khorasm	107	64	328	499	338,482	253,515	1226185	1,818,182
Namangan	217	199	354	770	707,542	874,341	1069122	2,651,005
Navoi	64	72	168	304	196,957	327,161	465391	989,509
Samarkand	88	317	684	1,089	372,679	861,218	2513676	3,747,573
Surkhandarya	138	100	474	712	509,619	384,274	1622743	2,516,636
Syrdarya	54	40	128	222	187,121	177,256	452694	817,071
Tashkent-City	1	504	0	505	6,140	2,470,140	0	2,476,280
Tashkent-Region	144	296	558	998	406,047	876,379	1598754	2,881,180
Total	**1,507**	**2,646**	**4,780**	**8,933**	**5,351,100**	**10,330,277**	**16,957,326**	**32,638,703**

Table 15: Mahalla List Provided by the NSO

Region name	**N of Districts**	**N of Mahallas**	**N of Population**	**N of Families**
Andijan	16	876	3,010,957	532,879
Bukhara	13	540	1,874,534	400,011
Fergana	19	993	3,522,087	716,359
Jizzakh	13	287	1,329,838	215,449
Karakalpakstan	16	412	1,873,629	316,702
Kashkadarya	15	726	3,130,222	591,824
Khorasm	12	499	1,818,182	340,531
Namangan	12	770	2,651,005	519,302
Navoi	10	304	989,509	207,236
Samarkand	16	1089	3,747,573	688,737
Surkhandarya	14	712	2,516,636	451,174
Syrdarya	11	222	817,071	152,059
Tashkent-City	1	505	2,476,280	700,875
Tashkent-Region	22	998	2,881,180	607,736
Total	190	8933	32,638,703	6,440,874

Table 16: Difference Between the Two Databases

		N of Mahallas		N of People		N of Families	
Region name	**District name**	**Passport**	**NSO**	**Passport**	**NSO**	**Passport**	**NSO**
Andijan	Andijon tumani	77	77	257,426	251,655	68,457	46,067
Andijan	Andijon shahar	83	83	372,899	427,400	103,396	69,695
Andijan	Asaka tumani	74	74	319,214	312,924	83,195	52,491
Andijan	Baliqchi tumani	66	66	194,531	195,025	51,419	33,638
Andijan	Buloqboshi tumani	37	37	139,220	132,867	36,364	24,074
Andijan	Bo‘ston tumani	25	25	71,665	69,211	17,999	13,858
Andijan	Jalaquduq tumani	63	63	179,801	176,563	47,113	34,298
Andijan	Izboskan tumani	63	62	231,465	227,071	59,935	40,512
Andijan	Marhamat tumani	48	48	165,442	168,731	43,478	30,834
Andijan	Oltinko‘l tumani	56	52	177,965	164,912	46,999	28,665
Andijan	Paxtaobod tumani	67	67	188,034	184,570	52,754	34,902
Andijan	Ulug‘nor tumani	21	20	59,661	57,143	16,087	10,855
Andijan	Xonobod shahar	14	14	41,144	40,718	10,406	8,094
Andijan	Xo‘jaobod tumani	37	37	107,041	105,157	25,924	21,314
Andijan	Shahrixon tumani	76	76	309,465	286,611	77,450	46,000
Andijan	Qo‘rg‘ontepa tumani	74	75	210,743	210,399	53,665	37,582
Bukhara	Buxoro tumani	36	36	163,939	160,884	41,422	35,511
Bukhara	Buxoro shahar	65	65	263,223	258,790	79,738	64,851
Bukhara	Vobkent tuman	44	44	136,158	133,217	36,161	29,978
Bukhara	Jondor tuman	52	52	171,217	170,708	45,492	34,268
Bukhara	Kogon tuman	23	21	82,257	79,610	20,453	16,718
Bukhara	Kogon shahar	22	21	60,429	60,230	16,440	13,520
Bukhara	Olot tumani	38	38	99,311	98,380	26,322	20,788
Bukhara	Peshko‘ tuman	37	36	117,568	118,000	22,200	22,135
Bukhara	Romitan tuman	45	45	136,200	135,666	34,895	26,665
Bukhara	Shofirkon tuman	50	50	176,255	170,747	45,017	36,322
Bukhara	G‘ijduvon tuman	75	75	299,474	304,400	80,339	65,293
Bukhara	Qorako‘l tuman	50	50	164,168	164,296	41,878	29,748
Bukhara	Qorovulbozor tuman	7	7	21,804	19,606	5,268	4,214
Fergana	Yozyovon tumani	33	33	103,366	105,601	26,268	20,634
Fergana	O‘zbekiston tumani	72	64	237,211	227,884	63,945	45,141
Fergana	Bag‘dod tumani	56	61	208,823	217,042	57,055	44,008
Fergana	Beshariq tumani	62	57	220,500	201,083	56,721	36,835
Fergana	Buvayda tumani	55	55	214,645	218,024	56,810	41,610
Fergana	Dang‘ara tumani	49	56	178,710	205,779	45,465	40,720
Fergana	Marg‘ilon shahar	54	54	219,700	229,525	54,645	41,135
Fergana	Oltiariq tumani	72	72	211,175	203,908	58,486	37,292
Fergana	Rishton tumani	69	67	206,089	199,330	53,485	36,661
Fergana	So‘x tumani	27	27	76,949	76,713	20,784	13,853
Fergana	Toshloq tumani	51	51	187,551	194,281	49,302	34,826
Fergana	Uchko‘prik tumani	49	50	225,744	224,943	60,371	49,459
Fergana	Farg‘ona tumani	76	51	225,508	141,187	61,206	29,427
Fergana	Farg‘ona shahar	70	70	286,626	273,658	96,706	78,510
Fergana	Furqat tumani	34	36	119,730	118,735	31,221	26,379
Fergana	Quva tumani	65	52	244,398	193,085	60,709	36,076
Fergana	Quvasoy shahar	30	24	91,446	68,792	25,935	16,024
Fergana	Qo‘shtepa tumani	51	48	165,700	182,049	47,121	37,904
Fergana	Qo‘qon shahar	66	65	240,719	240,468	64,004	49,865
Jizzakh	Arnasoy tumani	13	13	45,196	44,516	8,989	6,303
Jizzakh	Baxmal tumani	30	26	153,135	149,808	31,581	23,373
Jizzakh	Do‘stlik tumani	12	12	52,638	63,432	12,670	9,453
Jizzakh	Jizzax shaxar	34	34	173,928	172,454	37,360	28,786
Jizzakh	Zarbdor tumani	22	19	80,645	67,105	18,569	11,052
Jizzakh	Zafarobod tumani	10	10	42,742	48,173	10,123	7,055
Jizzakh	Zomin tumani	37	40	159,347	172,393	35,193	26,437
Jizzakh	Mirzacho‘l tumani	12	12	42,783	49,294	11,051	8,735
Jizzakh	Paxtakor tumani	14	14	72,800	71,857	15,709	12,173
Jizzakh	Forish tumani	25	22	90,885	89,692	18,885	16,005
Jizzakh	Sh.rashidov tumani	48	48	218,732	208,924	52,370	33,354
Jizzakh	Yangiobod tumani	8	8	25,650	27,200	6,166	4,895
Jizzakh	G‘allaorol tumani	29	29	169,787	164,990	39,052	27,828
Karakalpakstan	Amudaryo tumani	49	48	199,102	189,460	44,456	31,675
Karakalpakstan	Beruniy tumani	37	38	191,370	187,288	42,891	28,655
Karakalpakstan	Kegeyli tumani	19	18	93,998	88,100	18,876	14,519
Karakalpakstan	Konlikul tumani	11	11	51,000	49,800	9,937	8,594
Karakalpakstan	Muynok tumani	11	11	31,810	30,900	5,765	5,035
Karakalpakstan	Nukus tumani	10	10	52,316	52,291	11,032	9,949

Karakalpakstan	Nukus shahri	61	57	329,774	327,693	71,983	58,167
Karakalpakstan	Taxiatosh tumani	13	13	73,413	71,913	15,736	12,246
Karakalpakstan	Taxtakupir tumani	17	17	40,151	39,681	7,912	6,995
Karakalpakstan	To‘rtko‘l tumani	37	42	206,238	218,965	55,346	37,147
Karakalpakstan	Xujayli tumani	26	26	123,087	122,854	30,681	21,413
Karakalpakstan	Chimboy tumani	21	23	112,300	116,691	20,978	18,813
Karakalpakstan	Shumanay tumani	13	10	56,141	43,721	9,288	5,723
Karakalpakstan	Ellikkal'a tumani	36	36	157,601	154,717	36,901	24,482
Karakalpakstan	Qoraȳzak tumani	13	13	52,700	52,692	9,806	8,277
Karakalpakstan	Qo‘ng‘irot tumani	39	39	126,212	126,863	28,142	25,012
Kashkadarya	Dehonobod tumani	46	37	146,209	140,647	33,401	28,942
Kashkadarya	Kasbi tumani	41	40	175,067	183,600	41,472	32,204
Kashkadarya	Kitob tumani	59	59	262,631	254,109	64,216	47,771
Kashkadarya	Koson tumani	68	65	278,198	272,300	60,739	50,075
Kashkadarya	Mirishkor tumani	35	35	115,381	114,762	26,063	20,780
Kashkadarya	Muborak tumani	25	25	84,788	82,987	20,331	16,289
Kashkadarya	Nishon tumani	36	30	152,266	145,743	33,337	28,496
Kashkadarya	Chiroqchi tumani	86	81	414,602	389,293	93,040	69,204
Kashkadarya	Shahrisabz tumani	57	48	57,620	213,800	44,305	42,281
Kashkadarya	Shahrisabz shahar	40	40	138,309	135,567	32,802	23,459
Kashkadarya	Yakkabog‘ tumani	60	59	263,300	252,300	61,606	48,390
Kashkadarya	G‘uzor tumani	43	43	211,064	196,372	46,344	37,607
Kashkadarya	Qamashi tumani	59	51	270,800	259,599	69,437	53,043
Kashkadarya	Qarshi tumani	53	51	258,242	231,202	61,582	43,668
Kashkadarya	Qarshi shahar	62	62	212,233	257,941	48,416	49,615
Khorasm	Bog‘ot tumani	43	43	161,934	158,163	41,802	33,719
Khorasm	Gurlan tumani	50	50	145,586	143,645	41,211	26,044
Khorasm	Urganch tumani	58	58	195,521	190,090	50,287	34,791
Khorasm	Urganch shahar	38	38	149,451	145,987	47,933	32,689
Khorasm	Xiva tumani	34	28	148,972	143,453	40,858	24,965
Khorasm	Xiva shahar	21	21	92,156	89,936	24,136	15,763
Khorasm	Xonqa tumani	44	44	184,456	183,363	46,739	28,834
Khorasm	Shovot tumani	55	55	168,303	164,015	43,321	29,826
Khorasm	Yangiariq tumani	39	39	111,632	109,183	31,088	23,180
Khorasm	Yangibozor tumani	28	28	85,348	84,472	23,402	16,618
Khorasm	Qo‘shko‘pir tumani	50	50	162,224	165,568	46,030	32,210
Khorasm	Hazorasp tumani	59	45	254,994	240,307	69,175	41,892
Namangan	Kosonsoy tumani	59	60	216,875	199,700	48,015	35,190
Namangan	Mingbuloq tumani	40	40	121,407	118,619	29,996	28,823
Namangan	Namangan tumani	54	53	172,683	167,984	46,157	32,459
Namangan	Namangan shahar	102	102	553,068	548,675	158,907	111,362
Namangan	Norin tumani	57	57	160,533	157,397	42,750	31,101
Namangan	Pop tumani	77	77	209,938	207,861	61,448	41,220
Namangan	To‘raqo‘rg‘on tumani	68	68	225,299	223,639	59,919	41,553
Namangan	Uychi tumani	56	56	210,103	205,258	58,155	38,145
Namangan	Uchqo‘rg‘on tumani	64	64	167,958	167,238	43,432	31,791
Namangan	Chortoq tumani	57	52	185,297	190,871	47,005	40,749
Namangan	Chust tumani	70	70	259,700	254,900	61,215	46,724
Namangan	Yangiqo‘rg‘on tumani	71	71	217,200	208,863	57,938	40,185
Navoi	Zarafshon shahar	13	13	81,067	79,615	22,517	18,941
Navoi	Karmana tumani	39	40	137,889	135,421	35,904	27,871
Navoi	Konimex tumani	15	13	36,355	30,797	10,176	6,563
Navoi	Navbahor tumani	41	41	106,173	107,845	28,539	22,496
Navoi	Navoiy shahar	31	30	157,504	149,465	46,677	37,588
Navoi	Nurota tumani	32	32	92,551	92,471	22,121	17,048
Navoi	Tomdi tumani	7	7	9,767	14,473	2,264	1,985
Navoi	Uchquduq tumani	13	12	41,356	41,148	11,346	10,162
Navoi	Xatirchi tumani	68	68	193,379	191,700	44,900	36,148
Navoi	Qiziltepa tumani	48	48	139,270	146,574	38,986	28,434
Samarkand	Bulung‘ur tumani	55	55	180,957	178,173	39,532	32,136
Samarkand	Jomboy tumani	38	38	165,227	163,203	38,276	30,720
Samarkand	Ishtixon tumani	62	62	250,324	242,963	54,419	41,057
Samarkand	Kattaqo‘rg‘on tumani	69	69	263,702	252,663	62,093	49,152
Samarkand	Kattaqo‘rg‘on shahar	35	35	87,470	88,479	23,285	17,952
Samarkand	Narpay tumani	56	56	200,484	204,529	46,698	35,190
Samarkand	Nurobod tumani	37	35	146,409	144,502	34,439	27,664
Samarkand	Oqdaryo tuman	35	34	157,569	153,124	35,904	29,047
Samarkand	Payariq tumani	65	65	238,275	237,266	57,538	39,600
Samarkand	Pastdarg‘om tumani	106	106	360,851	356,730	82,472	63,617
Samarkand	Paxtachi tumani	59	59	145,921	155,111	42,593	41,640
Samarkand	Samarkand shahar	210	207	582,832	519,438	168,311	107,753

Samarkand	Samarqand tumani	74	77	266,765	246,175	70,853	42,214
Samarkand	Toyloq tuman	50	50	196,097	191,832	46,760	32,375
Samarkand	Urgut tumani	102	102	491,266	487,279	117,801	78,945
Samarkand	Qoʻshrabot tumani	42	39	126,318	126,106	27,406	19,675
Surkhandarya	Angor tuman	36	35	126,838	117,281	30,929	21,284
Surkhandarya	Boysun	41	40	119,144	115,698	26,963	24,894
Surkhandarya	Denov tuman	103	109	382,006	390,740	95,984	67,435
Surkhandarya	Jarqoʻrgʻon tuman	66	65	216,392	212,967	50,917	37,627
Surkhandarya	Muzrobod	37	37	131,281	135,490	29,942	24,743
Surkhandarya	Oltinsoy tumani	53	50	171,336	161,367	39,876	28,542
Surkhandarya	Sariosiyo tumani	61	57	204,833	194,408	46,677	32,941
Surkhandarya	Termiz tumani	34	35	122,505	124,273	29,266	22,471
Surkhandarya	Termiz shahar	30	30	130,622	127,130	32,263	26,048
Surkhandarya	Uzun tumani	45	45	166,577	169,884	39,282	29,468
Surkhandarya	Sherobod tumani	48	48	185,943	183,048	44,051	33,983
Surkhandarya	Shoʻrchi tumani	53	52	204,242	192,156	48,027	32,639
Surkhandarya	Qiziriq tuman	49	49	170,733	163,654	38,935	28,047
Surkhandarya	Qumqoʻrgʻon tuman	63	60	240,862	228,540	55,493	41,052
Syrdarya	Boyovut tumani	38	39	118,738	122,134	30,005	21,243
Syrdarya	Guliston tumani	25	29	81,675	105,211	20,376	18,254
Syrdarya	Guliston shahar	17	14	97,966	71,397	24,409	16,729
Syrdarya	Mirzaobod tumanpi	17	17	72,986	73,472	16,087	12,322
Syrdarya	Oqoltin tumani	12	10	47,736	36,974	12,073	7,011
Syrdarya	Sayxunobod tumani	19	19	73,462	72,211	16,955	12,970
Syrdarya	Sardoba tumani	15	15	61,121	59,227	14,072	9,316
Syrdarya	Sirdaryo tumani	38	38	124,013	119,050	32,187	24,353
Syrdarya	Xovos tumani	26	27	88,072	97,295	21,778	16,360
Syrdarya	Shirin shahar	7	6	19,275	18,500	5,288	4,567
Syrdarya	Yangier shahar	8	8	41,889	41,600	14,168	8,934
Tashkent-City	Toshkent shaxri	512	505	2,538,857	2,476,280	802,342	700,875
Tashkent-Region	Oʻrta chirchiq tumani	65	64	153,132	142,749	39,924	28,669
Tashkent-Region	Angren shahri	51	51	183,726	184,006	55,504	47,563
Tashkent-Region	Bekobod tumani	48	41	161,308	133,255	40,596	24,836
Tashkent-Region	Bekobod shahar	35	33	97,292	87,302	26,807	20,609
Tashkent-Region	Boʻka tumani	40	40	114,583	121,523	28,861	23,392
Tashkent-Region	Boʻstonliq tumani	59	57	165,575	174,714	47,242	38,790
Tashkent-Region	Zangiota tumani	86	77	236,168	206,754	61,330	39,397
Tashkent-Region	Nurafshon shahar	22	17	43,105	42,986	12,111	9,511
Tashkent-Region	Olmaliq shahar	43	43	132,692	130,594	41,589	34,068
Tashkent-Region	Oqqoʻrgʻon tumani	30	29	193,184	95,736	45,614	17,676
Tashkent-Region	Ohangaron tumani	29	29	94,364	93,705	24,422	17,498
Tashkent-Region	Ohangaron shahar	21	21	38,168	37,332	12,441	11,065
Tashkent-Region	Parkent tumani	56	54	150,398	147,377	37,962	25,580
Tashkent-Region	Piskent tumani	27	27	91,600	97,419	25,481	17,534
Tashkent-Region	Toshkent tumani	68	70	205,660	206,139	54,474	38,801
Tashkent-Region	Chinoz tumani	52	51	133,068	130,145	35,254	24,129
Tashkent-Region	Chirchiq shahar	44	44	155,850	122,507	47,680	39,607
Tashkent-Region	Yuqorichirchiq tumani	47	47	134,720	131,200	33,489	26,536
Tashkent-Region	Yangiyoʻl tumani	65	61	205,362	203,063	57,339	37,881
Tashkent-Region	Yangiyoʻl shaxar	15	14	63,732	58,390	19,302	14,045
Tashkent-Region	Qibray tumani	88	87	220,959	220,683	61,961	46,947
Tashkent-Region	Quyi chirchiq tumani	37	41	103,449	113,601	26,706	23,602

Annex B: Technical Description of the Fay-Herriot Model

The basic area-level model setup is as follows. Let P_i be the true average consumption incidence in each mahalla *i*, and let the sampling model be defined by:

$$p_i = P_i + e_i,$$

where p_i is the observed survey direct estimate of average consumption per capita P_i, and e_i is the sampling error associated with p_i, such that $e_i|P_i \sim N(0, \varphi_i)$ and φ_i are assumed to be known. The linking model is defined as:

$$P_i = X_i\beta + u_i,$$

where X_i denotes a vector of area characteristics, and u_i are independent and identically distributed random errors with $E(u_i) = 0$ and $Var(u_i) = \sigma_u^2$. The data on X_i are obtained from fully enumerated administrative sources and hence are free of sampling error. Combining the above sampling and linking models, it follows that the observed average consumption level from the survey can be modeled as follows:

$$p_i = X_i\beta + u_i + e_i.$$

Given this setup, the best linear unbiased estimator of $P_i = X_i\beta + u_i$, one that minimizes the mean squared error $MSE(\tilde{P_i}) = E(\tilde{P}_i - P_i)^2$ is:

$$\tilde{P}_i^{BLUP} = X_i\beta + u_i,$$

where $u_i = \gamma_i(p_i - X_i\beta)$, and $\gamma_i = \frac{\sigma_u^2}{\varphi_i + \sigma_u^2}$ is referred to as a "shrinkage factor". Given that σ_u^2 is unknown, the Best Linear Unbiased Predictor (BLUP) is replaced with its empirical counterpart EBLUP: $\hat{P_i}^{EBLUP} = \tilde{P}_i^{BLUP}(\hat{\sigma}_u^2)$, which can be rewritten as:

$$\hat{P_i}^{EBLUP} = \hat{\gamma_i} p_i + (1 - \hat{\gamma_i})X_i\tilde{\beta},$$

where $\tilde{\beta}$ is the Feasible GLS estimator for β and $\hat{\gamma_i} = \frac{\hat{\sigma}_u^2}{\varphi_i + \hat{\sigma}_u^2}$. Thus, $\hat{p_i}$ is a weighted average of the direct survey estimate p_i and the synthetic (model-based) estimate $X_i\tilde{\beta}$, and the weights are given by $\hat{\gamma}_i$. For p_i with smaller sampling variances φ_i the shrinkage factor gives higher weight to the direct estimate, while for p_i with higher sampling variances a higher weight is assigned to the synthetic estimate. In areas that are not part of the survey sample, the prediction is based on the synthetic estimate $X_i\hat{\beta}$, where $\hat{\beta} = \tilde{\beta}(\hat{\sigma}_u^2)$. The prediction error associated with $\hat{p}_i$ takes account of the sampling variance associated with p_i, as well as the uncertainty associated with the estimate of β and σ_u^2 (see Rao, 2003 for more details).

When calculating the term φ_i needed for the Fay-Herriot approach, there are several potential methods for considering the stratified and clustered two stage sample designs of the surveys used in this application. Common practice in the World Bank has been to obtain sampling variances associated with the area-level welfare measure by taking the variance estimate from the survey data source and dividing it by the sample size for each domain to obtain a set of "smoothed" sampling variance estimates. This ignores components of the clustered sample design; however, these smoothed sampling variances are commonly less volatile than alternatives. Another approach is to compute variance and the associated root mean square error of the mean using the linearized variance estimator approach—based on a first-order Taylor series (Wolter 2007). In sensitivity analyses this was the most stable variance measure, and the preferred approach for this application. Final results are quite similar when comparing the "smoothed" and "linearized" options described. For more detail on the trade-off between approaches for domain variance estimation, see Heeringa et. al., (2017); Molina and Rao (2010); and Wolter (2007).

The results of the SAE estimates are presented graphically in the following section. The model variables that are part of the X vector in the estimation procedure were chosen to maximize the ratio of explained variance to the total variance, as captured by the adjusted R^2.[15] There is no pre-set group of variables that are guaranteed to achieve that objective. Instead, automated variable selection using the stepwise approach was used.

[15] Adjusted R^2 is chosen instead of (unadjusted) R^2 because the latter is non-decreasing in the number of explanatory variables in the model.

Annex C: Results of Stakeholder Consultations

Table 17: Stakeholder Consultations on Index Weights by Indicator

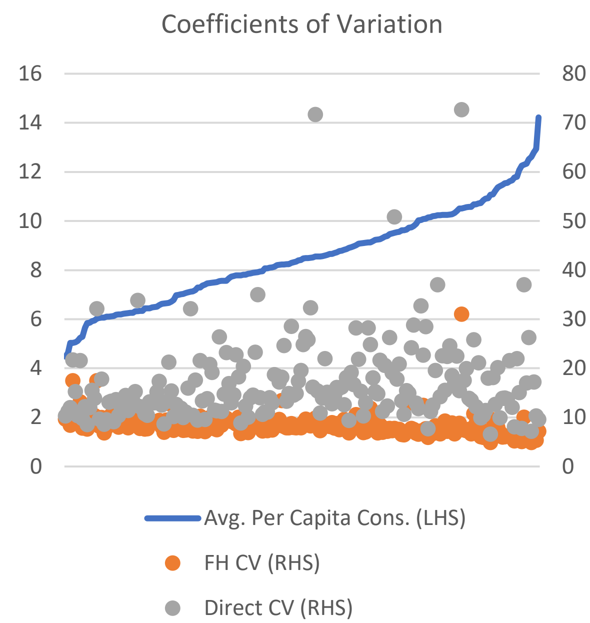
Question	Average (1-5)	Difference
How much weight should be placed on the mahalla being in the top two quintiles of single seniors per capita?	3.69	2%
How much weight should be placed on the mahalla being in the top two quintiles of people with disabilities per capita?	4.15	15%
How much weight should be placed on the mahalla being in the top two quintiles of retirees per capita?	3.54	-2%
How much weight should be placed on the mahalla being in the top two quintiles of people aged 100 or more per capita?	3.54	-2%
How much weight should be placed on the mahalla being in the top two quintiles of disabled and no support per capita?	4.31	19%
How much weight should be placed on the mahalla being in the top two quintiles of entrepreneurs per capita?	3.46	-4%
How much weight should be placed on the mahalla being in the top two quintiles of trade sector workers per capita?	3.31	-9%
How much weight should be placed on the mahalla being in the top two quintiles of the number of able bodied but not employed people per capita?	3.23	-11%
How much weight should be placed on the mahalla being in the top two quintiles of retail sector workers per capita?	3.15	-13%
How much weight should be placed on the mahalla being in the top two quintiles of workers in family businesses per capita?	3.38	-7%
How much weight should be placed on the mahalla being in the top two quintiles of young children per capita?	3.85	6%
How much weight should be placed on the mahalla being in the top two quintiles of lost breadwinner per family?	4.00	10%
How much weight should be placed on the mahalla being in the top two quintiles of families receiving SA per family?	3.69	2%
How much weight should be placed on the mahalla being in the top two quintiles of families in need of SA per family?	4.00	10%
How much weight should be placed on the mahalla being in the top two quintiles of difference between need and receiving, per family in the mahalla?	3.92	8%
How much weight should be placed on the mahalla having no hospital located within the mahalla?	3.00	-17%
How much weight should be placed on the mahalla having no local clinic located within the mahalla?	3.23	-11%
How much weight should be placed on the mahalla having no pharmacy located within the mahalla?	3.38	-7%
How much weight should be placed on the mahalla having no public bathrooms located within the mahalla?	3.15	-13%
How much weight should be placed on the mahalla being in the top two quintiles of density (apartments/families)?	3.38	-7%
How much weight should be placed on the mahalla being a medium-sized urban mahalla?	3.31	-9%
How much weight should be placed on the mahalla being in a district in top half of migrant sending locations?	3.69	2%

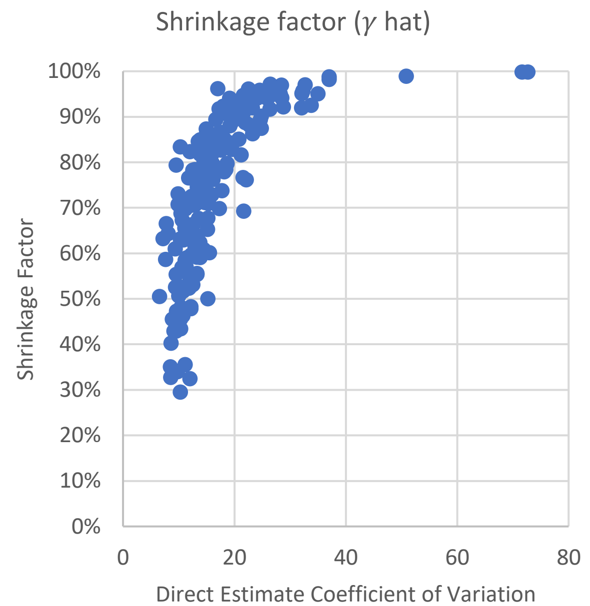
How much weight should be placed on the mahalla being in the top two quintiles of women as a share of total?	3.85	6%
How much weight should be placed on the local district having a poverty rate (defined as $3.2 per person per day) over 10 percent?	4.23	17%
How much weight should be placed on the mahalla being in the bottom 40 average per capita consumption?	4.00	10%
How much weight should be placed on the region having a higher than average increase food/medicine prices?	3.77	4%

Table 18: Stakeholder Consultations on Index Weights by Dimension

Question on Dimensions	Average (1-5)	Difference
How much weight should be placed on local elderly population and disability prevalence?	4.23	3.4%
How much weight should be placed on local disruption of economic activities?	4.00	-2.2%
How much weight should be placed on existing levels of local social assistance provision?	4.23	3.4%
How much weight should be placed on local availability of health services and the density of the local population?	3.85	-6.0%
How much weight should be placed on local rates of out-migration and reliance on remittance income?	3.92	-4.1%
How much weight should be placed on local estimates of poverty and average consumption per person?	4.31	5.3%

Annex D: Small Area Estimate Model Diagnostics

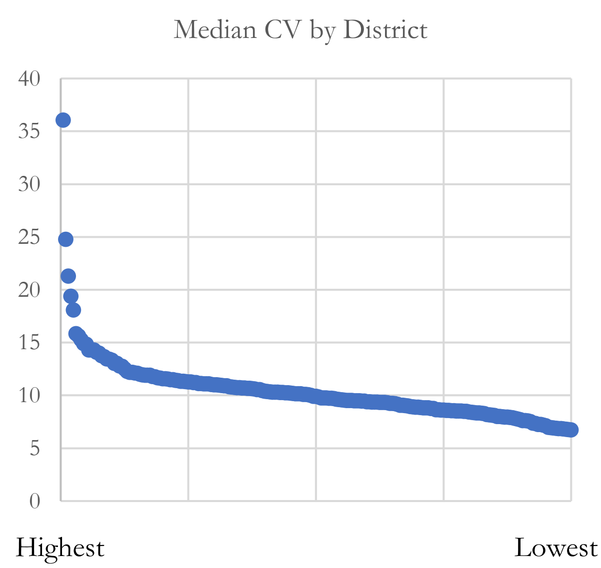




Notes: the left-had graph presents coeffici3nts of variation among within-sample mahallas. The right-had graph describes the mahalla-level shrinkage factor.

Table 19: Descriptive Statistics of Coefficients of Variation

Region	CV > 20	Average CV	Median CV
Andijan	1.7%	12.35	11.58
Bukhara	0.2%	9.19	8.86
Fergana	0.5%	9.36	9.09
Jizzakh	0.7%	9.73	9.21
Karakalpakstan	3.5%	12.46	11.91
Kashkadarya	0.9%	10.27	8.97
Khorezm	0.8%	9.91	9.66
Namangan	1.4%	11.01	9.47
Navoi	11.2%	13.29	11.01
Samarkand	5.6%	12.65	10.82
Surkhandarya	3.7%	13.60	11.52
Syrdarya	5.1%	14.27	12.42
Tashkent-City	1.0%	7.56	6.85
Tashkent-Region	5.7%	12.50	9.61
Total	2.7%	11.16	9.99



Annex E: Small Area Estimates Model Description

Table 20: Selected Fay-Herriot Model

	Per Cap. Cons.
Poverty Map	3.74***
	(0.48)
Share HH with Migrants	1,821.49***
	(5,026.24)
Number of Training Centers	0.59***
	(0.09)
Number of Cemeteries	1.12
	(0.10)
Number of Young Children	1.00***
	(0.00)
Number of Retails stores	0.98**
	(0.01)
Average air temperature	1.43**
	(0.23)
Number of Adults	1.00
	(0.00)
Number of families lost breadwinner	0.98**
	(0.01)
Beauty Salons	1.24*
	(0.14)
Number of Sports Fields	0.71**
	(0.10)
Number of Streets	1.00***
	(0.00)
Estimated GDP (Night Lights)	1.37
	(0.47)
Number aged 100+	1.07**
	(0.04)
Computer Service Providers	1.60***
	(0.17)
Constant	0.00***
	(0.00)
Observations	200
R-squared	0.633

Robust se in parentheses; *** p<0.01, ** p<0.05, * p<0.1; region Dummies not shown