WIDER Working Paper 2021/95

Informal freelancers in the time of COVID-19

Insights from a digital matching platform in Mozambique

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June 2021

Abstract: Despite the severe negative economic shock associated with the COVID-19 pandemic, evidence from many contexts points to a surge in sales on online platforms, as well as shifts in the composition of demand. This paper investigates how the pandemic has affected both the supply of and demand for informal manual freelancers in Mozambique. Using data from the digital labour marketplace *Biscate*, we quantify dynamics along four main dimensions: responses to infection rates, official restrictions on activity, changes in workplace mobility, and employment conditions. Overall, we find both positive and negative effects of the pandemic on growth in the supply of workers, which add up to a zero net effect on average. However, on the demand side, the contact rate and task agreement rate increased by around 50 per cent versus the 'no shock' counterfactual. These findings underline how the informal sector plays a valuable shock-absorbing role and that digital labour marketplaces can facilitate adjustments to economic shocks.

Key words: freelancers, COVID-19, economics shocks, Mozambique, informal sector

JEL classification: J23, J46, O17

Acknowledgements: We are extremely grateful to Giannis Panagiotou and Tiago Borges Coelho of UX for excellent collaboration. Thanks also to Ricardo Santos and Anna Schnupp for additional support with the data. This study falls under the project 'Inclusive growth in Mozambique—scaling-up research and capacity', implemented in collaboration between UNU-WIDER, the University of Copenhagen, University Eduardo Mondlane, and the Mozambican Ministry of Economics and Finance, financed through specific programme contributions by the governments of Denmark, Finland, and Norway.

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This study has been prepared within the UNU-WIDER project Inclusive growth in Mozambique – scaling-up research and capacity implemented in collaboration between UNU-WIDER, University of Copenhagen, University Eduardo Mondlane, and the Mozambican Ministry of Economics and Finance. The project is financed through specific programme contributions by the governments of Denmark, Finland, and Norway.

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ISSN 1798-7237 ISBN 978-92-9267-035-1

https://doi.org/10.35188/UNU-WIDER/2021/035-1

Typescript prepared by Gary Smith.

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1 Introduction

There is widespread evidence that informal workers in developing countries have been hard hit by the economic shock induced by the COVID-19 pandemic. As early as April 2020, the International Labour Organization estimated 1.6 billion informal sector workers were being severely affected, facing up to a 60 per cent drop in earnings (ILO 2020). Sadly, this dire prediction was not an exaggeration. In Peru, for instance, the second quarter of 2020 recorded a 70 per cent drop in labour income among the self-employed, compared to 25 per cent in Brazil and 10 per cent in Vietnam (ILO 2021). Household survey data from a diverse range of developing countries, summarized by Egger et al. (2021), similarly points to large negative impacts in general, but also more acute effects on the poorest. For example, in a nationally representative sample from Kenya, 53 per cent of lower socioeconomic status (SES) respondents reported a fall in employment versus 14 per cent of higher SES respondents; and none reported receiving any public assistance. In West Africa, Balde et al. (2020) find informal sector workers were 19 per cent more likely to report earnings losses due to the pandemic (with the average being 55 per cent).[1]

While the overall picture is undoubtedly negative, important caveats merit note. Within countries, large sectoral differences in the magnitude of economic impacts associated with the pandemic have emerged. Generally, tourism, restaurants, entertainment, transport, and (non-essential) in-store retail commerce have been most affected by restrictions on mobility. At least for high(er)-income countries, the key distinction has been between who can and cannot effectively work from home (Garrote Sanchez et al. 2021). At the same time, the disruption associated with the pandemic has created new opportunities. In particular, avoidance of face-to-face activities has led to a substantial shift towards online platforms. In Taiwan, for instance, Chang and Meyerhoefer (2021) find that an additional confirmed case of COVID-19 increased the value of online food sales by 5.7 per cent and the number of customers by 4.9 per cent. This trend is not limited to advanced countries. For instance, the stock price of *Jumia*, Africa's largest online shopping platform, increased over six-fold during 2020 on the back of increased traffic and sales volumes.[2]

In addition to changes in *where* transactions take place, the combination of increased time spent at home and lower expenditure on specific (face-to-face) services appears to have shifted the composition of demand. In particular, home improvement spend has recorded large increases in many different contexts. According to data from the United States, around three out of four homeowners carried out at least one home improvement project since the pandemic begun.[3] Tracking of social media and internet usage also points to booming interest in DIY projects.[4] In connection, demand for freelance contractors (handypeople), frequently encountered via online marketplaces, has surged. In South Africa, one digital platform matching freelance workers to demand for service tasks recorded a 750 per cent increase in the number of posted requests, comparing March 2021 to April 2020.[5]

In light of the uneven effects of COVID-19 across different sectors and workers, this paper leverages micro-data from *Biscate*, a digital platform for finding manual freelancers (e.g., plumbers, carpenters, hairdressers) in Mozambique, to investigate the dynamics of supply and demand for informal labour services during the COVID-19 pandemic. Although the platform is not representative of informal labour

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[1] For further discussion and evidence, see, for example: Alfaro et al. (2020), Bussolo et al. (2021), and Sumner et al. (2020).

[2] www.dw.com/en/coronavirus-pandemic-boosts-online-trade-in-africa/a-53752808.

[3] www.porch.com/advice/home-improvement-trends-covid.

[4] www.burke.com/wp-content/uploads/2020/05/Burke-Home-Improvement-COVID-19-Industry-Impact.pdf.

[5] www.engineeringnews.co.za/article/after-one-year-of-lockdown-growth-in-home-improvement-shows-no-signs-of-slowing-down-2021-03-29.

in the country, neither in general nor in specific sub-sectors, it nonetheless provides a unique real-time window on how different impact channels may have operated over the period. Also, similar to the analysis of Horton (2021) regarding how online Russian freelancers responded to the collapse of the ruble, it provides an opportunity to understand how behaviour on online marketplaces in low-income contexts responds to shocks.

As already indicated, the net direction and magnitude of the labour demand/supply effects of COVID-19 is not obvious *ex ante*, especially for specific types of labour. Economic loss associated with restrictions on business activity would be expected to weaken demand for goods and services throughout the economy. However, job loss or heightened employment uncertainty may push individuals to seek additional informal work opportunities, particularly via online platforms (see Cao et al. 2020; Stephany et al. 2020). And the combination of changes in the composition of demand may divert demand to specific kinds of (more flexible) labour services, such as those related to home improvement tasks.

To unpack these distinct channels of influence we focus on three main outcomes: the rate of growth in the number of active workers registered on the platform (capturing the supply side), and the telephone contact and task agreement rates (capturing the demand side). We then model how these outcomes have been affected by the number of positive COVID-19 cases, the severity of pandemic-related official restrictions, observed job-related mobility (as tracked by Google), and an index of current employment conditions. We estimate these relationships at different levels of aggregation, including by profession and province, incorporating various controls for (pre-existing) trends in the outcomes.

Our main finding is that the supply and demand for informal work through the *Biscate* platform has remained remarkably resilient. Despite some contraction on both sides of the market in the early phase, associated with more severe restrictions and (likely) health fears, we find a strong negative association between a sectoral index of employment conditions and supply-/demand-side outcomes—that is, lower index values are associated with more marketplace activity. We also find a net positive response to the pandemic on the demand side, suggesting that digital tools to facilitate matching for labour services can enhance the shock-absorbing role of the informal sector and allow entrepreneurs to take advantage of disruptions to 'business as usual'.

The remainder of the paper proceeds as follows: Section 2 provides an overview of the *Biscate* platform and the main outcomes used to measure supply- and demand-side dynamics. Section 3 describes how the COVID-19 pandemic has evolved, as well as the potential channels through which it may have affected the market for informal labour services served by *Biscate*. Next, in Section 4, we undertake an econometric analysis of recent trends on the platform, using a range of proxies to quantify the relevance and direction of different channels. To get a better understanding of the (net) dynamics over the COVID-19 period, we apply an event study design in Section 5. Finally, Section 6 concludes and draws some lessons.

2 The *Biscate* matching platform

Biscate is a free-to-use digital platform, launched in October 2016, that connects freelance workers with distinct manual professional skills, such as plumbers or hairdressers, to clients in order to undertake specific tasks.[6] In Portuguese 'biscate' literally means an odd-job, used to indicate a type of cash-in-

[6] The platform is owned and operated by the digital services company UX (www.ux.co.mz). It was established under a partnership between Vodacom (a leading mobile phone company in Mozambique), the Let's Work group of the World Bank, AIESEC (an international student association), Oxford Policy Management (OPML), IdeaLab, and UPA (a local NGO). See also: www.biscate.co.mz/sobre.

hand temporary work, usually based on a verbal agreement. As such, this platform consists of a quick and convenient way for informal workers to obtain work, as well as for potential clients to quickly find workers with particular technical skills for a discrete task. For clarity, *Biscate* provides a means to match supply and demand for informal labour for specific technical-professional service tasks sold to third parties and generally provided on-site (e.g., at the home of the client) for payment in cash. Naturally, this excludes a large swathe of informal labour in Mozambique, which is undertaken on an own-account basis, as in agriculture or petty commerce (for general discussion of the labour market in Mozambique, including the role of the informal sector, see Jones and Tarp 2013, 2015, 2016).

To access the service, prospective workers must register on the platform. Registering can be undertaken either directly via the internet or via any type of mobile phone. For the latter, the platform makes use of unstructured supplementary service data (USSD) codes, which is a protocol used to communicate via text message with the telephone service provider's computer servers. To register, workers must give their name, gender, the service (profession) they provide, as well as the province and district in which they reside. A profile is created for the worker on the platform, where clients can request their contact number to negotiate a service request.

Currently, *Biscate* has 18 professional categories, including carpentry, manicure, hairdressing, and gardening (see Appendix Table A1 for a full list). Although *Biscate* is free to use for both workers and clients, it is only available to users of the Vodacom mobile network. Therefore, any person with access to a mobile phone and a Vodacom number, which in 2019 accounted for around 50 per cent of all active numbers in the country,[7] can access the platform. Rates of mobile phone penetration in Mozambique are comparatively high—for example, as of January 2020 around half of Mozambican adults had access to a mobile connection.[8] Thus, it is reasonable to conclude that most (urban) informal workers have the technological means to register on *Biscate*. To date, more than 50,000 unique workers have registered on the platform.[9]

On the demand side, prospective clients must create an account (also using a Vodacom phone number), after which they can search for relevant workers from the profiles on the platform within a relevant profession and location. If they identify a suitable candidate they can then request the worker's phone number and enter into direct contact to negotiate a possible labour service. Contact requests and other search behaviour is registered on the platform; to date, 30,000 unique clients have been registered on the platform.

We partnered with *Biscate* to understand the impact of COVID-19 on informal workers. They provided us with anonymized individual-level data detailing, in addition to basic individual information (account creation date, location, profession, gender, experience, and education level), the number of contact requests and the number of agreed tasks (successful *biscates*) for each week since late 2016. The latter information is collected automatically by the platform by sending follow-up text messages to workers after their contact has been requested. However, since this information is only available from mid-2018 we start our analysis at this point, which also excludes the initial start-up period. From this data we create three primary outcome variables. Based on the number of workers, we calculate the rate of growth in the number of active registered workers, which is aimed to capture the labour supply side.[10] On the demand side, we calculate the rate of contact and agreement, which are the number of contacts

[7] Personal communication from the National Institute of Communications of Mozambique, 2 January 2019.

[8] http://datareportal.com/reports/digital-2020-mozambique, April 2021.

[9] www.biscate.co.mz/sobre.

[10] The platform has established an algorithm to de-list dormant workers (e.g. where their contact telephone number is no longer active), meaning this growth rate can be negative.

and work agreements divided by the total number of active workers. All these variables are represented as percentages.

Descriptive statistics for 2019 are set out in Table 1, showing average weekly province-level outcomes by profession and region (north, centre, and south). These show that the bulk of registered works are from the south and north, and that these regions also show comparatively higher rates of contact—for example, in the south the unconditional probability of agreeing a task was around 4 per cent versus 1 per cent in the centre. However, there are large differences across professions, both in terms of the average number of registered workers and agreement rates. Indeed, even in the south the latter range from over 16 per cent (cooking) to under 0.5 per cent (manicure).

Table 1: Average province-level outcomes, by region and profession in 2019

	Registered workers				Agreement rate			
	N	C	S	All	N	C	S	All
Cabeleireiro	251	131	509	278	6.30	2.96	10.45	6.22
Canalização	194	106	304	192	3.94	1.40	6.08	3.60
Carpintaria	156	95	262	163	2.52	1.38	4.49	2.64
Construção e Reparação	368	237	527	363	2.50	1.38	4.63	2.67
Costura	76	57	132	84	2.01	0.84	3.12	1.89
Cozinha	338	214	600	364	9.25	5.39	16.48	9.82
Electricidade	559	459	1,074	663	4.67	3.68	12.36	6.41
Entregas	177	98	229	162	2.94	1.78	3.73	2.73
Estofagem	9	8	15	10	0.17	0.20	0.23	0.19
Estética	10	9	27	15	0.29	0.22	0.44	0.31
Instalação de TV	88	85	187	114	0.92	0.74	2.06	1.16
Jardinagem	45	19	46	36	0.42	0.28	0.75	0.46
Manicure	10	5	13	9	0.29	0.12	0.42	0.25
Mecânica	139	122	244	161	1.02	0.86	2.37	1.33
Pintura	176	85	160	139	0.67	0.40	0.90	0.63
Reboque	8	9	37	16	0.27	0.23	0.56	0.33
Reparação de AC	102	69	151	103	0.55	0.25	0.88	0.53
Serralharia	138	83	124	114	0.34	0.23	1.18	0.53
Todos	158	106	267	168	2.20	1.26	4.09	2.37

Note: cells report the average number of registered workers in a given profession and the task agreement rate (in per cent) calculated at the province level in 2019; N, C, and S refer to the north, centre, and south regions, respectively; see Appendix Table A1 for a translation of profession names and categorization by broad type.

Source: authors' estimates.

Panel (a) of Table 2 provides further aggregate-level information, focusing on the period 2019–21. Here, we note consistent growth in the number of registered workers, which almost doubles from Q1 2019 to Q1 2021, but also a trend decline in demand-side outcomes, suggesting that supply growth has been steadily outpacing demand growth. This is supported by Figure 1, which plots the aggregate time series for the main outcomes of interest, indexed by the number of weeks before and after the start of the COVID-19 pandemic. While we cannot see any particularly obvious visual discontinuity associated with the (beginning of the) pandemic, we take note of the likely relevance of accounting for pre-existing trends in the subsequent analysis (see Section 4.1).

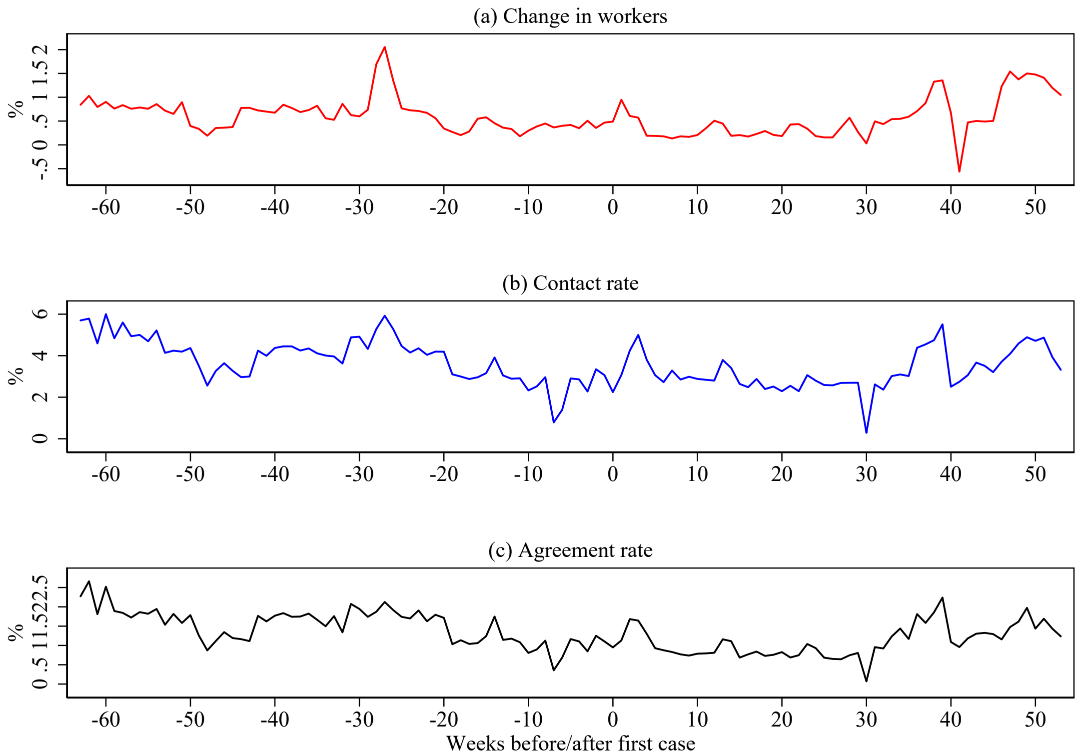
Table 2: Aggregate descriptive statistics by year and quarter (2019–21)

		2019				2020				2021
		Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1
(a)	Registered workers	24.49	26.89	30.74	32.81	33.94	35.96	37.82	40.32	43.02
	Female (%)	34.73	34.02	32.88	32.37	32.16	31.98	31.80	31.31	30.94
	Education (years)	8.01	7.99	7.95	7.94	7.93	7.93	7.78	7.64	7.54
	Experience (years)	5.35	5.36	5.38	5.39	5.39	5.37	5.40	5.41	5.41
	Contact rate	5.00	3.81	4.27	3.20	2.51	3.18	2.64	4.33	3.87
	Agreement rate	1.95	1.49	1.67	1.27	0.96	0.97	0.90	1.69	1.39
(b)	COVID–19 cases (m.a.)	0.00	0.00	0.00	0.00	0.18	13.90	110.98	92.84	538.72
	Stringency index	0.00	0.00	0.00	0.00	0.10	0.81	0.79	0.67	0.73
	Mobility index	0.00	0.00	0.00	0.00	0.07	−0.02	−0.07	−0.11	−0.21
	Employment index	0.03	0.12	0.02	0.05	0.01	−0.08	−0.02	−0.03	−0.17

Note: cells report aggregate (national-level) means by quarter and year for the indicated variables; registered workers are in thousands; stringency index, mobility index, and employment index are normalized to zero (within each sector/province) for the period January–March 2020.

Source: authors' estimates.

Figure 1: Time series of primary outcomes



Note: the plots show aggregate (national-level) averages per period, indexed by periods before and after the first case in the country.

Source: authors' estimates.

3 COVID-19 in Mozambique

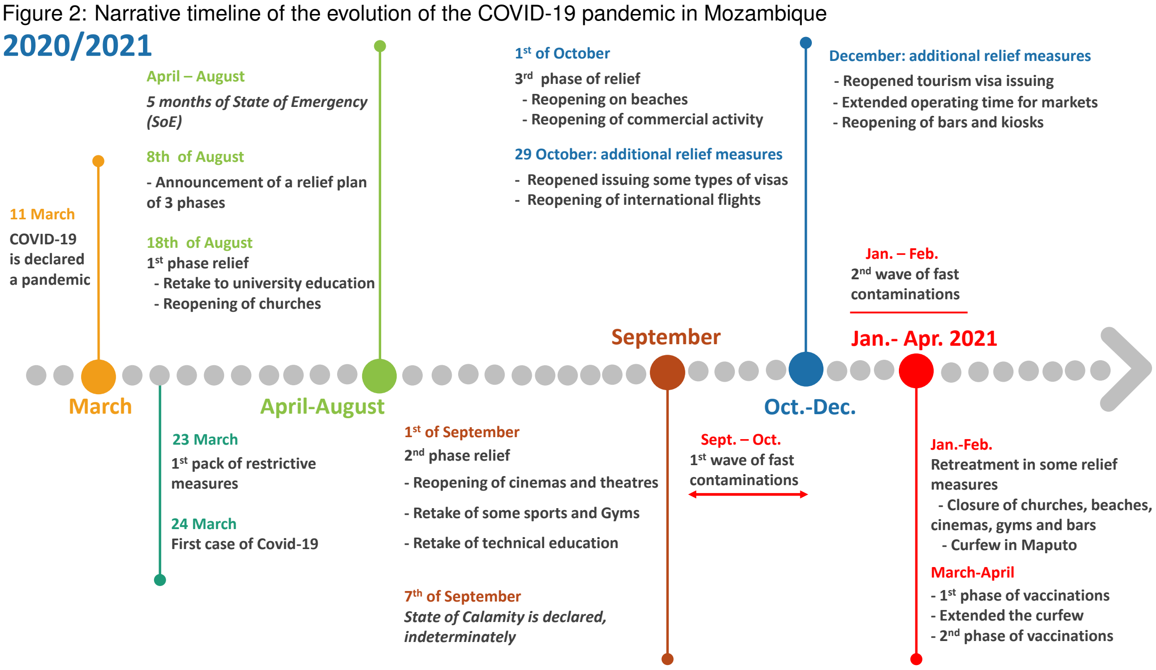
3.1 Timeline

An understanding of how the pandemic has evolved in Mozambique, including official responses, highlights the pertinence of taking account of distinct channels of impact on workers. Critically, although Mozambique's initial exposure to the virus was low, relatively strict measures were initially adopted to minimize the risks of propagation. Indeed, in line with the rapid growth of restrictions on cross-border movements across the globe in March 2021, restrictive measures began slightly before the country's first positive case, recorded on 22 March 2021. For example, on 20 March 2020 the Mozambican president announced, among other measures, the suspension to issuance of visas and cancelling of those already issued, closure of schools, and suspension of social events with more than 50 participants.

Despite having accumulated only eight positive cases, on 30 March 2020 the first state of emergency was announced, running from 1 April 2020 to 30 April 2020. This came with a set of further restrictive measures, including: prohibiting all types of public or private social events, cultural activities, and sports; stopping all non-essential movement across the national border; limiting circulation within the national territory; imposition of quarantine rules for travellers or the sick; closure of some commercial establishments; and imposition of rotating work arrangements (especially in the public sector). While this did not amount to a complete lockdown, these restrictions were particularly significant in some sectors (e.g. tourism and entertainment).

As summarized in Figure 2, due to the steady but comparatively moderate spread of infections, a state of emergency was maintained for approximately five months, lasting until the end of August 2020. However, at this time it was increasingly evident that the virus would not be eradicated and there was a need to adapt to a so-called *nova realidade* (new reality), giving breathing space to the economy. Thus, from early August onwards, relief measures were adopted in phases. By October 2020, most restrictive measures had been at least partially lifted, but some limitations remained—for example, issuing of visas continued to be restricted and some schools and commercial establishments remained closed.

Figure 2: Narrative timeline of the evolution of the COVID-19 pandemic in Mozambique



Source: authors' compilation.

In part due to constitutional limitations on the use of states of emergency, new legislation was adopted to allow for a (lesser) state of public calamity. Movement to this new public order regime was announced on 7 September and continues to the present time. However, relaxation of the most restrictive measures from August 2020 coincided with a first 'wave' of infections, which increased from an average of 70 daily cases in August to 160 cases in September, and 132 in October (i.e. the average daily cases more than doubled as measures were relaxed). This represented the sharpest increase experienced since the beginning of the pandemic and, compared to previous months, the number of deaths more than doubled and the country experienced a larger number of hospitalizations.

Despite these developments, additional restrictions were not introduced. For example, on 29 October the government simply called for more rigorous oversight of existing measures by the authorities, and some restrictions were even further relaxed, including issuing of tourism visas and the return of professional sports and national championships. On 17 December 2020 the government relaxed additional measures for the tourism sector, commerce, education, and social events. For example, the closing time of markets was extended from 5 p.m. to 8 p.m. and bars/kiosks were allowed to reopen, although for limited hours.

Arguably, this optimistic context contributed to a second wave of infections in the first months of the year, which also coincided with the emergence of the 'South African' variant of the virus. At the end of December, going through January, the country experienced an abrupt increase in infections, with over 600 daily positive cases on average in January alone. In response, starting on 15 January, the government reimposed some earlier restrictions. Among other measures, all commercial activities were set to close at 6 p.m., excepting restaurants, which could close at 8 p.m. on weekdays and 3 p.m. on weekends. Bars, nightclubs, kiosks, and beverage sales stalls were closed. Gyms, public swimming pools, and beaches were closed, as were cultural spaces like cinemas and museums. The maximum number of people at private social events was reduced to 30 in closed spaces and 50 in open spaces. Remote working was highly recommended, where possible.

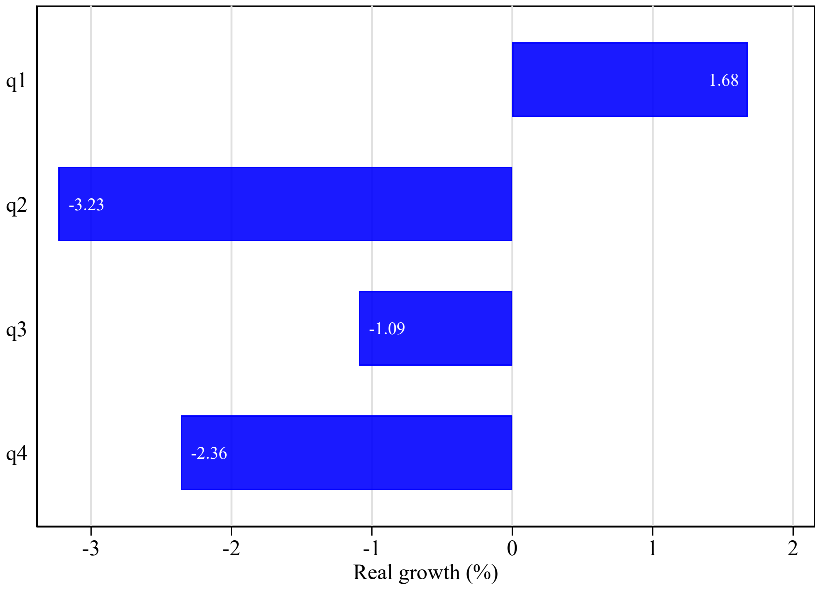
These measures did not appear to have any immediate impact on the growth of infections and, by February 2021, the daily average of positive cases had increased to around 720. In the face of growing pressure on the health system, the government imposed additional measures. Principally, starting from 5 February, a curfew was instigated in the Greater Maputo area between 9 p.m. and 4 a.m. Since then, the same economic restrictions have remained largely in force, even though the peak of the second wave has now passed. By mid-April 2021, while the number of new cases were fewer than 100 per day, the government had only decided to reopen schools and some national sports activities, and a curfew had been extended to cover all provincial capital cities.

3.2 Economic effects

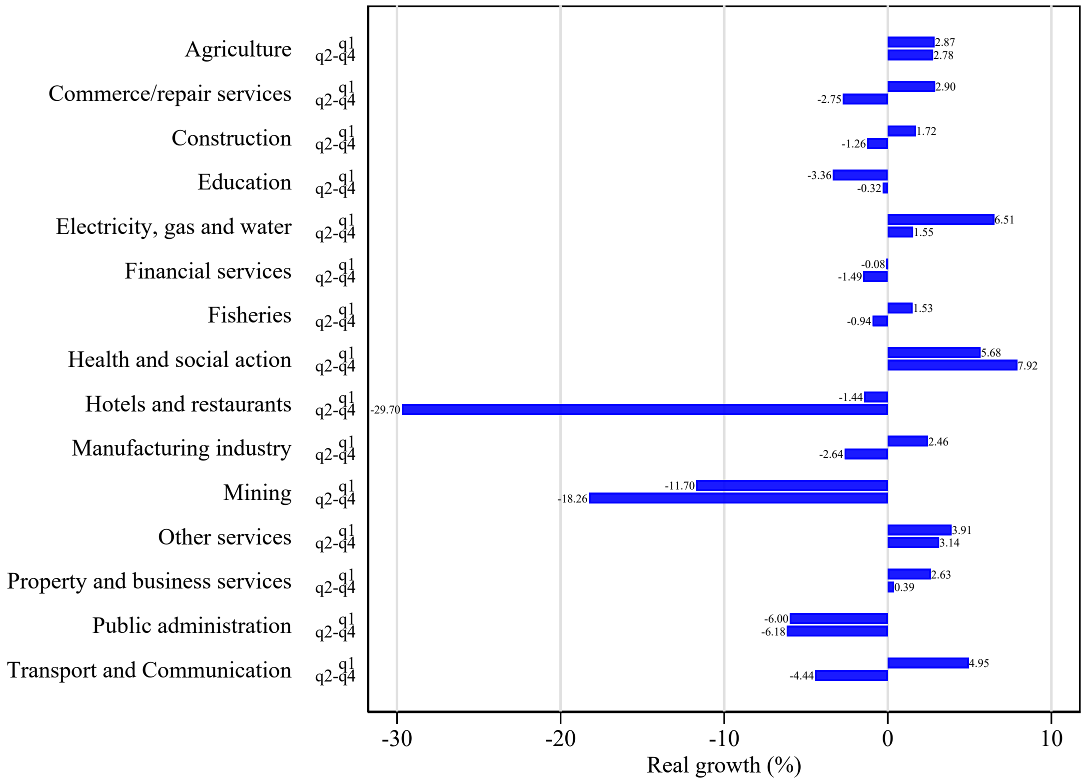
It is unquestionable that COVID-19 has been one of the largest global economic shocks in modern records (e.g. Padhan and Prabheesh 2021), from which Mozambique has not been spared. Comparing 2020 quarterly real GDP with the same period in 2019, the country only registered positive growth in the first quarter. As shown in Figure 3(a), all remaining quarters registered negative year-on-year growth. Overall, real GDP in 2020 recorded a fall of around 2.3 per cent versus 2019. From a more disaggregated perspective, the majority of sectors registered negative real growth in 2020. But, as in other countries (ILO 2020, 2021), some sectors suffered much more than others. For instance, the hospitality sector was worst hit by a large margin, recording an overall contraction of 30 per cent from the second to the fourth quarter compared to the same period in 2019 (Figure 3(b)). Double-digit contractions were only also recorded in the mining industry, largely reflecting global demand challenges; some sectors, such as agriculture and health, even sustained positive growth through the year.

Figure 3: Quarterly real GDP growth in Mozambique, 2020

(a) Economy-wide growth



(b) Sectoral growth



Note: all growth rates compare equivalent periods of 2020 versus 2019.

Source: authors' compilation from data provided by the National Statistics Institute (www.ine.gov.mz).

While comprehensive data regarding the magnitude and nature of the economic effects of COVID-19 remain elusive, early survey data collected by the National Institute of Statistics (INE 2020) confirm significant impacts across most sectors, with the hospitality sector particularly acutely affected. Their report estimates more than 70,000 small enterprises were negatively impacted by the pandemic, leading to extensive firm closures and the loss of at least 40,000 jobs. A case study of the beach tourism sector also found sales volumes fell by around 90 per cent in 2020 versus 2019 across a wide range of firms within the sector, as well as employment losses affecting around 60 per cent of workers (Aly et al. 2021).

Macroeconomic simulations have sought to isolate the (counterfactual) contribution of the pandemic to aggregate economic outcomes. As set out by Bertho et al. (2021), the COVID-19 shock caused the economy to contract by 3.26 per cent on aggregate, with the largest contractions (in terms of value added) being in the hospitality, trade, and transport sectors, all of which recorded declines of over 10 per cent. A complementary study at the microeconomic level similarly finds material increases in household poverty (Barletta et al. 2021), primarily driven by losses to income through employment. The authors find consumption poverty may have increased by almost 10 percentage points in 2020, pushing roughly two million people (>5 per cent of the population) below the official poverty line. For informal sector workers in particular, the UNDP (2020) estimates weekly profits among petty traders in Maputo fell by around 60 per cent during the early phase on the pandemic, with women much more affected than men.

3.3 Impact channels

As outlined above, existing studies suggest the economic shock associated with COVID-19 in Mozambique has been substantial; and this phenomenon has not been concentrated solely in the formal sector. It also merits note that, unlike in some other countries where temporary public support has been able to cushion some of the (employment) effects of the pandemic on the poorest (e.g. Barnes et al. 2021), such support has been almost completely absent in Mozambique to date.[11] Nonetheless, reflecting on the specific impact channels through which the pandemic may have operated, the net effects may be more complex than a simple uni-directional contraction on both the demand and supply sides of the market for informal labour. And this is especially plausible in Mozambique, where no hard lockdown was enacted, and the health burden of the virus has remained comparatively light, particularly in certain regions.

Expounding on this, Table 3 sets out four distinct—yet, unlikely independent—channels through which COVID-19 may have affected either the supply of or demand for informal labour services of the form available on *Biscate* (see Section 2). The first is the (endogenous) reaction to the virus itself, whereby individuals choose not to engage in specific activities for fear of exposing themselves or their families to the virus. For informal workers, this could entail limiting both job search and work availability, and in extreme cases moving residence to areas of perceived lower risk. For example, Valsecchi and Durante (2020) show that during localized negative health shocks in Italy, such as experienced during the COVID-19 pandemic, people tend to migrate from higher risk (outbreak) to lower risk (non-outbreak) regions. Along the same lines in India, COVID-19 triggered massive migration out of cities, with millions marching back to their home states, mostly due to unemployment, fear, and uncertainty (Mukhra et al. 2020).

Broadly, then, we expect that fear of the virus would be likely to dampen activity on both sides of the market for informal labour tasks. However, a caveat is that fear of the virus may primarily lead individuals to avoid undertaking certain activities in specific customary locations, such as shops and

[11] A temporary cash transfer programme directed towards the urban poor has been under development, but implementation has been very slow.

marketplaces, redirecting the same underlying demand elsewhere—for example, from the formal to the informal sector. Hairdressing is one example—rather than attending a salon, individuals may prefer to invite a stylist to their own home, where they can better control infection risks. Also, since information and expectations are not static, responses to the same health situation early in the pandemic may not be the same as later. For these reasons, we classify the direction of this effect on the demand side as ambiguous (denoted '?' in Table 3).

Table 3: Summary of potential impact channels of COVID-19 on informal labour services

	Effect direction	
Channel	Supply side	Demand side
Virus fear	–	?
Business restrictions	?	?
Increased free time	+	+
Income loss	+	?

Source: authors' estimations.

The second channel refers to formal government restrictions placed on business activities, ranging from temporarily shutting down certain establishments (e.g. bars and gyms) to reducing worker numbers or opening times. This channel is likely to pertain primarily to formal establishments and/or workers operating from fixed locations. To the extent that individuals continue to be permitted to leave their place of residence during usual working hours (as in Mozambique), we thus expect such restrictions to have less 'bite' for mobile providers of informal services. Indeed, increased restrictions on fixed-location businesses may push affected (formal sector) workers into the mobile informal segment, as well as directly raise demand for such services. To give another example, reduced operating hours at (informal) marketplaces or shops may prompt individuals to look elsewhere for help with simple repair services. So, as before, disruption caused by COVID-19 may displace activity, rather than only dampen it, thereby generating new opportunities within the specific domain served by *Biscate*. So, again, we classify the direction of this effect as ambiguous.

The third channel captures the implications of additional leisure time, which is likely to be an indirect consequence of both increased social distancing (virus fear) and formal business restrictions, including school closures. With less time spent at fixed locations outside the home, we hypothesize that availability to undertake (local) informal tasks should increase. Furthermore, the combination of additional free time and reduced supply of certain goods and services (e.g. entertainment) could well stimulate individuals to invest in new projects, such as home improvements. As noted, there is ample evidence of this trend elsewhere—for example, one report states that the US online re-modelling platform Houzz recorded a 58 per cent increase in demand for professional contractors to work on home improvements for the year to June 2020.[12] For this reason, we expect this channel may well operate in a positive direction on both sides of the market.

Finally, there is the knock-on effects of lost income, such as due to foregone employment or wage reductions. On the supply side of the *Biscate* market, our expectation is that this would tend to have a positive effect, reflecting low entry costs and the notion that at least some informal work is undertaken either as a last resort (where formal opportunities are exhausted) or on a supplementary basis (Jones and Tarp 2015). On the demand side, the effect is ambiguous. To the extent that informal services represent an inferior and thus cheaper substitute to conventional alternatives, then one might expect demand to increase as (aggregate) incomes fall. Equally, the broad range of suppliers on *Biscate* (at least in some locations/professions) may well be attractive, allowing buyers to seek out a more suitable

[12] www.cnbc.com/2020/08/07/pandemic-home-remodeling-is-booming-what-your-neighbors-are-doing.html.

and competitively priced provider than existing contacts. The fact that this can be done using digital tools, rather than in person, may be particularly appealing.

In sum, we hypothesize that the disruptive nature of COVID-19 is likely to be associated with a complex range of effects across multiple channels. Within the specific domain of informal labour services, which are task-specific and mobile in nature, COVID-19 would seem to present challenges *and* opportunities. Of course, perceived health risks and formal restrictions on economic activity would be expected to dampen this market in general. However, potential displacement of demand from formal to informal services, redirection of search from in-person to online tools, substitution towards inferior services, and low entry costs into this market segment all raise the possibility that both demand and supply may have been affected positively during the pandemic. In light of this ambiguous net effect, we now move to the empirical analysis.

4 Econometric analysis

4.1 Empirical strategy

The previous section outlined four different channels through which COVID-19 may have affected the supply of and demand for informal labour services in Mozambique. While we make no claim that these channels are either comprehensive or exhaustive, we nonetheless seek to quantify their empirical relevance. To do so, we use weekly micro-data from the *Biscate* platform covering the period starting June 2018 to the end of March 2021. To identify the distinctive contribution of each of the four channels, we use the following core specification, stated here at an aggregate-level:

$$
\begin{aligned}
y_t = \alpha + \beta\ \text{Post}_t + \lambda\ \text{Cases}_t + \gamma\ \text{Restrictions}_t + \delta\ \text{Mobility}_t + \theta\ \text{Income}_t \\
+ \text{Year}_t + \text{Month}_t + \varepsilon_t \qquad (1)
\end{aligned}
$$

where t indexes time and y is the dependent variable—one of either: the rate of growth in registered workers; the worker contact rate; or the task agreement rate. Each of the variables 'Cases', 'Restrictions', 'Mobility', and 'Income' represent a separate proxy for one of the four channels of interest (see above). This specification effectively represents a period-to-period (year-to-year) generalized difference-in-difference specification (c.f. Bandiera et al. 2005; Cao et al. 2020; Horton 2021), where the various channels—which are normalized to zero in the pre-COVID period and show either no or minimal variation in this period (see below)—capture the intensity of exposure to different types of COVID-19 effects from March 2021 onward.

The raw underlying variables on which the four main proxies are based are as follows:

1. '*Cases*' captures the perception of risks associated with the virus, represented by the seven-day rolling average of diagnosed COVID-19 cases, available at the province level.[13]

2. '*Restrictions*' is the original Oxford (Blavatnik School of Government) stringency index that measures the overall strictness of policies enacted by governments to restrict people's behaviour, with values ranging from 1 to 100. The data is available only at the national level, but on a daily basis, from which we calculate weekly averages.[14]

[13] This data was manually collated from daily bulletins provided by the National Health Institute, available at: http://covid19.ins.gov.mz.

[14] For further details and source data, see: www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker.

3. '*Mobility*' is the original Google Mobility Index for travel to/from a workplace taken from their Community Mobility Reports, available separately for each province, which indicate the negative or positive deviation of mobility compared to baseline days. A baseline day represents the *normal* level of mobility for a given day of the week, calculated as the median value from the five-week period running from 3 January to 6 February 2020.[15]

4. '*Income*' is the monthly current employment conditions index, taken from the National Institute of Statistics' series of Indicators of Economic Confidence and Conditions (IECC), based on a survey of firms across multiple sectors. Since this index is available at the level of each broad economic production sector, we match professions in the *Biscate* data to a relevant economic sector and use this particular measure of employment conditions.[16]

For ease and consistency of interpretation, we normalize all four of the above variables to take a mean of zero over the immediate pre-COVID period (if not already zero), at the lowest level of aggregation at which they are observed (e.g. sector/province), to which we then apply the inverse hyperbolic sine (IHS) transform, meaning the coefficients in Equation (1) will approximately represent semi-elasticities. After controlling for fixed year and month effects as per Equation (1), the variable 'Post'—which is a dummy variable taking a value of 1 for the entire post-COVID period, defined as all weeks after the first registered case in Mozambique—captures the remaining average systematic variation in the outcome associated with this period and which is unexplained by the included channels.

With respect to the structure of the data, the variables of interest are observed at different levels of aggregation and frequencies. To take full advantage of the *Biscate* data, which is available on a weekly basis, we retain this periodization throughout (i.e. time is indexed in weeks). Figure 4 plots aggregate trends in the four measures. Consistent with the narrative of Section 3, we observe that they do not all follow the same path. In particular, the most stringent official measures were enacted early on, even though the number of cases was low. Also, despite initial reductions in the mobility and employment indices at the start of the crisis, they reach their lowest values during the second wave, in early 2021.

It merits note that, in order to capture trends in the supply of registered workers, aggregation at a level above the individual is inevitable (Horton 2021). Although a highly granular analysis that distinguishes between specific professions and locations is feasible, a concern is that data at this level will be noisy due to small numbers of registered workers in specific province–profession combinations. For example, as seen in Table 1, in 2019 the average province had only 10 upholsters registered on the platform versus more than 600 registered electricians. Differences across provinces are also pertinent—Nampula and Maputo City account for almost 40 per cent of all workers, including approximately 40 per cent of electricians. One strategy to deal with these differences is to apply supply- or demand-side weights (see further below). Another, which also directly accounts for the higher level of aggregation at which the independent variables are observed (e.g. by province), is to collapse further upwards, the extreme case being to run the analysis at the national level only.

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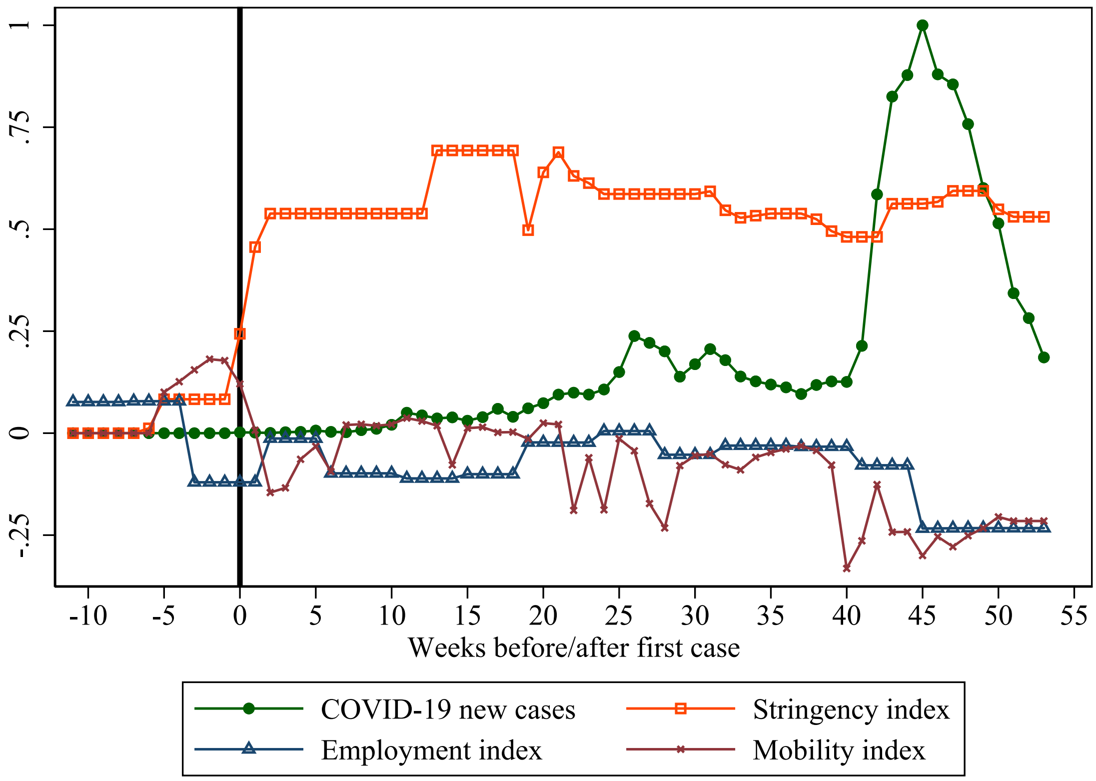
[15] Since mobility data before 2020 is not available, we set all values in this period as equal to the baseline period. For further details and source data, see: www.google.com/covid19/mobility.

[16] See Appendix Table A1 for the match of professions to aggregate sectors; from the IECC data we use the specific index '*emprego actual*'. Since data from March 2021 is not available, we presume this observation is unchanged from the previous month. For further information, see: www.ine.gov.mz/estatisticas/estatisticas-economicas/icce.

Figure 4: Aggregate time series of key explanatory variables (impact channels)



Note: the plot shows average national weekly values of the main explanatory variables over the period 2020–21; the number of COVID-19 cases is transformed to range from 0 to 1.

Source: authors' compilation.

In practice, given the advantages and disadvantages associated with aggregation procedures (e.g. Reynolds and Amrhein 1998), we report results at alternative levels. This ranges from province × professions (11×18 = 198 cells), professions only, provinces only, and the national level, using a time series of 150 observations for each cell. For analyses below the national level, a full set of fixed effects are included, allowing the intercept and time effects to vary at the lowest level of aggregation chosen (the panel unit level). Additionally, to account for latent trends, we run specifications that allow for either linear or quadratic trends at the cell level. To account for the potential dependence of the dependent variables on the existing size of the market, we include the lagged value of the natural logarithm of the number of registered workers on the site (for each cell). We also include a small number of additional dummy variables to account for: the first/last week of the month, periods when survey and verification notices were pushed to clients on the platform, and rare moments of platform outage. Thus, our most complete specification is as follows:

$$y_{ijt} = \alpha_{ij} + \beta\ \text{Post}_t + \lambda\ \text{Cases}_{it} + \gamma\ \text{Restrictions}_t + \delta\ \text{Mobility}_{it} + \theta\ \text{Income}_{jt}$$
$$+X'_{ijt}\eta + \pi_{ij}t + \varphi_{it}t^2 + \text{Year}_{ijt} + \text{Month}_{ijt} + \varepsilon_{ijt} \quad (2)$$

where X is the standard vector of controls; i indexes provinces; and j indexes professions.[17] This can be interpreted as a kind of triple differences-in-differences specification, where the estimated main coefficients capture the deviation in the outcome from the estimated trend associated with the channels of interest $(\lambda, \gamma, \delta, \theta)$, plus remaining systematic unexplained variation (β).

[17] We do not include additional controls capturing the age, gender, or experience of the workers on the platform. In part this is because many such observations are missing; also, at an aggregate level, this information is generally not observed by clients.

Finally, in all analyses below the national level we exclude cells corresponding to very small numbers of workers, where outcomes such as the contact or agreement rate are likely to be noisy. To do so, we count the maximum number of active workers in each cell during the pre-COVID period. All cells with a maximum of under 25 are then excluded—that is, cells effectively must have a minimum of 25 active workers in the most recent period to remain in the sample. In addition, we construct and apply sample weights, which reflect the relative importance of a given cell (e.g. province) in the data. Specifically, for each time period the weight attributed to each cell is its relative proportion in the total active worker stock.[18]

4.2 National-level findings

Turning to the results, we start at the national level as per Equation (1). Columns (1) to (5) of Table 4 report OLS results (with Newey–West standard errors), where each of the main variables of interest is entered individually in the model; in column (6) are estimates for the complete model, where they are entered jointly. Results for the three different outcomes are reported in panels (i) through (iii), and the full set of control variables plus year/month effects are included throughout. The estimates in column (1) indicate the overall average effect associated with the COVID-19 period (March 2020 onwards), after adjusting for the included background controls. Here we note there is no discernible change in the growth rate of registered workers on aggregate, but a non-trivial (in relative terms) net increase in the rate of contact and task agreement rate on average, both significant at the 10 per cent level. This provides a first indication of a positive demand-side response.

Appendix Figure A1, sub-figure (i) in both parts, provide a visualization of the results from column (1) of Table 4. Concretely, they plot the trajectory of two outcomes (the active worker growth rate and the agreement rate) after removing the contribution of the standard control variables. The plotted lines effectively correspond to national-level estimates of: $\hat{\beta}\ \text{Post}_t + \hat{\varepsilon}_t$ from Equation (1), but in which all coefficients on the COVID channels are set to zero ($\lambda = \gamma = \delta = \theta = 0$). The horizontal lines in the figures report the average trajectory before and after the start of the pandemic, which is centred on zero in the pre-COVID period by definition. Effectively, this amounts to a crude regression discontinuity design, with time as the running variable, and where $\hat{\beta}$ captures a (weighted) average net effect associated with COVID-19.

Looking at the specific channels, on a standalone basis the number of daily positive COVID-19 cases would appear to influence supply growth—for example, a doubling of cases is associated with a 0.18 point fall in the registration rate. The stringency index is also associated negatively with worker supply, but shows a strong and large positive relationship with initial demand (the contact rate). Indeed, recalling that the mean contact rate in 2019 was only around 4 per cent, the estimated coefficient suggests that a doubling of stringency was associated with an approximate 50 per cent increase in the contact rate. This would be consistent with a mechanism whereby restrictions on supply in the formal sector (or in fixed locations), or perceptions of health risks associated with these restrictions, push individuals to seek more flexible alternatives in informal labour services.

We find no evidence of an association between mobility (staying at home) and dynamics on the platform. However, the two demand-side outcome variables are both strongly and negatively associated with variation in the employment index. As such, this channel may well (partially) account for the average mean effect found in column (1) of panels (ii) and (iii)—that is, the negative values of the employment index registered through the COVID-19 period, especially in early 2021 when infection rates were highest, indicate these were associated with higher levels of effective demand. The direction of this effect supports

[18] We find no evidence that our results are sensitive to this weighting procedure. Results available on request.

an interpretation that informal labour services can be inferior in nature, or minimally they are primarily attractive on the price dimension.

Table 4: Aggregate least squares time series analysis

	(1)	(2)	(3)	(4)	(5)	(6)
(i) Δ Workers						
COVID-19 period	–0.13					0.54**
	(0.19)					(0.21)
New cases (roll av.)		–0.18***				–0.19**
		(0.05)				(0.07)
Stringency index			–0.53*			–1.52**
			(0.30)			(0.66)
Mobility index				0.09		–0.94
				(0.67)		(0.67)
Employment index					–1.46	–2.81***
					(0.99)	(1.06)
Obs.	149	149	149	149	149	149
RMSE	0.28	0.27	0.28	0.29	0.28	0.24
(ii) Contact rate						
COVID-19 period	1.56**					1.75
	(0.69)					(1.95)
New cases (roll av.)		0.14				–0.23
		(0.24)				(0.28)
Stringency index			2.48**			–0.14
			(1.23)			(3.59)
Mobility index				–0.66		0.59
				(2.67)		(2.75)
Employment index					–5.43***	–3.01
					(1.99)	(2.46)
Obs.	149	149	149	149	149	149
RMSE	0.95	0.98	0.96	0.99	0.96	0.94
(iii) Agreement rate						
COVID-19 period	0.41*					0.86
	(0.24)					(0.68)
New cases (roll av.)		–0.03				–0.15
		(0.10)				(0.12)
Stringency index			0.50			–0.48
			(0.50)			(1.36)
Mobility index				–0.02		0.20
				(1.07)		(1.06)
Employment index					–1.63*	–1.06
					(0.84)	(1.07)
Obs.	149	149	149	149	149	149
RMSE	0.40	0.40	0.40	0.40	0.40	0.39

Note: columns (1)–(4) report results from aggregate-level regressions of the indicated dependent variable using a specification including one primary explanatory variable; column (5) combines all of the main channels simultaneously; standard control variables, including the one-period lag (log.) of active workers and month/year fixed effects included throughout; Newey–West standard errors reported (in parentheses).

Source: authors' estimates.

Turning to the joint aggregate-level model in column (6), on the demand side we see the direction and approximate magnitude of the coefficients stay broadly the same, but they lose significance. On the supply side, we find a different tendency—combining the different channels sharpens their individual contributions and yields a positive systematic residual effect during the COVID-19 period (0.54 points), as well as larger negative effects associated with both the stringency and employment indices. Since these effectively operate in opposite directions, this could well explain the insignificant average net effect found in column (1); we return to this in Section 5.

4.3 Disaggregate findings

Table 5 elaborates on the full specification, covering analysis at different levels of aggregation—shown separately in panels (i) to (iv)—and also now adding controls for latent trends. The models reported in sub-columns (a) repeat the previously reported specification without trends, but (still) *with* unit-specific year and month effects; sub-columns (b) add linear trends at the unit level; and sub-columns (c) add quadratic trends at the same level. Thus, the results in panel (i) sub-columns (a) simply repeat the joint results from Table 4, and all other results represent elaborations on this specification.

Table 5: Least squares analysis of complete model at alternative levels of aggregation

	(1) Δ Workers			(2) Contact rate			(3) Agreement rate		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
(i) Aggregate level									
COVID-19 period	0.54**	0.45**	0.43**	1.75	1.86	1.31	0.86	0.85	0.66
	(0.21)	(0.20)	(0.18)	(1.95)	(1.91)	(1.32)	(0.68)	(0.68)	(0.49)
New cases (roll av.)	–0.19**	–0.22***	–0.22***	–0.23	–0.18	–0.08	–0.15	–0.16	–0.12
	(0.07)	(0.07)	(0.08)	(0.28)	(0.31)	(0.33)	(0.12)	(0.13)	(0.14)
Stringency index	–1.52**	–1.33**	–1.36**	–0.14	–0.38	–0.96	–0.48	–0.46	–0.66
	(0.66)	(0.66)	(0.64)	(3.59)	(3.55)	(3.04)	(1.36)	(1.34)	(1.19)
Mobility index	–0.94	–0.92	–0.92	0.59	0.55	0.42	0.20	0.20	0.15
	(0.67)	(0.66)	(0.66)	(2.75)	(2.83)	(2.93)	(1.06)	(1.07)	(1.10)
Employment index	–2.81***	–2.82***	–2.88***	–3.01	–2.99	–4.15	–1.06	–1.06	–1.45
	(1.06)	(1.04)	(1.05)	(2.46)	(2.48)	(2.71)	(1.07)	(1.08)	(1.16)
Obs.	149	149	149	149	149	149	149	149	149
RMSE	0.24	0.24	0.24	0.94	0.94	0.87	0.39	0.39	0.37
(ii) By province									
COVID-19 period	0.49	0.45	0.39	1.49	1.63	1.23	0.80	0.83	0.67
	(0.33)	(0.33)	(0.33)	(1.46)	(1.44)	(1.15)	(0.55)	(0.55)	(0.45)
New cases (roll av.)	–0.05*	–0.06*	–0.10**	–0.16*	–0.15*	–0.06	–0.04	–0.04	–0.00
	(0.03)	(0.03)	(0.04)	(0.08)	(0.08)	(0.11)	(0.04)	(0.04)	(0.05)
Stringency index	–2.34***	–2.33***	–2.23***	–1.06	–1.08	–1.74	–1.23	–1.23	–1.48
	(0.65)	(0.65)	(0.59)	(2.74)	(2.73)	(2.27)	(1.07)	(1.07)	(0.91)
Mobility index	–0.90**	–0.93**	–0.99**	–1.22	–1.14	–1.06	–0.32	–0.31	–0.24
	(0.44)	(0.44)	(0.46)	(1.56)	(1.56)	(1.62)	(0.65)	(0.65)	(0.66)
Employment index	–3.25***	–3.29***	–3.38***	–4.11**	–3.94**	–5.34***	–1.56**	–1.52**	–2.07***
	(0.78)	(0.78)	(0.77)	(1.75)	(1.75)	(1.88)	(0.69)	(0.69)	(0.76)
Obs.	1,639	1,639	1,639	1,639	1,639	1,639	1,639	1,639	1,639
RMSE	0.49	0.49	0.49	1.44	1.44	1.41	0.56	0.56	0.55
(iii) By profession									
COVID-19 period	0.62**	0.58**	0.50*	1.88	1.97	1.40	0.91	0.91	0.68*
	(0.28)	(0.29)	(0.26)	(1.56)	(1.55)	(1.07)	(0.56)	(0.57)	(0.40)
New cases (roll av.)	–0.18***	–0.19***	–0.25***	–0.29*	–0.27	–0.26	–0.16**	–0.16**	–0.15*
	(0.05)	(0.05)	(0.06)	(0.17)	(0.17)	(0.19)	(0.07)	(0.07)	(0.08)
Stringency index	–0.97*	–0.88	–0.68	0.37	0.22	–0.16	–0.33	–0.33	–0.48
	(0.53)	(0.54)	(0.49)	(2.99)	(2.98)	(2.28)	(1.13)	(1.14)	(0.90)
Mobility index	–0.55	–0.54	–0.52	0.97	0.95	0.84	0.34	0.34	0.29
	(0.44)	(0.43)	(0.42)	(2.07)	(2.07)	(2.01)	(0.78)	(0.79)	(0.76)
Employment index	–0.86***	–0.86***	–1.04***	–1.81**	–1.82**	–3.03***	–0.49*	–0.49*	–1.02***
	(0.30)	(0.30)	(0.31)	(0.73)	(0.74)	(0.78)	(0.28)	(0.28)	(0.31)
Obs.	2,682	2,682	2,682	2,682	2,682	2,682	2,682	2,682	2,682
RMSE	0.42	0.42	0.41	1.59	1.60	1.53	0.65	0.65	0.63
(iv) By province and profession									
COVID-19 period	0.62**	0.42	0.47	1.37	1.63	1.33	0.76	0.82	0.70
	(0.30)	(0.28)	(0.32)	(1.31)	(1.36)	(1.15)	(0.50)	(0.52)	(0.44)
New cases (roll av.)	–0.05	–0.12**	–0.18***	–0.29***	–0.22***	–0.22**	–0.08**	–0.06*	–0.06
	(0.03)	(0.05)	(0.06)	(0.08)	(0.08)	(0.10)	(0.04)	(0.03)	(0.04)
Stringency index	–1.75***	–1.76***	–1.51***	–0.64	–0.63	–0.98	–1.03	–1.02	–1.18
	(0.60)	(0.53)	(0.57)	(2.45)	(2.52)	(2.22)	(0.95)	(0.98)	(0.86)
Mobility index	–0.63*	–0.47	–0.67*	–0.64	–0.79	–0.61	–0.11	–0.17	–0.07
	(0.36)	(0.36)	(0.40)	(1.42)	(1.44)	(1.47)	(0.60)	(0.60)	(0.61)
Employment index	–1.05***	–1.33***	–1.28***	–2.69***	–2.40***	–3.20***	–0.86***	–0.78***	–1.17***
	(0.33)	(0.38)	(0.34)	(0.72)	(0.71)	(0.82)	(0.27)	(0.27)	(0.32)
Obs.	22,670	22,670	22,670	22,670	22,670	22,670	22,670	22,670	22,670
RMSE	1.06	1.04	1.02	3.18	3.13	3.11	1.32	1.31	1.29

Note: columns report results from regressions on the form of equation (2); panels (i)-(iv) indicate the level of aggregation at which panel units are defined (and outcomes measured); dependent variables indicated in the main column headers; standard control variables, including the one-period lag (log.) of active workers, month/year and unit fixed effects included throughout; all fixed effects are specified separately for each panel unit – i.e., the lowest level of aggregation; sub-column (a) is the baseline specification; sub-column (b) includes a linear trend for each panel unit; sub-column (c) includes a quadratic trend for each panel unit; for panel (i) Newey-West standard errors reported (in parentheses); for all other panels, standard errors are clustered at the year × week level.

Source: authors' estimates.

What do we learn? Overall, on the supply side (worker registration growth; in super-column 1) the results are remarkably consistent across levels of aggregation as well as regardless of what form of (latent) trends are included. We observe offsetting tendencies associated with a substantial negative association with both the stringency and employment indices. On the demand side, the direction and approximate magnitude of coefficients are also stable across the various specifications. However, statistical significance becomes sharper as degrees of freedom increase. Below the national level we find a strong and significant relationship between the employment index and demand for informal labour services. For instance, the estimates in panel (iv) sub-columns (c) suggest that a *halving* of the employment index is associated with a 3.2 and 1.2 percentage point *increase* in the contact and agreement rates, respectively.

In addition to the above, results from the more disaggregate specifications generally suggest a moderate negative effect of the daily number of COVID-19 cases (health risks) on both the demand and supply sides. Again with reference to panel (iv) sub-columns (c), a doubling of COVID-19 cases is associated with a concurrent 0.18 point drop in the growth rate of active workers, a 0.22 point drop in the rate of contact, and a 0.06 point drop in the agreement rate. Furthermore, in these most complete specifications, which include latent quadratic trends, although the residual systematic effect associated with the COVID-19 period is always positive, it is never statistically significant. In other words, the postulated channels would seem to account for much of the systematic variation in outcomes during the pandemic.

4.4 Robustness

We recognize that our ability to precisely identify causal effects is limited. We do not have any 'control' groups that were plausibly unaffected by the virus—recall, the whole country was exposed to restrictions—and we rely on proxies to capture different effect channels. Furthermore, inclusion of latent time trends in the model may well capture some part of the (unobserved) effects associated with COVID-19. To address this concern, we implement a preliminary de-trending procedure. Following Kleven et al. (2014), this involves projecting an outcome of interest on a set of trends for the pre-treatment period only, then applying estimates of the contribution of these trends to the full period to derive residuals (see also Bhuller et al. 2013; Oster 2018). These residuals, or the de-trended outcome, thereby represent the difference in the path of the outcome variable to its expected path had the observed pre-treatment trend continued. To do so, we first estimate the following relationship (for the quadratic case at the aggregate level):

$$\forall t \text{ s.t. } \text{Post}_t = 0 : y_t = \alpha + \pi_d t + \varphi_d t^2 + \varepsilon_t \tag{3}$$

Then we construct the de-trended outcome, covering the full period:

$$\tilde{y}_t = y_t - (\hat{\alpha} + \hat{\pi}_d t + \hat{\varphi}_d t^2) \tag{4}$$

which is then used as the dependent variable in the complete specification, but now without including additional trends since these have been accounted for in the first step.

Table 6 reports the results from this procedure, organized in similar fashion to before.[19] Sub-columns (a) report baseline results without any de-trending, repeating the estimates reported in sub-columns (a) of Table 5. Sub-columns (b) apply the de-trending with a linear pre-trend specification; sub-columns (c) de-trend using a quadratic pre-trend; and, as before, we implement the de-trending at the lowest level of aggregation in each dataset.[20] Overall, the results are highly consistent with previous estimates, as well as across specifications (models), thereby suggesting the main findings are robust to alternative approaches to addressing latent trends in the data. But there are some differences. The de-trended results yield somewhat more conservative response magnitudes. For instance, coefficient estimates in

[19] See also Appendix Figure A1, sub-panels (ii) and (iii), for the crude aggregate regression discontinuity visualizations with adjustment for pre-trends.

[20] For instance, for the provincial-level aggregation we allow separate pre-trends for each province.

panel (iv) for both the case numbers and employment index are smaller under the pre-trend adjustment procedure. However, the (positive) systematic residual associated with the supply side is now statistically significant.

Table 6: Least squares analysis of complete model at alternative levels of aggregation with prior de-trending

	(1) Δ Workers			(2) Contact rate			(3) Agreement rate		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
(i) Aggregate level									
COVID-19 period	0.54**	0.55**	0.47**	1.75	1.79	1.98	0.86	0.87	0.96
	(0.21)	(0.21)	(0.21)	(1.95)	(1.95)	(2.09)	(0.68)	(0.68)	(0.75)
New cases (roll av.)	–0.19**	–0.18**	–0.18**	–0.23	–0.21	–0.21	–0.15	–0.15	–0.15
	(0.07)	(0.07)	(0.08)	(0.28)	(0.28)	(0.28)	(0.12)	(0.12)	(0.12)
Stringency index	–1.52**	–1.54**	–1.53**	–0.14	–0.22	–0.23	–0.48	–0.51	–0.51
	(0.66)	(0.66)	(0.61)	(3.59)	(3.59)	(3.77)	(1.36)	(1.36)	(1.44)
Mobility index	–0.94	–0.95	–0.95	0.59	0.57	0.58	0.20	0.19	0.20
	(0.67)	(0.68)	(0.68)	(2.75)	(2.77)	(2.79)	(1.06)	(1.07)	(1.09)
Employment index	–2.81***	–2.81***	–2.92***	–3.01	–3.00	–2.72	–1.06	–1.06	–0.92
	(1.06)	(1.06)	(1.08)	(2.46)	(2.46)	(2.46)	(1.07)	(1.07)	(1.07)
Obs.	149	149	149	149	149	149	149	149	149
RMSE	0.24	0.24	0.24	0.94	0.94	0.97	0.39	0.39	0.40
(ii) By province									
COVID-19 period	0.49	0.51	0.40	1.49	1.53	1.69	0.80	0.81	0.91
	(0.33)	(0.33)	(0.30)	(1.46)	(1.45)	(1.54)	(0.55)	(0.55)	(0.60)
New cases (roll av.)	–0.05*	–0.05	–0.05	–0.16*	–0.16*	–0.18**	–0.04	–0.03	–0.03
	(0.03)	(0.03)	(0.03)	(0.08)	(0.08)	(0.08)	(0.04)	(0.04)	(0.04)
Stringency index	–2.34***	–2.35***	–2.42***	–1.06	–1.07	–0.87	–1.23	–1.23	–1.17
	(0.65)	(0.65)	(0.59)	(2.74)	(2.73)	(2.87)	(1.07)	(1.07)	(1.14)
Mobility index	–0.90**	–0.89**	–0.98**	–1.22	–1.19	–1.39	–0.32	–0.31	–0.39
	(0.44)	(0.44)	(0.46)	(1.56)	(1.56)	(1.58)	(0.65)	(0.65)	(0.67)
Employment index	–3.25***	–3.23***	–3.50***	–4.11**	–4.06**	–3.56**	–1.56**	–1.54**	–1.28*
	(0.78)	(0.78)	(0.79)	(1.75)	(1.75)	(1.79)	(0.69)	(0.69)	(0.71)
Obs.	1,639	1,639	1,639	1,639	1,639	1,639	1,639	1,639	1,639
RMSE	0.49	0.49	0.50	1.44	1.44	1.46	0.56	0.56	0.58
(iii) By profession									
COVID-19 period	0.62**	0.64**	0.55**	1.88	1.93	2.03	0.91	0.92	0.99
	(0.28)	(0.28)	(0.26)	(1.56)	(1.56)	(1.63)	(0.56)	(0.56)	(0.60)
New cases (roll av.)	–0.18***	–0.17***	–0.15***	–0.29*	–0.28*	–0.19	–0.16**	–0.15**	–0.11
	(0.05)	(0.05)	(0.05)	(0.17)	(0.17)	(0.17)	(0.07)	(0.07)	(0.07)
Stringency index	–0.97*	–0.99*	–1.12**	0.37	0.28	–0.15	–0.33	–0.36	–0.56
	(0.53)	(0.53)	(0.47)	(2.99)	(2.99)	(3.12)	(1.13)	(1.13)	(1.20)
Mobility index	–0.55	–0.55	–0.61	0.97	0.96	0.80	0.34	0.34	0.26
	(0.44)	(0.45)	(0.45)	(2.07)	(2.06)	(2.11)	(0.78)	(0.78)	(0.81)
Employment index	–0.86***	–0.86***	–1.10***	–1.81**	–1.80**	–2.02***	–0.49*	–0.49*	–0.57**
	(0.30)	(0.30)	(0.30)	(0.73)	(0.73)	(0.73)	(0.28)	(0.28)	(0.29)
Obs.	2,682	2,682	2,682	2,682	2,682	2,682	2,682	2,682	2,682
RMSE	0.42	0.42	0.43	1.59	1.59	1.60	0.65	0.65	0.66
(iv) By province and profession									
COVID-19 period	0.62**	0.63**	0.50*	1.37	1.73	1.80	0.76	0.89	0.96
	(0.30)	(0.30)	(0.26)	(1.31)	(1.44)	(1.48)	(0.50)	(0.55)	(0.58)
New cases (roll av.)	–0.05	–0.05	–0.04	–0.29***	–0.14*	–0.14*	–0.08**	–0.02	–0.00
	(0.03)	(0.03)	(0.04)	(0.08)	(0.08)	(0.08)	(0.04)	(0.04)	(0.03)
Stringency index	–1.75***	–1.77***	–1.87***	–0.64	–0.55	–0.53	–1.03	–1.00	–1.02
	(0.60)	(0.59)	(0.52)	(2.45)	(2.64)	(2.69)	(0.95)	(1.02)	(1.07)
Mobility index	–0.63*	–0.64*	–0.73*	–0.64	–1.08	–1.22	–0.11	–0.28	–0.37
	(0.36)	(0.36)	(0.37)	(1.42)	(1.46)	(1.47)	(0.60)	(0.61)	(0.62)
Employment index	–1.05***	–1.06***	–1.40***	–2.69***	–2.10***	–2.20***	–0.86***	–0.65**	–0.63**
	(0.33)	(0.33)	(0.32)	(0.72)	(0.70)	(0.70)	(0.27)	(0.27)	(0.27)
Obs.	22,670	22,670	22,670	22,670	22,670	22,670	22,670	22,670	22,670
RMSE	1.06	1.07	1.22	3.18	3.16	3.33	1.32	1.32	1.44

Note: this table mirrors Table 5, the only difference being the specification of unit-level trends; sub-column (a) is the unchanged baseline specification; in sub-column (b) we remove a linear pre-trend for each panel unit in a zero-stage regression; in sub-column (c) we remove a quadratic pre-trend for each panel unit; panels (i)–(iv) indicate the level of aggregation at which panel units are defined (and outcomes measured); dependent variables indicated in the main column headers; standard control variables, including the one-period lag (log.) of active workers, month/year, and unit fixed effects included throughout; all fixed effects are specified separately for each panel unit; for panel (i) Newey–West standard errors are reported (in parentheses); for all other panels, standard errors are clustered at the year × week level.

Source: authors' estimates.

To further consider the robustness of our results we return to the complete model estimated at the province × profession level, as in Equation (2), and apply a series of sample restrictions. These are reported in Table 7. In panel (i) of the table we raise the pre-COVID observation count threshold (previously fixed at 25) to 50, 100, and 200 when moving from sub-columns (a) to (c) consecutively. In panel (ii) we limit the analysis to each of the three broad regions of the country: in sub-columns (a) the south; sub-columns (b) the centre; and sub-columns (c) the north. In panel (iii) we consider specific sub-groups of professions, as defined in Appendix Table A1, namely: in sub-columns (a) the industrial professions; in sub-columns (b) the remaining personal/retail service professions; and in sub-columns (c) the combination of all professions primarily exercised in person. While there is some variation in coefficient estimates, our main results are remarkably consistent. Put differently, our findings are similar across provinces (regions) and professions, and there is no evidence they are driven by idiosyncratic responses in any one of them.

Table 7: Least squares analysis of complete model applying sub-sample restrictions

	(1) Δ Workers			(2) Contact rate			(3) Agreement rate		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
(i) Cell size restrictions									
COVID-19 period	0.52	0.49	0.49	1.89	1.86	1.60	0.89	0.96*	0.84*
	(0.32)	(0.32)	(0.34)	(1.47)	(1.39)	(1.26)	(0.56)	(0.52)	(0.44)
New cases (roll av.)	–0.15***	–0.15***	–0.16***	–0.25**	–0.21*	–0.16	–0.09	–0.07	–0.03
	(0.05)	(0.06)	(0.05)	(0.12)	(0.13)	(0.13)	(0.05)	(0.05)	(0.06)
Stringency index	–1.64***	–1.51***	–1.36**	–1.97	–2.07	–1.35	–1.59	–1.60	–1.12
	(0.57)	(0.57)	(0.58)	(2.83)	(2.64)	(2.38)	(1.11)	(1.03)	(0.88)
Mobility index	–0.68	–0.65	–0.58	–1.45	–1.09	–0.07	–0.54	–0.06	0.30
	(0.41)	(0.42)	(0.44)	(1.76)	(1.64)	(1.62)	(0.74)	(0.68)	(0.68)
Employment index	–1.34***	–1.22***	–1.23***	–3.35***	–3.35***	–3.03***	–1.35***	–1.27***	–0.80**
	(0.33)	(0.34)	(0.34)	(1.00)	(0.94)	(0.87)	(0.40)	(0.38)	(0.35)
Obs.	19,094	13,730	7,770	19,094	13,730	7,770	19,094	13,730	7,770
RMSE	1.11	1.07	0.85	3.68	3.23	2.64	1.65	1.44	1.17
(ii) Regions									
COVID-19 period	0.38	0.72	0.47	1.88	1.68	2.00	1.15*	0.57	0.74
	(0.32)	(0.51)	(0.29)	(1.81)	(1.26)	(1.51)	(0.62)	(0.54)	(0.52)
New cases (roll av.)	–0.25***	–0.19*	–0.09**	–0.09	–0.53**	–0.29	–0.07	–0.20***	–0.04
	(0.06)	(0.11)	(0.04)	(0.20)	(0.21)	(0.21)	(0.08)	(0.08)	(0.08)
Stringency index	–1.48***	–2.42**	–1.10**	–2.20	–3.29	–1.10	–2.62**	–1.41	–0.94
	(0.53)	(0.98)	(0.55)	(3.55)	(2.44)	(2.98)	(1.25)	(1.07)	(1.12)
Mobility index	–0.71	–0.72	–0.48	–3.39	–0.83	–0.47	–1.83*	0.36	–0.41
	(0.48)	(0.49)	(0.39)	(2.47)	(1.95)	(1.99)	(0.99)	(0.66)	(0.85)
Employment index	–1.47***	–1.20***	–1.09***	–5.02***	–2.32**	–2.72**	–1.46***	–1.54***	–1.26***
	(0.45)	(0.37)	(0.27)	(1.27)	(1.16)	(1.05)	(0.52)	(0.50)	(0.44)
Obs.	8,195	7,902	6,573	8,195	7,902	6,573	8,195	7,902	6,573
RMSE	0.88	1.77	0.81	4.38	3.95	3.35	1.85	1.79	1.76
(iii) Specific professions									
COVID-19 period	0.40*	0.71	0.42	0.88	3.58	1.87	0.48	1.56*	0.90
	(0.24)	(0.49)	(0.31)	(1.03)	(2.40)	(1.54)	(0.40)	(0.87)	(0.60)
New cases (roll av.)	–0.14***	–0.14**	–0.14***	–0.31***	–0.15	–0.18	–0.06	–0.11	–0.07
	(0.03)	(0.06)	(0.05)	(0.11)	(0.19)	(0.12)	(0.04)	(0.08)	(0.06)
Stringency index	–1.49***	–1.93**	–1.70***	0.32	–5.63	–2.79	–0.96	–2.62	–1.93
	(0.43)	(0.86)	(0.57)	(1.97)	(4.65)	(2.96)	(0.79)	(1.74)	(1.19)
Mobility index	–0.53	–0.92	–0.77*	–2.05	–1.15	–1.66	–0.42	–0.93	–0.75
	(0.33)	(0.57)	(0.41)	(1.45)	(2.62)	(1.82)	(0.56)	(1.10)	(0.80)
Employment index	–1.51***	–1.23***	–1.59***	–2.79***	–4.01**	–4.38***	–1.01**	–1.80***	–1.77***
	(0.46)	(0.32)	(0.39)	(1.00)	(1.58)	(1.23)	(0.42)	(0.68)	(0.49)
Obs.	15,948	6,722	14,922	15,948	6,722	14,922	15,948	6,722	14,922
RMSE	0.80	1.58	1.17	3.53	4.47	3.78	1.43	2.29	1.80

Note: this table exclusively employs the specification reported in panel (iv) sub-column (c) of Table 5, namely being the full model with quadratic unit-specific trends at the province × profession level; here, panels and sub-columns implement alternative sample restrictions; in panel (i) we increase the pre-COVID cell size threshold (number of workers) to 50, 100, and 200 in sub-columns (a)-(c) respectively; in panel (ii) we look at the (a) southern, (b) centre, and (c) northern regions; and in panel (iii) we consider sub-groups of professions, namely: (a) the industrial professions, (b) remaining personal/retail service professions, and (c) professions primarily exercised indoors; dependent variables indicated in the main column headers; standard control variables, including the one-period lag (log.) of active workers, month/year, and unit fixed effects included throughout; standard errors (in parentheses) are clustered at the year × week level.

Source: authors' estimates.

5 Event study analysis

As a final exercise we probe the overall dynamics of the COVID-19 response on both the supply and demand sides of the market for informal labour services. The previous section indicated that different effect channels *have* operated in different directions, meaning the net effect is not immediately obvious. Furthermore, as Wolfers (2006) highlights, response dynamics may vary over time, contrary to what was implicitly assumed above. To investigate possible heterogeneity in the net response over time, we adopt an event study framework. In crude terms, the intention is to track an outcome variable before and after the event of interest (exposure to some intervention or shock) after removing effects of all other (nuisance) confounding factors, such as seasonal factors or pre-existing trends. While in our case we cannot compare a treated group to a set of controls, we can nonetheless verify whether any kind of discontinuity in the trajectory of the outcome coincides with the pandemic period.

Our generic event study specification is represented as follows:

$$y_{ijt} = \alpha_{ij} + \sum_{n=-a}^{b} \beta_n \times 1[t=n] + X'_{ijt}\eta + \text{Year}_{ijt} + \text{Month}_{ijt} + \varepsilon_{ijt} \tag{5}$$

where the set of coefficients: $\beta_{-a}, \ldots, \beta_b$ represent period-specific effects; and scalars $-a, b$ mark the start and end time periods of interest. We set $t = 0$ to coincide with the beginning of the COVID-19 period; so, β_0 captures the effect at the start of the event period. In practice, to facilitate interpretation, we estimate separate coefficients for sequential blocks of four weeks and collapse all observations more than 24 weeks before the pandemic onset into the first coefficient; and we bundle the last few observations into the final coefficient. Thus, the analysis window covers approximately 6 months 'before' and 12 months 'after' the start of the pandemic. Furthermore, in order to normalize the coefficients spanning the (long) pre-event period, we follow the guidance of Borusyak and Jaravel (2018) and normalize two temporally distant coefficients to zero (namely, months -5 and -1). As before, we run results for models both with and without adjustment for pre-existing trends.

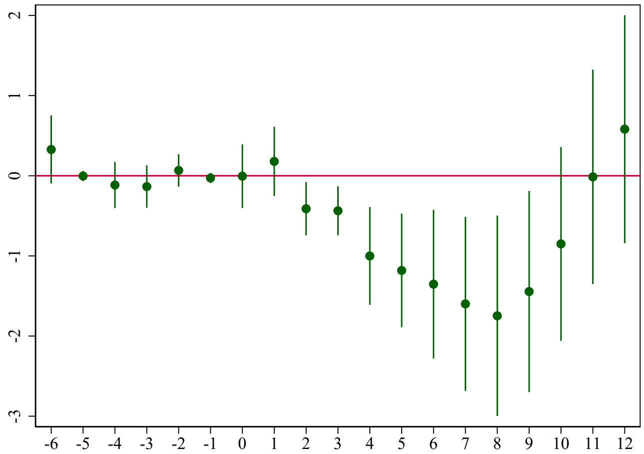
Figures 5–7 visualize the event study analysis for econometric models estimated at the national, province, and province $\times$ profession levels, respectively, in all cases making prior adjustments for quadratic pre-trends (as per the approach reported in sub-columns (c) of Table 6). Corresponding plots for models estimated without any adjustment for (prior) trends are found in Appendix Figures A2–A4. The plots show the point estimates and 95 per cent confidence intervals for the full set of β_n coefficients.

Overall, the figures reveal a heterogeneous (over time) dynamic response to the COVID-19 pandemic in the market for informal labour services. Two particular points merit note. First, none of the plots provide evidence of systematic trends in the outcomes prior to the crisis (i.e. before period zero); and this remains the case even when we do not adjust for possible pre-trends. In contrast, all outcomes appear to broadly follow three broad phases during the COVID-19 period—namely: (1) a positive bump at the onset of the crisis (weeks 1–4; periods 0 and 1), followed by (2) a downturn through most of 2020 (periods 2–8), and (3) a recovery from week 35 onwards (roughly, from November 2020).

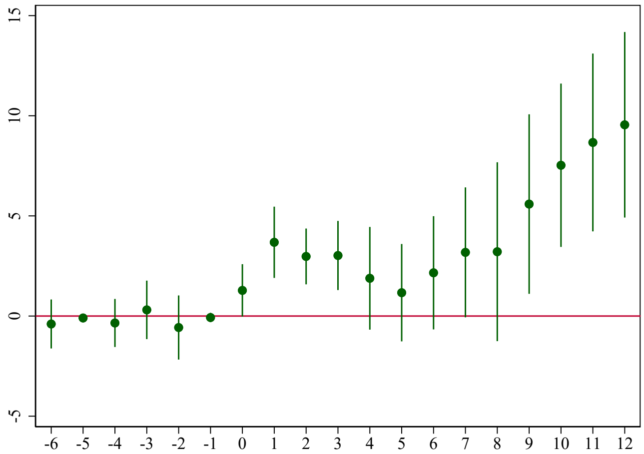
The initial positive response to the pandemic is most evident on the demand side. Nonetheless, all outcomes show a (trend) decline over period (blocks) 1–5, which effectively coincides with the state of emergency. As discussed in Section 3, this was also a period in which there was no significant cumulative numbers of infections. Put differently, in Figure 7 the response at period 1 (corresponding to 4–7 weeks after the first case) is positive and significant for all outcomes. However, this is not sustained and the supply side suffers a particularly dramatic decline, with coefficients in the negative domain from periods 2 through 8. In contrast, the demand side does not enter negative territory and registers large positive coefficients (point estimates) in the final periods.

Figure 5: Event study results estimated at the national level (adjusting for quadratic pre-trend)

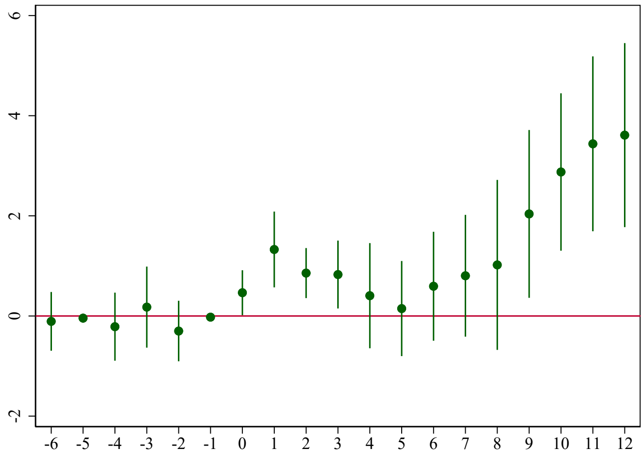
(a) Δ Workers



(b) Contact rate



(c) Agreement rate

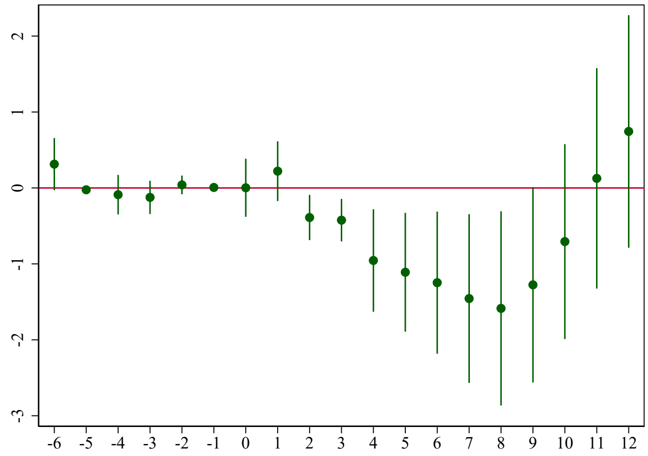


Note: the figure plots period-specific estimates as per Equation (5) using data aggregated to the national level with prior adjustment for a quadratic pre-trend; standard errors clustered to the year × week level.

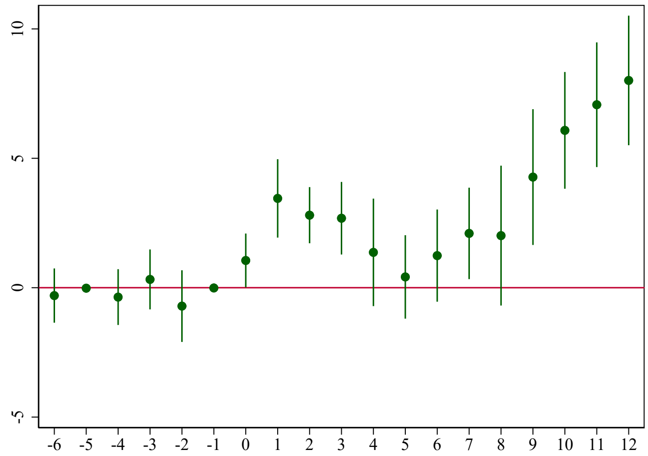
Source: authors' estimates.

Figure 6: Event study results estimated at the province level (adjusting for quadratic pre-trend)

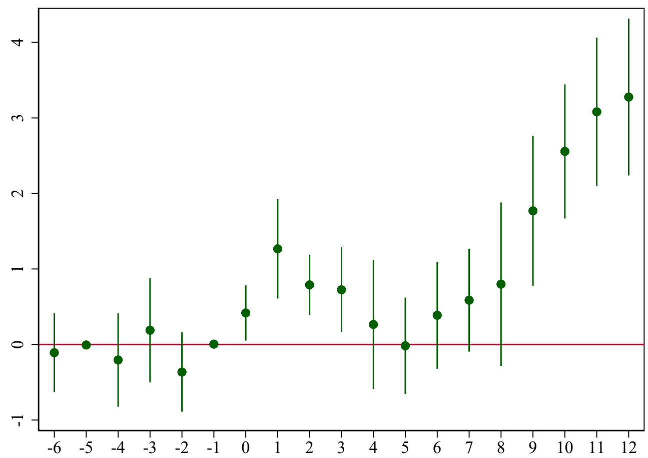
(a) Δ Workers



(b) Contact rate



(c) Agreement rate

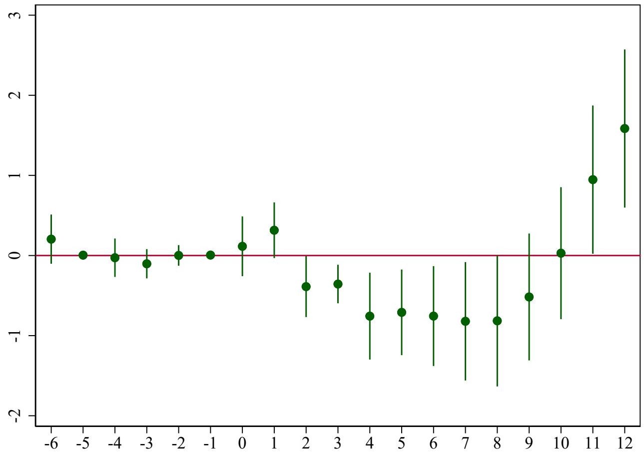


Note: the figure plots period-specific estimates as per Equation (5) using data aggregated to the province level with prior adjustment for a quadratic pre-trend; standard errors clustered to the year × week level.

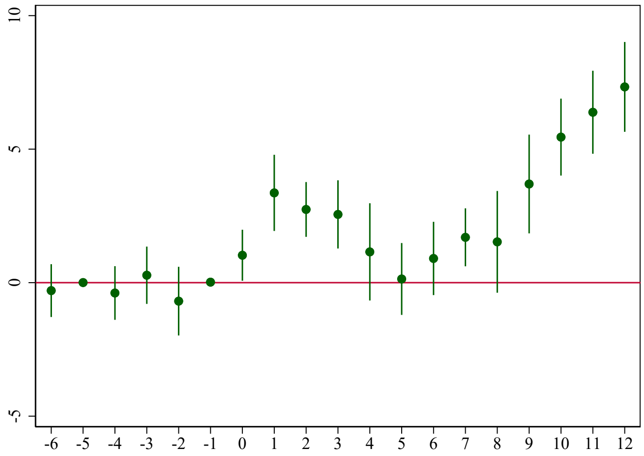
Source: authors' estimates.

Figure 7: Event study results estimated at the province × profession level (adjusting for quadratic pre-trend)

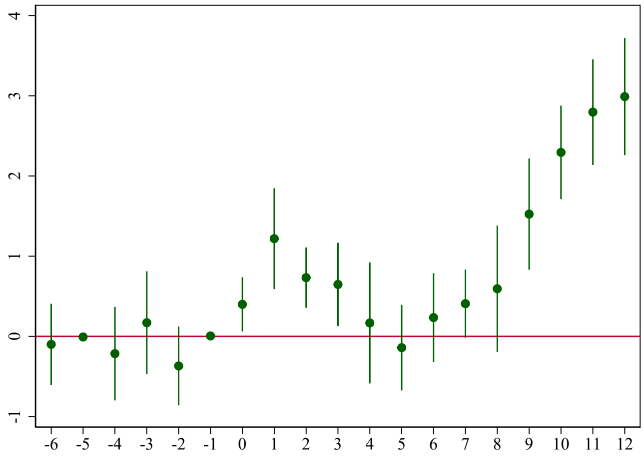
(a) Δ Workers



(b) Contact rate



(c) Agreement rate



Note: the figure plots period-specific estimates as per Equation (5) using data aggregated to the province × profession level with prior adjustment for a quadratic pre-trend; standard errors clustered to the year × week level.

Source: authors' estimates.

We can also use the event study estimates to derive the net effect associated with the pandemic, calculated as the simple average of the set of coefficients in the COVID-19 period only—that is, the mean of $\beta_0 \ldots, \beta_{12}$.[21] These point estimates and 95 per cent confidence intervals are reported in column (1) of Table 8, shown at different levels of aggregation (denoted 1–4), all based on models adjusting for quadratic pre-trends. Regardless of the level of aggregation employed, the results are clear and qualitatively consistent with the crude (aggregate) regression discontinuity results presented in Section 4.2. Namely, the net effect on the supply side is not different from zero, suggesting the early decline was offset later in the period overall. On the supply side, the net effect is positive, amounting to roughly a 3 percentage point increase in the contact rate and a 1 percentage point increase in the task agreement rate relative to the 'no shock' counterfactual. Critically, these effect magnitudes are large in relative terms. Comparing against the corresponding average outcomes recorded in 2019, they both represent an approximate 50 per cent increase.

Table 8: Average of event study coefficients during the COVID-19 period

		(1) Baseline		(2) Residualized	
Outcome	Level	Mean	95 per cent CI	Mean	95 per cent CI
Δ Workers	1	–0.71	[–1.30, –0.13]	–0.48	[–1.02, 0.06]
	2	–0.29	[–0.67, 0.09]	–0.04	[–0.41, 0.33]
	3	–0.62	[–1.25, 0.01]	–0.40	[–1.02, 0.21]
	4	–0.16	[–0.57, 0.24]	0.13	[–0.27, 0.54]
Contact rate	1	4.15	[2.15, 6.14]	2.02	[–0.06, 4.11]
	2	3.02	[1.76, 4.29]	0.83	[–0.53, 2.19]
	3	3.27	[2.13, 4.41]	0.91	[–0.38, 2.20]
	4	2.92	[2.15, 3.69]	0.66	[–0.28, 1.59]
Agreement rate	1	1.42	[0.65, 2.18]	0.65	[–0.16, 1.47]
	2	1.00	[0.52, 1.48]	0.20	[–0.33, 0.72]
	3	1.22	[0.77, 1.67]	0.37	[–0.15, 0.88]
	4	1.07	[0.76, 1.38]	0.26	[–0.12, 0.64]

Note: columns (1) and (2) show the simple average of event study coefficients in the COVID-19 period only, based on models specified following Equation (5), run at alternative levels of aggregation (1 = national; 2 = by province; 3 = by profession; 4 = province × profession) and applying prior adjustment for a quadratic pre-trend; column (2) makes an additional prior adjustment for the four observed channels of interest via a residualization procedure; 95 per cent confidence intervals are shown in brackets.

Source: authors' estimates.

Of course, event study estimates capture the combined impact of various channels at any given point in time, as well as other (unobserved) period-specific effects. This begs the question: what share of the estimated coefficients can be attributed to the observed channels, as represented by the proxies used in Section 4? To provide an indicative answer to this question, we remove the contribution of the observed channels via a further prior adjustment procedure. Namely, we project each outcome against the four proxy variables; only then do we estimate the event study regression (see Equation 5), using the residuals derived from this prior model. The mean results from this analysis are reported in column (2) of Table 8, and selected corresponding event study plots are found in Appendix Figures A5–A7. In all but one case the mean (net effect) estimate shrinks towards zero, and in so doing they generally also fall in magnitude by at least one-half. Moreover, all estimates of the 95 per cent confidence interval now span zero, suggesting that at least a substantial component of the primary event study results (in column 1) are driven by these effect channels.

[21] As is well-known, difference-in-difference estimates—captured in column (1) of Table 4—will not generally coincide with the simple average of the corresponding event study coefficients (see Gibbons et al. 2019; Goodman-Bacon 2018).

6 Conclusion

This paper started out by highlighting the uneven nature of the effects of the COVID-19 pandemic. Despite clear evidence of a severe negative economic shock in general, the combination of a shift towards online platforms and changes in the composition of demand have also created opportunities. In particular, we hypothesized that some positive effects may be present for the specific domain of manual freelancers on online marketplaces. Restrictions on formal activities or services provided at fixed locations may divert demand elsewhere, encouraging individuals to use new channels to search for workers. More time spent at home may have induced individuals to complete home repair projects, raising demand for specific types of goods and services. And informal services may be inferior in nature and price-competitive, so shocks to income may increase demand in this segment.

Connecting to the relatively small literature on the impacts of the pandemic on 'gig economy' workers (Cao et al. 2020), the purpose of this paper was to investigate how such dynamics have played out in Mozambique, both overall and through different potential channels of impact. To do so, we leveraged data from the *Biscate* platform, a digital tool to facilitate the matching of technical-professional workers to demand for specific tasks (e.g. finding a plumber to repair a sink), and analysed how observable components of supply and demand have changed over the pandemic period. Running a wide range of different models, at alternative levels of aggregation and controlling for latent (pre-)trends, we found remarkably consistent results. Outcomes on both the supply and demand sides, respectively captured by the growth rate in active workers on the platform and rates of contact and task agreement, showed a strong negative partial association with the monthly (sector-specific) employment index. In other words, the substantial worsening of employment conditions during the COVID-19 period was associated with increases in both supply and demand on the platform. We also found evidence for a moderate negative effect on both sides of the market associated with the (rolling average) of daily positive COVID-19 cases. For instance, a doubling of cases was associated with a 0.18 fall in the rate of growth of workers. And on the supply side, we found a strong negative impact of official restrictions, proxied by the government stringency index.

An event study analysis helped nuance our understanding of these trends. Here we saw three broad phases of the response—an immediate positive response (particularly on the demand side), a longer downturn (most pronounced on the supply side), followed by strong positive growth in the most recent period, which coincided with the most acute wave of infections. Looking on average over the pandemic period, we concluded that positive and negative influences on the supply of workers yielded an approximate net average effect of zero relative to the counterfactual of no shock. On the demand side, we saw net increases overall. Up to the end of March 2020, we estimate the pandemic has been associated with a 1 percentage point increase in the overall task agreement rate, which corresponds to a 50 per cent increase above the mean agreement rate in 2019.

We make no claim that our analysis is representative of the informal sector in Mozambique. Workers registered on *Biscate* are predominantly urban, literate, have some professional experience, and have regular access to digital tools (at least a mobile phone). As such, they may have already been in a relatively privileged position compared to other workers in the informal sector. Even so, some broader lessons can be drawn. Perhaps most obviously, disruption to usual market conditions often brings new opportunities in specific segments. Digital marketplaces, such as *Biscate*, that facilitate labour matching and support price competition are likely to be important, being useful vehicles through which more entrepreneurial or quick-to-adapt individuals can thrive. Clearly, preferences to use these tools have not been diminished by the COVID-19 shock. The absence of negative overall impacts in our data also supports the view that informal work can be an important shock-absorber, especially where government assistance either to formal sector workers or affected communities has been minimal, as in Mozambique. In turn, we recommend that further support to digital marketplaces for informal (freelance) labour may be a relevant tool in the poverty-reduction toolbox, especially where they can be combined with products to actively enhance income smoothing.

References

Alfaro, L., O. Becerra, and M. Eslava (2020). 'EMEs and COVID-19: Shutting Down in a World of Informal and Tiny Firms'. Working Paper 27360. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w27360

Aly, A., J. Guambe, S. Jones, I. Manhique, S. Matola, E. Mazive, J. Mouco, Z. Numaio, and O.S. e Gimelgo Xirinda (2021). 'O impacto da COVID-19 no sector de turismo: O caso da Praia de Tofo'. Unpublished Report. Maputo: Ministério da Economia e Finanças.

Balde, R., M. Boly, and E. Avenyo (2020). 'Labour Market Effects of COVID-19 in Sub-Saharan Africa: An Informality Lens from Burkina Faso, Mali and Senegal'. MERIT Working Paper 2020-022. Maastricht: UNU-MERIT.

Bandiera, O., I. Barankay, and I. Rasul (2005). 'Social Preferences and the Response to Incentives: Evidence from Personnel Data'. *Quarterly Journal of Economics*, 120(3): 917–62. https://doi.org/10.1093/qje/120.3.917

Barletta, G., F. Castigo, E.-M. Egger, M. Keller, V. Salvucci, and F. Tarp (2021). 'The Impact of COVID-19 on Consumption Poverty in Mozambique'. Working Paper. Helsinki: UNU-WIDER.

Barnes, H., G. Espi-Sanchis, M. Leibbrandt, D. McLennan, M. Noble, J. Pirttilä, W. Steyn, B. van Vrede, and G. Wright (2021). 'Analysis of the Distributional Effects of COVID-19 and State-Led Remedial Measures in South Africa'. WIDER Working Paper 2021/68. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/2021/006-1

Bertho, R., M. Chelengo, S. Jones, M. Keller, I.H. Mussagy, D. van Seventer, and F. Tarp (2021). 'The Macroeconomic Impact of COVID-19 in Mozambique: A Social Accounting Matrix Approach'. Working Paper. Helsinki: UNU-WIDER.

Bhuller, M., T. Havnes, E. Leuven, and M. Mogstad (2013). 'Broadband Internet: An Information Superhighway to Sex Crime?'. *Review of Economic Studies*, 80(4): 1237–66. https://doi.org/10.1093/restud/rdt013

Borusyak, K., and X. Jaravel (2018). 'Revisiting Event Study Designs, with an Application to the Estimation of the Marginal Propensity to Consume'. Unpublished Working Paper. Cambridge, MA: Harvard University.

Bussolo, M., A. Kotia, and S. Sharma (2021). 'Workers at Risk: Panel Data Evidence on the COVID-19 Labor Market Crisis in India'. Policy Research Working Paper 9584. Washington, DC: World Bank Group. https://doi.org/10.1596/1813-9450-9584

Cao, X., D. Zhang, and L. Huang (2020). 'The Impact of COVID-19 Pandemic on Gig Economy Labor Supply'. Working paper, NYU Stern School of Business, Rochester, NY. http://dx.doi.org/10.2139/ssrn.3666725

Chang, H.-H., and C.D. Meyerhoefer (2021). 'COVID-19 and the Demand for Online Food Shopping Services: Empirical Evidence from Taiwan'. *American Journal of Agricultural Economics*, 103(2): 448–65. https://doi.org/10.1111/ajae.12170

Egger, D., E. Miguel, S.S. Warren, A. Shenoy, E. Collins, D. Karlan, D. Parkerson, A.M. Mobarak, G. Fink, C. Udry, M. Walker, J. Haushofer, M. Larreboure, S. Athey, P. Lopez-Pena, S. Benhachmi, M. Humphreys, L. Lowe, N.F. Meriggi, A. Wabwire, C.A. Davis, U.J. Pape, T. Graff, M. Voors, C. Nekesa, and C. Vernot (2021). 'Falling Living Standards During the COVID-19 Crisis: Quantitative Evidence from Nine Developing Countries'. *Science Advances*, 7(6): eabe0997. https://doi.org/10.1126/sciadv.abe0997

Garrote Sanchez, D., N. Gomez Parra, C. Ozden, B. Rijkers, M. Viollaz, and H. Winkler (2021). 'Who on Earth Can Work from Home?'. *The World Bank Research Observer*, 36(1): 67–100. https://doi.org/10.1093/wbro/lkab002

Gibbons, C.E., J.C.S. Serrato, and M.B. Urbancic (2019). 'Broken or Fixed Effects?' *Journal of Econometric Methods*, 8(1). https://doi.org/10.1515/jem-2017-0002

Goodman-Bacon, A. (2018). 'Difference-in-Differences with Variation in Treatment Timing'. Working Paper 25018. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w25018

Horton, J.J. (2021). 'The Ruble Collapse in an Online Marketplace: Some Lessons for Market Designers'. Working Paper 28702. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w28702

ILO (2020). 'ILO Monitor: COVID-19 and the World of Work'. Third edition. Briefing Note. Geneva: ILO.

ILO (2021). 'ILO Monitor: COVID-19 and the World of Work'. Seventh edition. Briefing Note. Geneva: ILO.

INE (2020). 'Resultados Do Inquérito Sobre Impacto Do COVID-19 Nas Empresas: Abril-Junho 2020'. Technical report. Maputo: Instituto Nacional de Estatística.

Jones, S., and F. Tarp (2013). 'Jobs and Welfare in Mozambique'. Working Paper 2013/045. Helsinki: UNU-WIDER.

Jones, S., and F. Tarp (2015). 'Priorities for Boosting Employment in Sub-Saharan Africa: Evidence for Mozambique'. *African Development Review*, 27(S1): 56–70. https://doi.org/10.1111/1467-8268.12139

Jones, S., and F. Tarp (2016). 'Mozambique: Growth Experience Through an Employment Lens'. In H. Bhorat and F. Tarp (eds), *Africa's Lions: Growth Traps and Opportunities for Six African Economies*.Washington, DC: Brookings Institution Press.

Kleven, H.J., C. Landais, E. Saez, and E. Schultz (2014). 'Migration and Wage Effects of Taxing Top Earners: Evidence from the Foreigners' Tax Scheme in Denmark'. *Quarterly Journal of Economics*, 129(1): 333–78. https://doi.org/10.1093/qje/qjt033

Mukhra, R., K. Krishan, and T. Kanchan (2020). 'COVID-19 Sets Off Mass Migration in India'. *Archives of Medical Research*, 51(7): 736–38. https://doi.org/10.1016/j.arcmed.2020.06.003

Oster, E. (2018). 'Diabetes and Diet: Purchasing Behavior Change in Response to Health Information'. *American Economic Journal: Applied Economics*, 10(4): 308–48. https://doi.org/10.1257/app.20160232

Padhan, R., and K. Prabheesh (2021). 'The Economics of COVID-19 Pandemic: A Survey'. *Economic Analysis and Policy*, 70: 220–37. https://doi.org/10.1016/j.eap.2021.02.012

Reynolds, H., and C. Amrhein (1998). 'Some Effects of Spatial Aggregation on Multivariate Regression Parameters'. In D.A. Griffith, C.G. Amrhein, and J.-M. Huriot (eds), *Econometric Advances in Spatial Modelling and Methodology: Essays in Honour of Jean Paelinck*. Boston, MA: Springer.

Stephany, F., M. Dunn, S. Sawyer, and V. Lehdonvirta (2020). 'Distancing Bonus or Downscaling Loss? The Changing Livelihood of Us Online Workers in Times of COVID-19'. *Tijdschrift voor Economische en Sociale Geografie*, 111(3): 561–73. https://doi.org/10.1111/tesg.12455

Sumner, A., C. Hoy, and E. Ortiz-Juarez (2020). 'Estimates of the Impact of COVID-19 on Global Poverty'. Working Paper 2020/43. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/2020/800-9

UNDP (2020). 'Inquérito Sobre O Impacto Do COVID-19 No Sector Informal De Maputo: Resultados Do Estudo Da Linha De Base'. Unpublished Report. Mozambique: United Nations Development Programme.

Valsecchi, M., and R. Durante (2020). 'Internal Migration and the Spread of COVID-19'. Working Paper w0276. Moscow: New Economic School (NES).

Wolfers, J. (2006). 'Did Unilateral Divorce Laws Raise Divorce Rates? A Reconciliation and New Results'. *American Economic Review*, 96(5): 1802–20. https://doi.org/10.1257/aer.96.5.1802

Appendix A

Table A1: Classification of professions on the *Biscate* platform

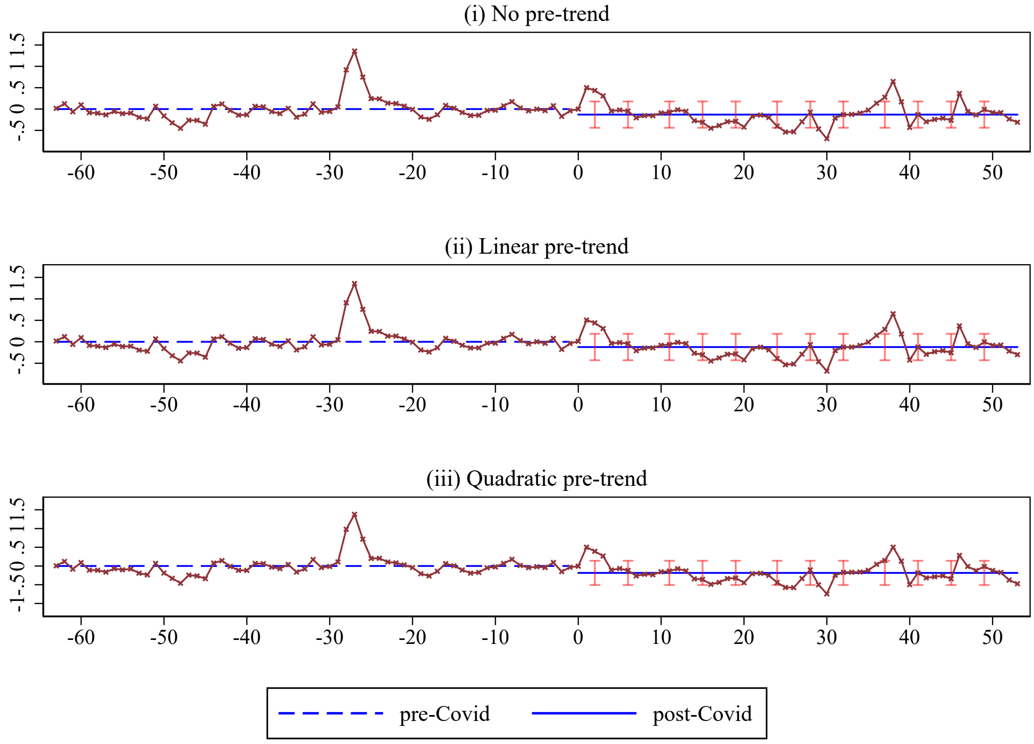
Portuguese	English	Industry	Services	In person
Cabeleireiro	Hairdressing	0	1	1
Canalização	Plumbing	1	0	0
Carpintaria	Carpentery	1	0	0
Construção e Reparação	Construction/repair	1	0	0
Costura	Sewing	0	1	1
Cozinha	Cooking	0	1	0
Electricidade	Electrician	1	0	0
Entregas	Delivery	0	1	0
Estofagem	Upholstery	1	0	0
Estética	Beauty	0	1	1
Instalação de TV	TV installation	1	0	0
Jardinagem	Gardening	1	0	0
Manicure	Manicure	0	1	1
Mecânica	Mechanic	1	0	0
Pintura	Painting	1	0	0
Reboque	Towing	1	0	0
Reparação de AC	AC repair	1	0	0
Serralharia	Metalwork	1	0	0

Note: classification, as indicated in the last three columns, are our own.

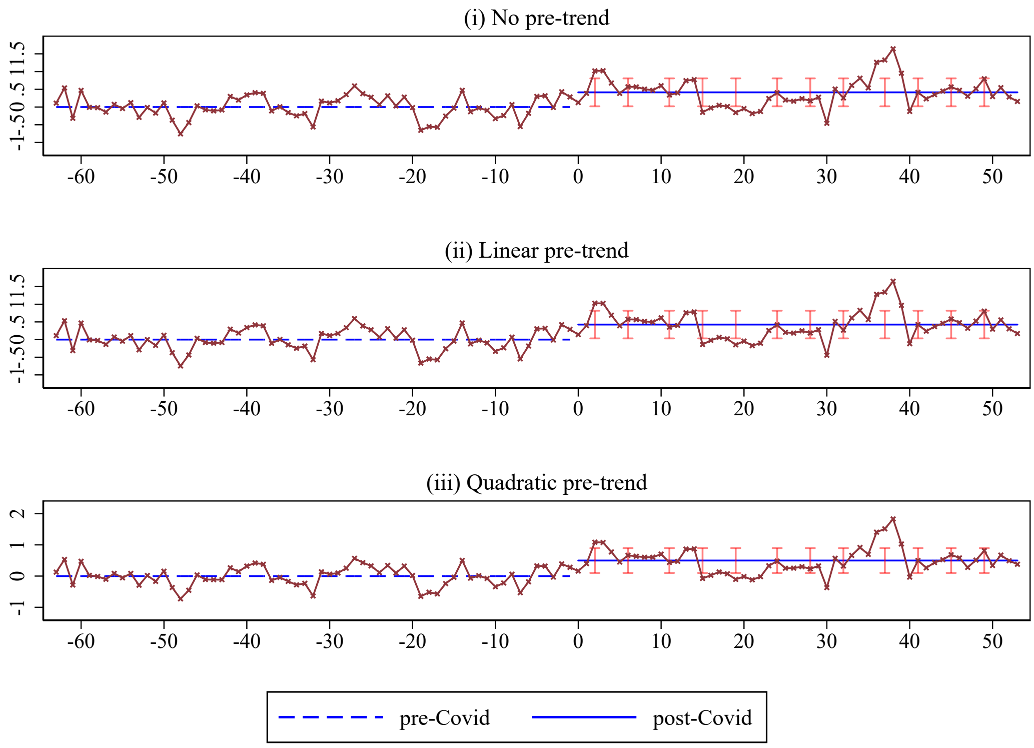
Source: authors' compilation.

Figure A1: Trajectory of aggregate outcomes after adjusting for confounding factors, including pre-trends (2019-onwards)

(a) Δ Workers



(b) Agreement rate

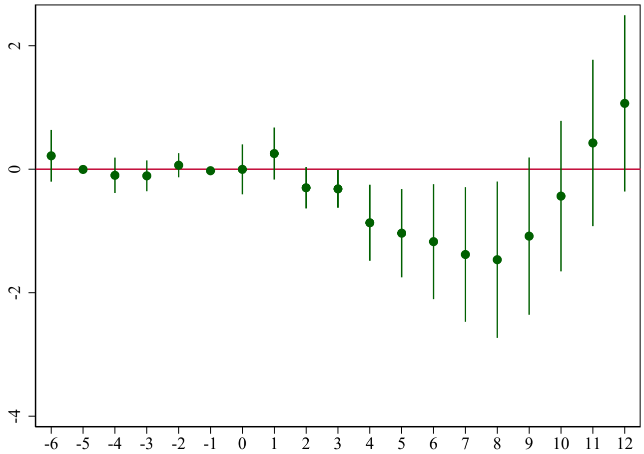


Note: the plots show trends of outcomes after removing contributions of time fixed effects and control variables; horizontal lines indicate averages before/after the start of COVID-19; sub-figures (ii) and (iii) adjust for linear and quadratic pre-trends, respectively.

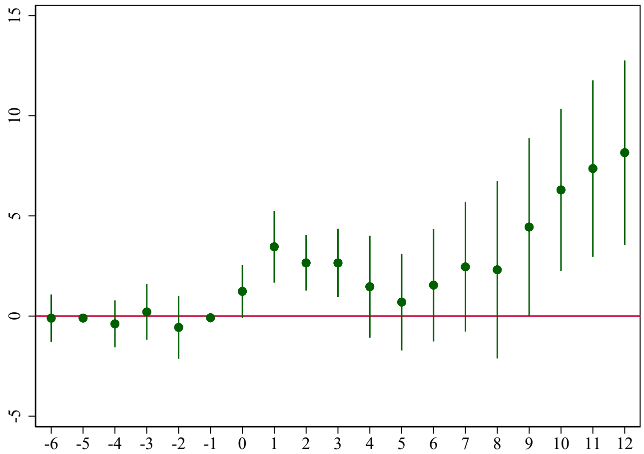
Source: authors' estimates.

Figure A2: Event study results estimated at the aggregate level

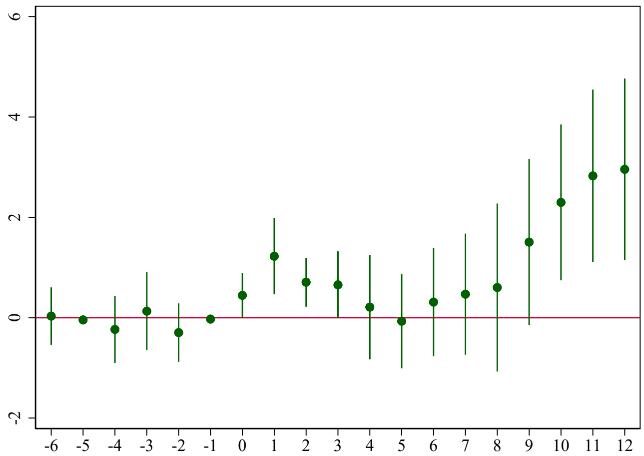
(a) ∆ Workers



(b) Contact rate



(c) Agreement rate

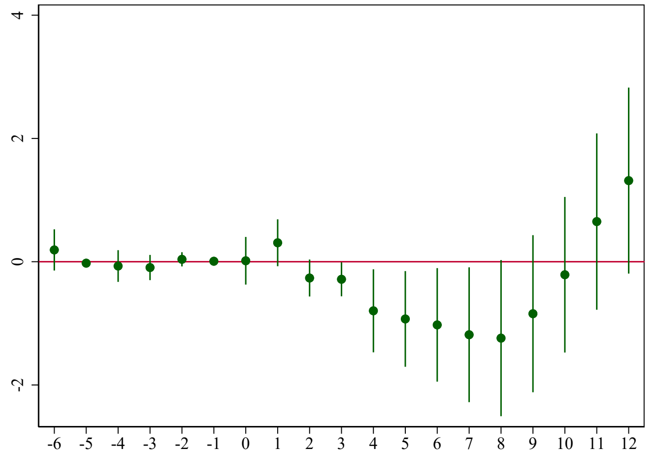


Note: the figure plots period-specific estimates as per Equation (5) using data aggregated to the national level without prior adjustment for pre-trends; standard errors clustered to the year $\times$ week level.

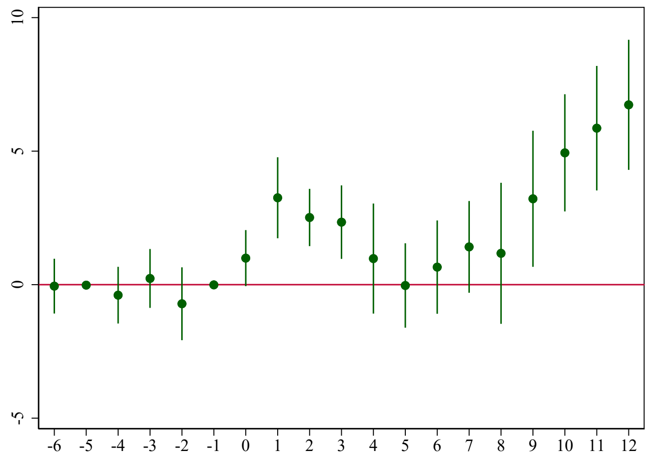
Source: authors' estimates.

Figure A3: Event study results estimated at the province level

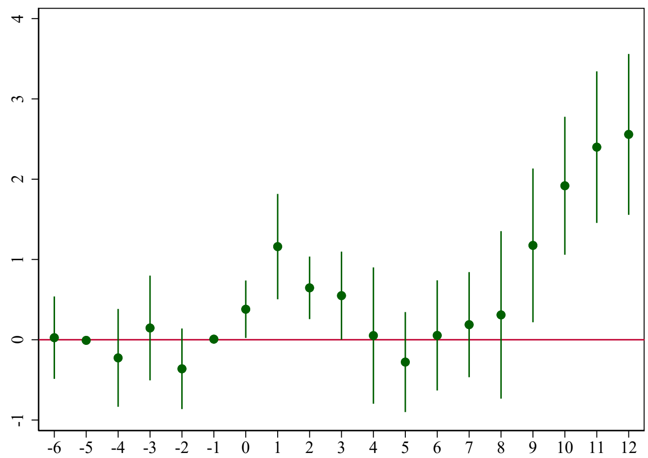
(a) Δ Workers



(b) Contact rate



(c) Agreement rate

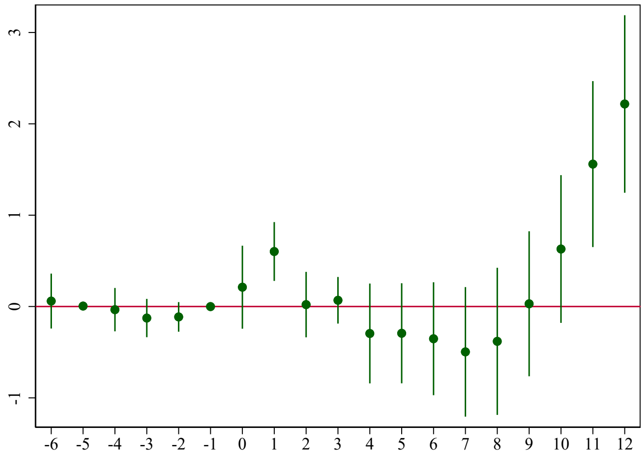


Note: the figure plots period-specific estimates as per Equation (5) using data aggregated to the province level without prior adjustment for pre-trends; standard errors clustered to the year $\times$ week level.

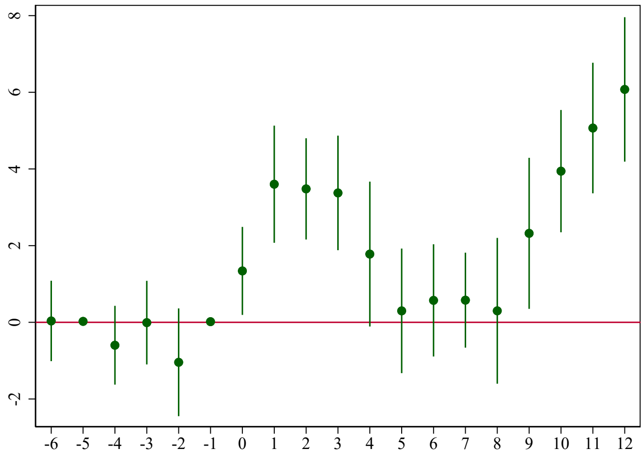
Source: authors' estimates.

Figure A4: Event study results estimated at the province × profession level

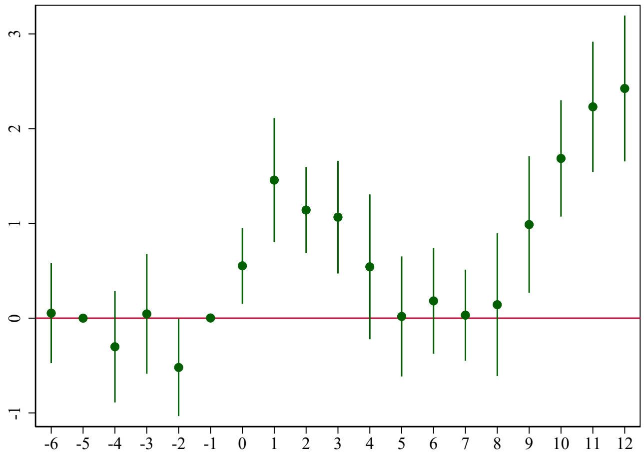
(a) Δ Workers



(b) Contact rate



(c) Agreement rate

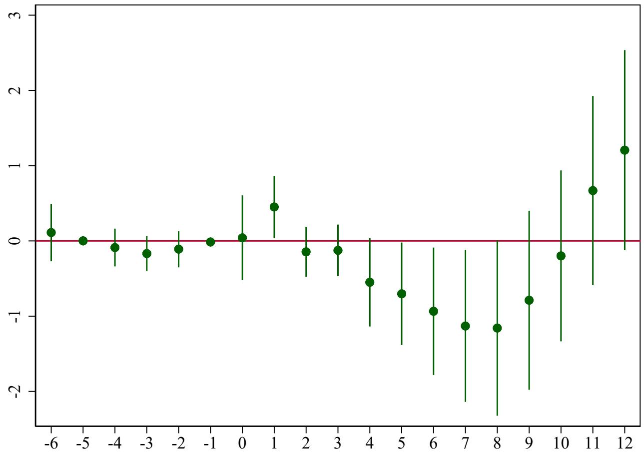


Note: the figure plots period-specific estimates as per Equation (5) using data aggregated to the province × profession level without prior adjustment for pre-trends; standard errors clustered to the year × week level.

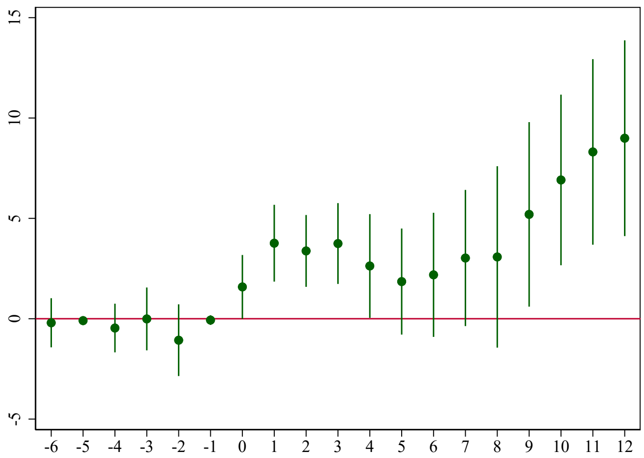
Source: authors' estimates.

Figure A5: Event study results estimated at the aggregate level with prior linear adjustment for main effect channels

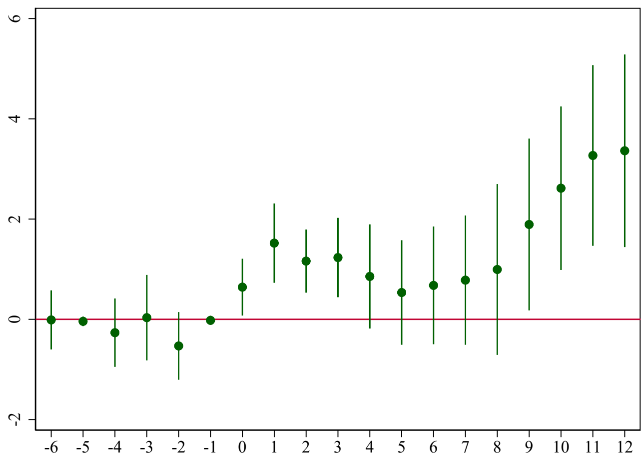
(a) Δ Workers



(b) Contact rate



(c) Agreement rate

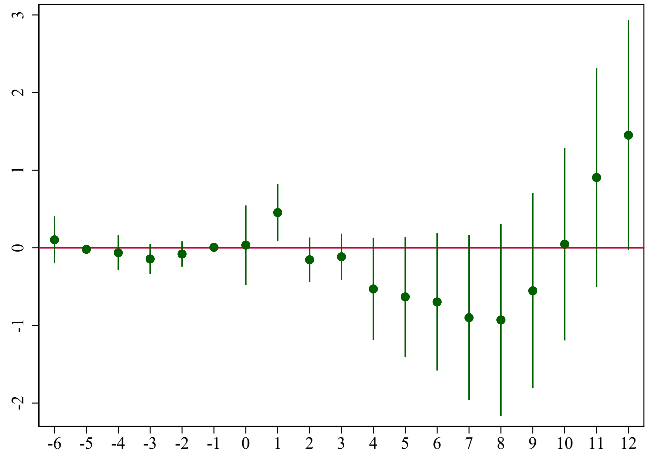


Note: the figure plots period-specific estimates as per Equation (5) using data aggregated to the national level with prior linear adjustment for the four main effect channels; standard errors clustered to the year × week level.

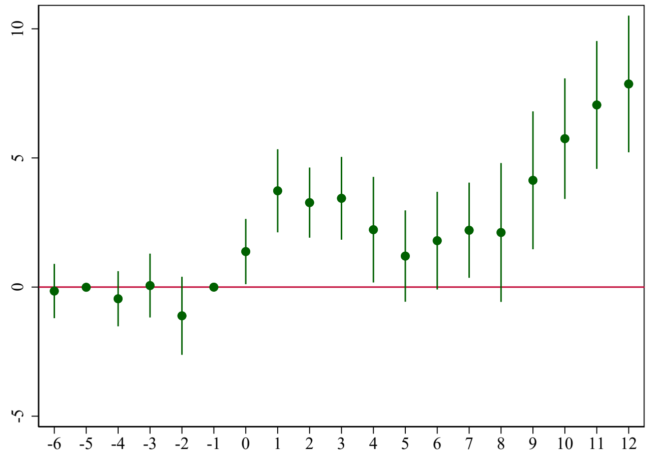
Source: authors' estimates.

Figure A6: Event study results estimated at the province level with prior linear adjustment for main effect channels

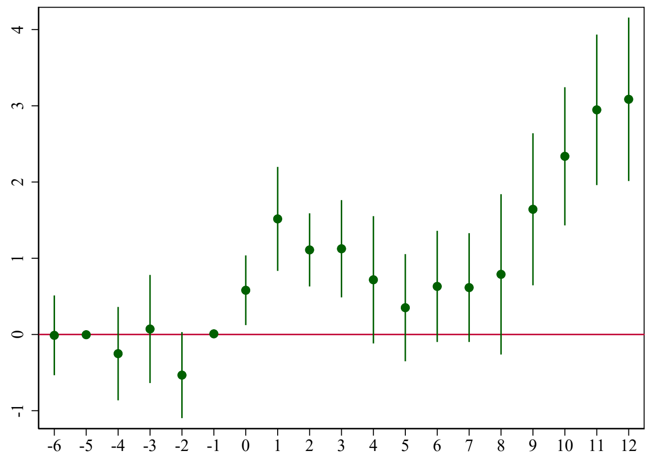
(a) Δ Workers



(b) Contact rate



(c) Agreement rate

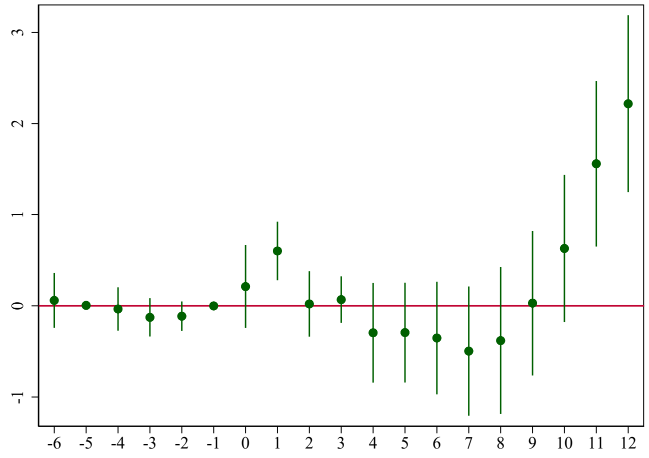


Note: the figure plots period-specific estimates as per Equation (5) using data aggregated to the province level with prior linear adjustment for the four main effect channels; standard errors clustered to the year × week level.

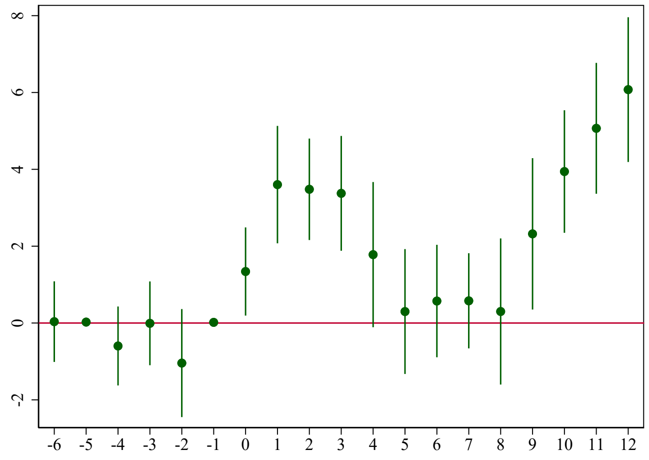
Source: authors' estimates.

Figure A7: Event study results estimated at the province × profession level with prior linear adjustment for main effect channels

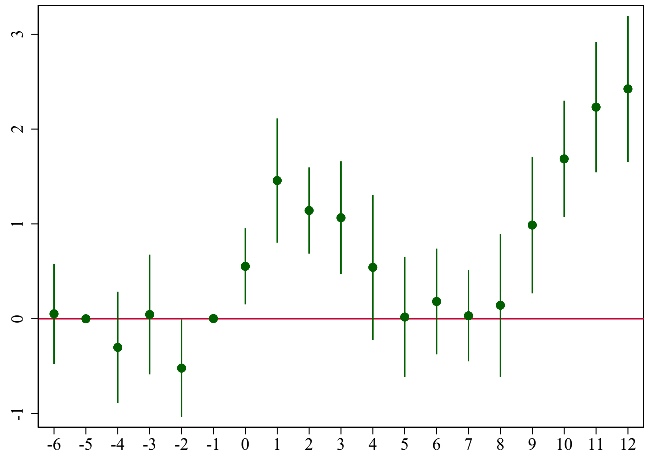
(a) Δ Workers



(b) Contact rate



(c) Agreement rate



Note: the figure plots period-specific estimates as per Equation (5) using data aggregated to the province × profession level with prior linear adjustment for the four main effect channels; standard errors clustered to the year × week level.

Source: authors' estimates.