Trade-displaced or trade-stuck? Self-employed workers and adaptation to trade shocks in low-income countries

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Abstract

This paper studies the impact of trade shocks on self-employed workers in low-income countries. Using establishment-level census data and job spell-level survey data, I study an import tariff shock affecting self-employed retailers in Rwanda and show that the characteristics of self-employment work in low-income countries imply specific adjustment patterns to trade shocks. I find that the informality and unemployment channels, often put forward in studies of richer countries, are not at play here. Rather, the self-employed have specific margins in the face of a negative earnings shock, such as reallocation of hours across multiple jobs. I summarize these novel results into a simple framework of time allocation with multiple job holdings. The model predicts heterogeneity in adjustment strategies depending on the quality of outside options. Given that women experience worse outside options in the Rwandan labor market, I test the model by looking at gender-specific trajectories, after giving suggestive descriptive evidence. I produce evidence of sizeable heterogeneity in adaptation strategy: in particular, while men shift hours away from affected retail jobs toward other paid occupations, women abandon their other jobs and increase hours worked in retail, even though hourly wages are decreasing in that occupation. The effects are still visible 15 months after the shock. My results stress the need for research on trade shocks and the self-employed, in particular as their increased risk of being stuck in decreasingly lucrative occupations makes targeted trade adjustment assistance policies crucial.

JEL: O17, J62, F16
Keywords: Self-employment, Time allocation, Trade shocks

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Sub-Saharan Africa is the region of the world with the lowest share of salaried workers: 24.5% in 2019 (ILOSTAT). While trade policy is a strategical pillar or regional development, as the African Continental Free Trade Area discussions show, research on trade and labor markets has been focused on salaried workers' outcomes and little is known about the way that trade impacts the majority of workers in the sub-continent: the self-employed. This paper offers to fill this gap. Using a tariff shock that weighed on self-employed retailers in Rwanda, and comprehensive data on formal and informal workers and establishments, I answer this question: How do the self-employed adjust to trade shocks in low-income countries?

Trade adjustment is more relevant than ever in a world where protectionist policies are on the rise, as in the case I study. In 2016, the East African Community announced the implementation of prohibitive import tariffs on used clothes imports, a North-South trade that represented a sizable share of urban households' clothing consumption - around 75% in Tanzania, for example [Foundation, 2017]. Faced with threats of exclusion from the African Growth Opportunity Act, a free trade agreement with the United States, all EAC countries abandoned the project, except for Rwanda which increased its tariffs tenfold in June 2016. The apparel sector's exclusion from AGOA followed in 2018. The measure aimed to recapture domestic demand and develop the apparel industry. Its most immediate effect, however, was to dramatically decrease used clothes imports and to increase their prices, first at local wholesalers, and in the hands of retailers - a workforce almost entirely made up of self-employed workers[1]. How the policy impacted them is understudied, as self-employed are not subject to the same adaptation margins as others: they cannot be fired, they can exert control over their working hours, and they are more likely to be holding several jobs at once - their adaptation strategies differ from the standard reallocation framework. It is also crucial from a policymaking perspective, as the policy's impacts are most likely to be borne by those least able to implement these reallocation strategies.

The context that I investigate and the data that I leverage to do so both allow me to bring novel evidence to the question of labor market adjustment to trade shocks in low-income countries. First, the shock that I study affects an overwhelmingly self-employed workforce, in contrast with trade liberalization shocks that often harm larger, industrial firms. Beyond its relevance to my question, this context entails different reallocation mechanisms than those previously put forward [Ponczek and Ulyssea, 2021, Dix-Carneiro and Kovak, 2019, McCaig and Pavcnik, 2018, Erten and Keskin, 2021, Topalova, 2010], mostly unemployment and informality. The setting I study has different potential impacts, because if workers are self-employed, they do not have to be laid off as a response to a negative shock. As a consequence, informality does not have to be an "unemployment buffer" [Ponczek and Ulyssea, 2021] if workers are not losing their employment. Given its prevalence[2], trajectories in and out of informality could also be rarer. With no safety nets, unemployment or inactivity are not the obvious adaptation mechanisms either, and I find evidence that none of these well-known mechanisms are likely to happen in contexts of prevalent self-employment in low-income countries. I show this in sectors outside of manufacturing and in Sub-Saharan Africa, where evidence has been scarce

[1] 89% according to my job-spell level data, the Integrated Household Living Conditions Survey, both pre-and post-shock

[2] In the sector of interest, self-employment in sales, 72% of job spells were not declared to the Rwanda Revenue Authority or sector authorities in 2013 (IHLCS 2013).

due to data unavailability [McCaig and McMillan, 2020], and through a protectionist shock, providing timely insights as trade wars are becoming a more important part of the trade shock literature.
The data that I use allows me to drop several common assumptions, notably that informal workers and establishments are similar to formal ones [3], and that time allocation across multiple jobs is exogenous to shock. Through access to licensed datasets, I was able to use administrative census data on both formal and informal establishments and map all individual firms in used clothing retail, regardless of their formality status. Fine-grain survey data allowed me to quantify workers' outcomes at the ISIC-3 digit level, for all of their jobs throughout the year. Quantifying reallocation at a lower scale than the individual level matters, because a sizeable share of the Rwandan workforce - about 28% in 2016[4] and 36% of self-employed - holds several jobs at once, shedding doubt on the assumption that time allocation across different jobs within the week stays constant in the face of a job-specific shock. Dropping this assumption brings several novel insights on patterns of substitution within individuals, across jobs in the same week.

Similarly to established literature on regional effects of trade shocks [Dix-Carneiro and Kovak, 2017, 2019, Ponczek and Ulyssea, 2021, McCaig and Pavcnik, 2018, Autor et al., 2023, Topalova, 2010, Bas and Bombarda, 2023], I use an index of pre-shock exposure to used clothing trade which I build with Census data for all establishments, formal and informal. Because zones more exposed to the shock could be different in a wealth of aspects, I further introduce variation at the individual level with a dummy for having had a job in self-employed retail with a start date before the shock. I study common adjustment margins: first, earnings and hours worked at the job level, before turning to earnings and hours across all jobs in a given week, which allows me to explore time reallocation across jobs for multiple job holders. I then study reallocation across sectors, occupations, and in infra-individual terms, such as the number and overlapping of jobs through the year and week. I also consider migration. I develop a simple framework to speak to my results and test it by disentangling outcomes across gender, through a quadruple-difference.

The first set of results, the trade shock's effect on exposed self-employed retail workers, brings novel insights to the trade shock literature. Most striking is the absence of an unemployment or informality response, contrary to most case studies of other trade-induced negative earnings shocks in developing countries [Dix-Carneiro and Kovak, 2019, Erten and Keskin, 2021, McCaig and Pavcnik, 2018]. Contrary to these results, a) self-employed retailers in more exposed areas are not more or less likely than those less exposed to become inactive, unemployed or do formal activities during the week. This is the case even though b) their earnings from retail are negatively affected, through slower turnover growth, and even though c) this translates into their income across earnings sources, which also decreases relatively to retailers in protected areas, with effects remaining even more than a year after the shock. Rather than going into unemployment or informality, or even decreasing hours at the affected job, d) workers tend to increase total hours worked during the week at other jobs to maintain income, and to e) overlap their multiple jobs to a higher extent: they have the same number of jobs throughout the year, but these jobs tend to last longer, indicating longer periods where jobs

[3] as in works using formal-only panels like Dix-Carneiro and Kovak [2017] or Dix-Carneiro and Kovak [2019], for example, although informality is explored as an adjustment margin at the regional level. McCaig and Pavcnik [2018] is an important exception

[4] Source: Integrated Household Living Conditions Survey 2016

overlap. Finally, while f) there is no spatial reallocation, g) workers also reallocate across jobs, with fewer of these workers likely to do unpaid family work and evidence of more choosing to do wage farm work and sales work outside of retail. These results illustrate self-employment-specific adaptation margins: first, although the import tariff resulted in higher per-unit clothing costs, the channel through which profits decrease is through sales, not expenditures, indicating price pass-through or decrease in quantities sold on the part of retailers. Second, workers are not abandoning their retail jobs: they increase the total hours worked during a week and months worked at each job, overlapping them more. These are channels that cannot be exerted within the boundaries of a salaried job.

I rationalize these findings in a model of time allocation with a production-constrained retail sector and another option, part-time by nature, informed by the used clothes supply chain and the part-time nature of the jobs workers reallocate their time toward. It predicts different reallocation patterns conditional on the quality of available outside options, which I test by looking at trajectories for men and women.

Indeed, I uncover striking heterogeneity when looking at gender-dependent trajectories. I find although i) all retail job wages grow slower in more affected areas, ii) women's retail jobs are subject to an additional negative impact. While iii) the impact on earnings in men's jobs is no longer significant once one allows for gender-dependent trends, and disappears altogether when considering the jobs in which they are still working on the week of the interview, iv) women's jobs are persistently hit, at the weekly level but even more so when considering hourly earnings. Indeed, the null results on hours worked at retail jobs were masking contrary trends: while men are decreasing hours worked at retail jobs, women are v) increasing them to mitigate income losses, leading to vi) a decrease in hourly income relative to men, compensated for by more hours worked. This surprising result suggests a limited capacity to reallocate toward more lucrative activities. While nobody is abandoning the retail jobs, vii) patterns in take-up of new jobs are also the opposite: when women work more at their affected jobs, they do so by giving up on their other employment, often unpaid family work. On the contrary, men are reallocating hours in retail toward other, paid jobs. Although men seem to be reallocating away from these shocks, they are not entirely giving up on these affected retail jobs, but rather diversifying their working hours - a result which suggests that their outside employment options were part-time by nature and speaks to the general quality of the labor market in my setting.

My results suggest that women are getting stuck in less and less lucrative occupations following a trade shock, indicating exclusion from other working arrangements, and adding to the finding that entrepreneurship is partly involuntary in settings or for populations with limited outside employment options. The abandonment of unpaid family member jobs, especially as it bears no consequence on household-level consumption, indicates that the activities that are abandoned were in-house non-lucrative jobs, suggesting that they were bringing utility either to women themselves, or other members of the household such as children, and entailing empowerment consequences beyond gendered adaptation strategies.

My paper relates to the flourishing literature on regional and individual impacts of trade shocks. The ”China Shock” was one of the first case studies for spatial exposure to trade shocks, with Autor et al. [2013] finding that US labor markets initially more exposed to import competition from China experienced higher levels of unemployment, lower labor force participation, and reduced wages compared to less exposed ones.

In developing countries, unemployment has also been shown to be a possible response to higher exposure to liberalization-induced trade competition, like in Brazil [Dix-Carneiro and Kovak, 2017, 2019] where workers initially employed in the tradable sector became unemployed and reallocated to lower-paid jobs. However, with big informal sectors, unemployment responses tend to be weaker than in richer countries, confirming that informality is an "unemployment buffer" [Ponczek and Ulyssea, 2021]: individuals transition toward informality rather than unemployment if they can, ie without strict labor law enforcement. Where workers cannot go informal, they will be unemployed for longer, but without more cumulative earnings losses [Ponczek and Ulyssea, 2021, Dix-Carneiro et al., 2021]: informality is not a "welfare buffer". Trade policy can also influence formality through export prospects: McCaig and Pavcnik [2018] show that the Vietnam - U.S. Trade Agreement led workers to reallocate toward the formal, exporting sector. Finally, Bas and Bombarda [2023] shows that formalization can emerge from input trade liberalization and that it is skill-biased. I contribute by studying these commonly considered responses, and showing that, when self-employment is prevalent in the affected setting, they are not automatic. These are novel results partly because the existing literature has been mostly focused on Latin America [**?**], mostly for data reasons. Evidence on the Sub-Saharan African region is scarce, as noted in McCaig and McMillan [2020] in their study of Botswana, as are studies of protectionist shocks in developing countries, and the data and setting that I exploit allow me to speak to these understudied areas. Additionally, I explore several novel margins, hours and multiple job holdings that the self-employed can play upon, which reduce their likelihood to be displaced from trade and make them more likely to be stuck in an industry and employment form.

Through this attention to the ability to reallocate, I also bring value to the factor mobility literature. Reallocation following a shock is imperfect: exposed regions and individuals face earnings decreases and do not respond automatically through migration or sectoral reallocation [Topalova, 2010], leading to widening gaps between exposed and non-exposed regions as time passes [Dix-Carneiro and Kovak, 2019]. Most empirical studies find that the most immobile factors are the most vulnerable segments of the population, such as those with the least resources in Topalova [2010], older workers from less internationally integrated regions in McCaig and Pavcnik [2018], women in Macchiavello and Morjaria [2021], or less skilled workers in Bas and Bombarda [2023] or Keller and Utar [2023]. This phenomenon is formalized in Adão [2016], in which different categories of the population have different structures of comparative advantages in a given sector. I also find that workers who are hit by the shock are not mobile enough to mitigate its effect entirely, and complement existing findings by disentangling heterogeneity in shock impact - the direct shock on job-level earnings - from heterogeneity in reallocation responses - the extent to which that earnings shock is translated to losses in personal income. Exploring variation in the quality of one's outside options allows me to uncover two contrasting trends of shock adaptation, with women investing more and more time into the affected occupation. These gendered trajectories from trade are done through abandoning unpaid jobs and spending more time outside, which means that gender-neutral trade policy does not only result in gendered shock mitigation but also empowerment effects, a finding that is supported by flourishing literature on the empowerment effect of labor market shocks, such as the Erten and Keskin [2021] study of liberalization episodes in Cambodia or the Sanin [2021] study of the impacts of implantation of coffee mills in Rwanda on intimate partner violence.

Finally, I bring novel evidence to two strands of the self-employment literature. In contrast with other regions where younger generations increasingly access salaried jobs, self-employment is not declining in Sub-Saharan Africa [Bandiera et al., 2022b], and it is thus crucial for informing policy to produce evidence that takes this working arrangement into account. I show that women do not reallocate away from retail self-employment when it gets less lucrative, suggesting that their self-employment tends to be a constrained choice, driven by budget imperatives rather than entrepreneurial spirit. These results are in line with previous works on survival self-employment in Sub-Saharan Africa [Bandiera et al., 2022b, Margolis, 2014, Gindling et al., 2016] and cross-country evidence that women are over-represented in "survivalist" firms that do not have growth prospects and are not credit-constrained [Grimm et al., 2012]. As countries develop and the organization of labor changes, women exit self-employment much later than men [Bandiera et al., 2022a], which suggests differential reactions to national policies. Second, as I find differential impacts on self-employed earnings even though workers are selling the same category of products, I also speak to the literature interested in income gaps within self-employment, which are higher than in any other working arrangement in most countries [Heath et al., 2015]. Recent works have pointed to customer discrimination and segregated markets within self-employment leading to self-employed women gathering in a smaller number of jobs, leading to higher competition and different ways of accommodating positive demand shocks than men [Hardy and Kagy, 2020]. I contribute to this literature by showing a natural experiment leading to a negative earnings and demand shock in a self-employed occupation. In the descriptive evidence put forward in Section 5, I show that women experience systemically more crowded industries, which could explain the disproportionate impact on their earnings within the affected profession, through the crowding channel put forward in Hardy and Kagy [2020] and which I use to check my theoretical framework's predictions for lower employment options outside of retail. I add value to this recent literature by also exploring time inputs, and offering evidence that in settings where workers frequently hold multiple jobs at the time, reallocation can take the form of a rearranging of hours rather than the exit of a profession - complementing works on gendered crowding of industries and lack of outside options such as Sharma [2023] which focuses on a shock within wage employment and finds gender-dependent exit rates.

The rest of the paper is organized as follows. Section 1 describes the context. Section 2 presents the data. Section 3 outlines the methodology and section 4 presents results on earnings and income, sectoral and spatial reallocation. Section 5 formalizes the findings into a stylized framework. Section 6 checks the assumptions of the model concerning the quality of outside options through gender differentiation in the empirical analysis, and presents the results. Section 7 concludes.

1 Rwanda's 2016 tariff increase on *caguwa* imports

The used clothes sector in domestic demand and Rwandan clothing trade

Used clothing, a sizeable and growing trade, flows from rich countries to poorer, mostly African ones. In 2020, 4 out of the 5 top importers of used clothes were Sub-Saharan African countries, each importing over 100 million dollars of these goods each year [Cobbing et al., 2022]. Used clothes, or *caguwa* in Kinyarwanda[5], have alternatively been praised for offering a cheap clothing option to urban households and

[5]the official language of Rwanda, spoken throughout the country

blamed for the underdevelopment of the textile and garment sector, with Frazer [2008] attributing up to 40% of the decrease in the apparel sector's share of manufacturing and of jobs across most countries of the continent to that trade. Other issues, such as cultural ones, have also been raised by citizens and governments eager to curb these imports supposedly crowding out traditional clothing and from which a sizeable share immediately goes from bales to landfills [Cobbing et al., 2022]. The notion of dignity was a central communication pillar when Rwanda's intent to ban *caguwa* imports was made public in 2016, through an East Africa Community[6] common project to raise tariffs on second-hand clothing imports [Wolff, 2021]. Faced with threats of exclusion from the Africa Growth and Opportunity Act[7]'s apparel section, all EAC countries abandoned the project, except Rwanda. The tariff increase[8] was implemented in 2016 and Rwanda was suspended from AGOA in 2018. In the meantime, there was no sizeable substitution of domestic production to these imports, as shown by the resolution to not implement further tariff hikes beyond 2.50 USD /kg as initially planned[9], because of the nascent quality of the Rwandan textile and garment industry.
The measure was implemented 6 months from the first EAC-wide proposal and was efficient in curbing imports of second-hand clothes: Figure 1 and Figure 2 represent, respectively, the evolution of new and used clothing imports in Rwanda (volume and value) and the ratio of clothing prices over the general consumer price index for urban and rural areas. We can see that after 2016, the volume of used clothes imported to Rwanda decreased persistently, consistently with the per kg. tariff. Unit prices for new clothes also decreased slightly for 2017, but their average unit value stayed much higher (around fourfold), meaning that new clothing does not represent a direct substitute for used clothing demand after the shock. New clothes remain on an increasing trend in terms of import volumes. As a result of the measure, we can also see that the years-long decreasing trend of clothing prices relative to other goods' prices halts. The stop is quicker in urban than in rural areas, which we can attribute to stocks depleting faster in the former or to slower supply chains for the latter. The tariff increase seems to have had impacts on country-level measures such as imports and prices. This provides strength to the argument that the shock was powerful enough to fuel adaptation response, as I later show in individual-level data.

Used clothing supply chain and the characteristics of used clothing retail work

Used clothing is a prevalent industry employing many of the urban areas' workforce in African countries. For example, 121,000 direct jobs are created from that industry in Kenya [Wolff, 2021], and my estimates based on pre-shock plant-level census data suggest that *caguwa* retail could have represented up to 1/8 of the retail sector as a whole in the most exposed districts before the shock. The used clothing supply chain still remains to be quantified, but qualitative accounts of used clothing trade in neighboring countries [Brooks and Simons, 2012, Brooks, 2012, Mesa, 2021] or political economy studies of the measure [Behuria, 2019] all refer to clothes arriving in bulk at wholesalers, before being bought in bales by retailers. This process holds characteristics that set it apart even from new clothing retail: first, although the bales can sorted and

[6] Customs Union comprising Kenya, Rwanda, Uganda, Burundi, Tanzania, with the DRC and South Sudan having joined after 2016

[7] AGOA, a program allowing selected African countries to export certain goods to the US duty-free

[8] From 0.5 to 5 dollars/kg on used shoes and 2.5 dollars/kg on used clothing according to the government framework, vis [2000]

[9] Strategy For The Transformation Of Textile, Apparel And Leather Sectors in Rwanda, MINICOM 2022

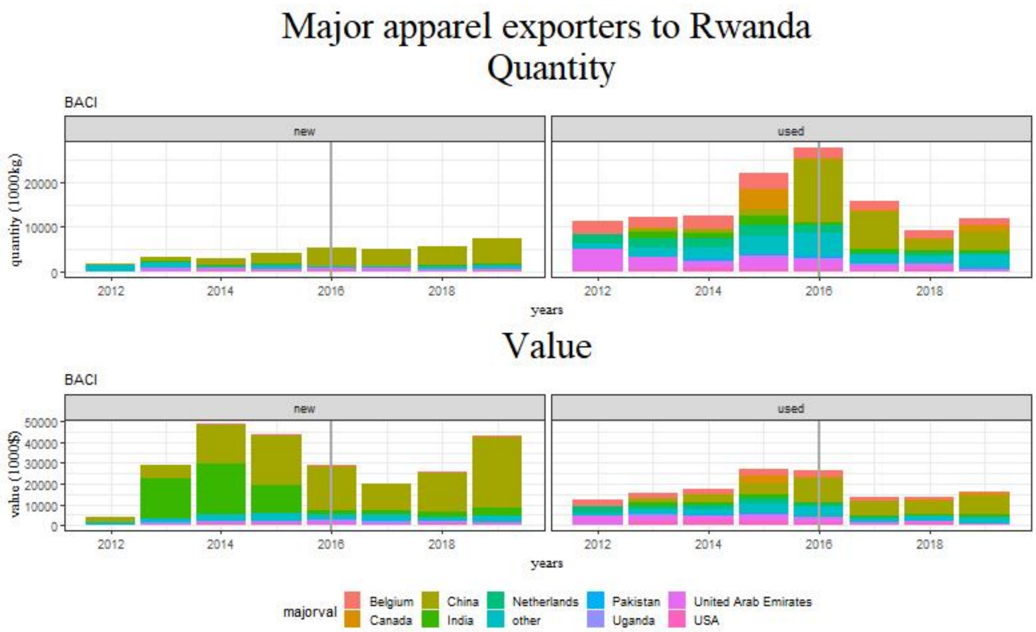

Figure 1: Import volumes and values

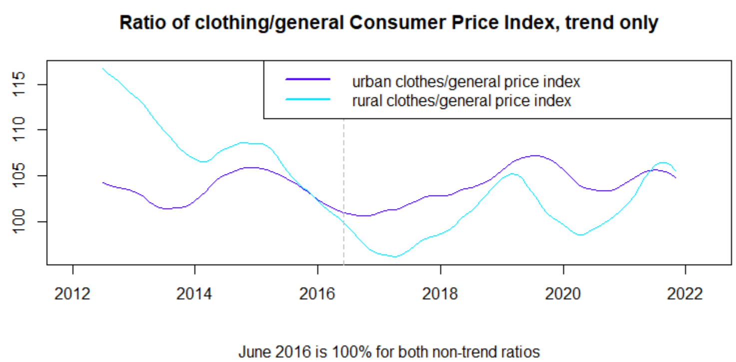

Figure 2: Prices

classified by categories, the specific pieces of clothing cannot be observed before purchase, and this adds uncertainty to the retailers' livelihoods - especially when bales are not adapted to local meteorological conditions or tastes [Cobbing et al., 2022]. Most importantly, the structure of the supply chain, with plane- or truck-dependent international arrivals at wholesalers' precincts, means that supply is fragmented: replenishing stock might not always be possible once one is done with their bale, a fragmented supply chain alluded to in qualitative counts of used clothing trade in neighboring countries (Mesa [2021] in the DRC). Additionally, most $caguwa$ retailers officiate at stalls and have limited power to build inventory: when Kenya installed a temporary, Covid-driven ban on $caguwa$, retailers declared only having about a month's worth of inventory, which seems to be also true of Rwanda given how fast prices rose after June 2016.
In terms of working conditions, $caguwa$ retailers are overwhelmingly self-employed, more so than other clothing retailers (in plant-level censuses, 60% of clothing retail workers are self-employed, against more than 93% of $caguwa$ retail workers), and mostly, although not entirely (84% against 71% for clothing retail) informal, meaning that the corresponding individual firms are not declared to administrative or local authorities. This did not stop the occupation from being a lucrative option in terms of hourly wages: although my worker survey data does not separate $caguwa$ from other retailers, I am able to show in Figure 3 that retailers in zones highly exposed to $caguwa$ were making more than other occupations [10], while this is less true after the shock. Although retail is most retailers' main occupation of the week in 2013, they are also much more likely than the rest of the population to be exercising another occupation, paid or unpaid (Appendix C): they are not allocating their time to retail entirely, in spite of its lucrative aspect and possibly because of aforementioned input constraints. As a second job, 81% of women and 60% of men with a secondary job outside of $caguwa$ are doing agriculture. While men do other retail jobs (10%), women do not have access to that option outside of $caguwa$. The discrepancy between men and women is driven by women not accessing salaried retail work, which less than 1% of women with another job than $caguwa$ do, versus around 5% of men. Although $caguwa$ provides women with one retail work option, the rest of the sector is not a possibility for all of them, as shown in Figure 4[11]. I detail the survey data behind these insights in the next section.

2 Data

In my empirical strategy, I use two sources of variation: pre-shock spatial exposure to $caguwa$ and having been a self-employed retailer before the shock. I first present the databases that allow me to build the spatial exposure index, the Establishment and Population Censuses, before turning to survey data for occupational variation and outcomes.

Spatial index of $caguwa$ intensity: the Establishment Censuses and the 2012 Housing and Population Census

To build a spatial index of $caguwa$ exposure, I use the Establishment Census, an administrative census of all establishments in Rwanda, whether formal or informal, collected every 3 years with 100 000 to 200 000

[10] for salaried occupations, this is wages, and for self-employed retailers, this is profits

[11] **??** in the appendix illustrate the distribution of other jobs held by $caguwa$ workers.

Figure 3: Evolution of the retail earnings premium

observations each round. $Caguwa$ retail sales is a very precise category that is not explicitly classified in the Census. however, I was able to access both the 4-digit industrial sector (ISIC) classification of the establishment and an enumerator-written description of the main economic activity for all rounds, including the 2014, the last round before the shock. Creating an indicator for whether $caguwa$ is written in the establishment description is a lower-bound for $caguwa$ retail, as enumerators often write "clothing retail" without further detail. Therefore, one can only use it assuming that, conditional on being a $caguwa$ retailer, the enumerator specifying writing $caguwa$ in the establishment description is orthogonal to other establishments characteristics we are interested in (for example, the manager's sex). Discussions with the National Institute of Statistics of Rwanda confirmed that no specific directions were given in the description of the main economic activity concerning clothing retail.

I use two other alternatives to check my results' robustness: first, I discretize the spatial exposure variable, isolating the top 10% more exposed states as this is the threshold where I see a jump in $caguwa$ prevalence, in subsection A.1. I also create an indicator for being likely to be a $caguwa$ retail establishment even though $caguwa$ is not included in the establishment description, to solve for the fact that in some small administrative zones, there might be a very small number of enumerators, leading to imprecise spatial estimates if the decision to write $caguwa$ is enumerator-dependent. Using the 2014 $caguwa$ variable, I select firms with similar characteristics[12] than the firms for which $caguwa = 1$. These characteristics match political science literature on used clothes retailers [Brooks and Simons, 2012, Brooks, 2019], and to check their validity further, I compute inclusion and exclusion error for my $caguwa$ variable. My indicator misses 5% of establishments for which the enumerator wrote $Caguwa$ and includes 3.5% of establishments for which the enumerator did not write $caguwa$ - an upper bound for inclusion error, as one establishment could be $caguwa$ without it being written. Results with these alternative indexes are similar to the main ones and are included in subsection A.3.

[12](firms that do not sell in special economic zones, whose owners are Rwandan or part of the EAC, that are sole enterprises, and that have less than 3 employees)

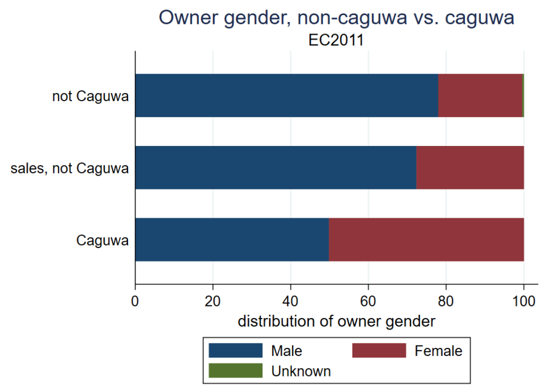

Figure 4: Distribution of owner sex

The Establishment Census also includes the sex of the owner, on which the creation of the indicator for $caguwa$ is not based. We can see in Figure 4 that women are over-represented as owners of individual businesses in used clothes retail, not only relative to all businesses but also to other businesses in the sales ISIC sector, pointing to a higher concentration of self-employed women in that industry.

With my pre-shock $caguwa$ indicator, I construct a ratio of the total number of workers working in $caguwa$ establishments in a given zone over the total active population of that zone:

$$Exp = \frac{\text{Caguwa workers}(EC)_{2014}}{\text{Active population}_{HPC,2012}}$$

I construct this exposure at the scale of two administrative entities: the district, of which there are 30, and the sector, of which there are 416 in Rwanda. Figure 5 shows district-level exposure to the used clothing trade. We can also see that exposure is correlated to airports, major cities, and roads, but imperfectly so. Sellers' location, and thus spatial exposure to the shock is expected to be very polarized for two reasons. First, used clothing retail is usually concentrated in specific markets [Brooks and Simons, 2012]. Rwanda's very hilly geography and the socio-economic status of $caguwa$ sellers make it unlikely that workers in that sector are living very far from where they work. Second and related to the more cultural aspect of the used clothing trade, taste for pre-owned garments seems to be concentrated in urban zones in most countries [Brooks, 2019].

Workers' earnings, occupational choices, and migration outcomes: the Integrated Household Living Conditions Survey

My empirical strategy relies on both spatial exposure to $caguwa$ trade and belonging to the treated category of self-employed retailers[13], with a start date before the shock so that there is no reverse causality in occupational choice. I do this for two reasons: first, using a spatial index only would compare states with widely different industrial compositions, such as the size of retail, making the parallel trend assumption dubious. Additionally, my worker survey does not disaggregate to the $caguwa$ level, and I thus depart from

[13] ISIC 2-digit category: retail sales

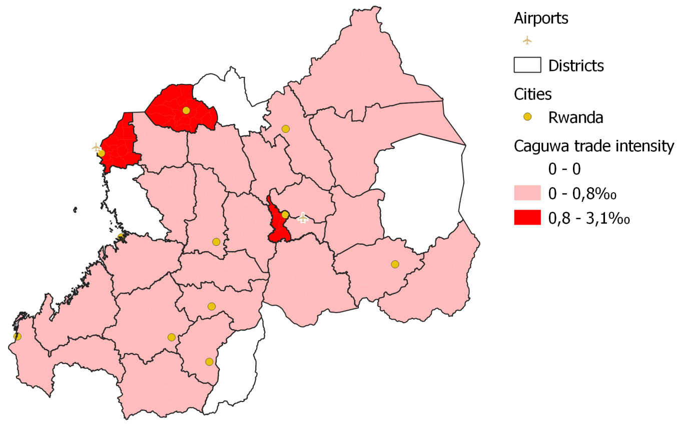

Figure 5: District-level *caguwa* exposure

the assumption that retailers in more *caguwa* intensive areas are more likely to be *caguwa* retailers. The labor information that I use pertains to the 2013 and 2016 rounds of the Integrated Household Living Conditions Survey, a cross-sectional database that represents of 60,000 individuals (30,000 working age, 75,000 job spells) each round and collects information about migration, work history, and socio-demographic situation. The data features information on earnings (wages for salaried workers and profits, as turnover minus expenses, for self-employed workers), working status, and sector information for each job performed during the year. I denote as self-employed retailers individuals who were retailers before June 2016, even if they stopped in the meantime[14]. Another crucial aspect of that dataset is its interest in seasonality: for each round, an equal number of households are interviewed each month of the year, granting me a two-year window of observation each round. Appendix C present descriptive statistics for all the outcomes that we look at.

3 Empirical Strategy

My empirical analysis relies on a triple-difference strategy that exploits two sources of variation in shock exposure. The first one is belonging to a region more exposed to the tariff increase, in line with the regional effects of shocks literature [Topalova, 2010, Dix-Carneiro and Kovak, 2017, Kovak and Morrow, 2022]. When looking at a shock only hitting one industry, however, we might be worried that individuals in less exposed zones are not on similar trends of with respect to their earnings, their migration, or sectoral reallocation outcomes due to differences in industry composition across regions. Also, in my household data I can not disaggregate beyond belonging to retail, and am thus unable to access *caguwa* retailers per se. For this reason, I use both spatial variation and a dummy for working in retail with a start date anterior to the June

[14]That is true until June 2017, at which point individuals who stopped immediately after the shock will not be denoted *cagwua* if they do not declare that job spell anymore, which if it is the case, would bias our coefficients on retail gap toward the null. In our results, we do not see any trend in affected workers to abandon their jobs.

2016 tariff shock [15]. This triple-difference design relies on the assumption that the trend in the retail-non-retail gap in more exposed zones was parallel to the trend in the retail-non-retail gap in less exposed zones, for every value of the exposure index.

$$\begin{aligned} Y_{i,d,t} =& \alpha + \beta_1 post_t \times DE_{d(i,t-1)} \times SES_i \\ &+ \beta_2 post_t \times DE_{d(i,t-1)} + \beta_3 post_t \times SES_i + \beta_4 DE_{d(i,t-1)} \times SES_i \\ &+ \beta_5 post_t + \beta_6 DE_{d(i,t-1)} + \beta_7 SES_i + \beta_8 X_{i,d,t} + \gamma_d \times \delta_{rur_l} + trimester_t + \varepsilon_{i,d,t} \end{aligned} \tag{1}$$

For individual i living in location l of district d at time t. SES_i denotes having been a self-employed retail seller within the year (as the survey asks respondents to enumerate all of their jobs throughout the past year) with a start date before the shock. $DE_{d(i,t-1)}$ is district-level pre-shock $caguwa$ exposure in the district individuals lived in a year ago, to avoid migration-driven reverse causality. $X_{i,d,t}$ controls include age, student and recent migrant status (except in the migration equations), education, gender, marital status, and role in the household, a dummy for being in sales and another one for being self-employed (except in equations looking at the working status and occupational code of jobs held by individuals). Trimester fixed effects (starting at the dry season in December rather than in January) avoid seasonality-related biases in earnings, migration, and labor outcomes. Rural-district fixed effects absorb time-invariant characteristics for rural/urban zones of each district that might affect our outcomes. When allowing for heterogeneous trends by sex, my main specification becomes

$$\begin{aligned} &Y_{i,d,t} = \alpha + \beta_1 post_t \times sex_i \times DE_{d(i,t-1)} \times SES_i \\ &+ \beta_2 sex_i \times DE_{d(i,t-1)} \times SES_i + \beta_3 post_t \times DE_{d(i,t-1)} \times SES_i + \beta_4 post_t \times sex_i \times SES_i + \beta_5 post_t \times sex_i \times DE_{d(i,t-1)} \\ &+ \beta_6 post_t \times sex_i + \beta_7 post_t \times DE_{d(i,t-1)} + \beta_8 post_t \times SES_i + \beta_9 sex_i \times DE_{d(i,t-1)} + \beta_{10} sex_i \times SES_i + \beta_{11} DE_{d(i,t-1)} \times SES_i \\ &+ \beta_{12} post_t + \beta_{13} sex_i + \beta_{14} DE_{d(i,t-1)} + \beta_{15} SES_i + \beta_{16} X_{i,d,t} + \gamma_d \times \delta_{rur_l} + trimester_t + \varepsilon_{i,d,t} \end{aligned} \tag{2}$$

The assumption behind this specification is that the evolution of the gender gap in retail sales in more exposed zones was parallel to the evolution of the gender gap in non-retail sales in more exposed zones, or to the evolution of the gender gap for retailers in less exposed zones. Standard errors are clustered to the IHLCS cluster level.

First, I investigate individual income, aggregating over jobs in the case of multiple job holding and only taking into account jobs worked during the interview week. Using Equation 1, I look at the log of the last weekly income and at the log of hourly income. I also consider the total hours worked this week. The reason for considering both weekly and hourly income is disentangling between who compensates for hourly wage decreases by substituting between jobs and who compensates by working more in the affected jobs. Finally, I study household-level consumption, using consumption data from the IHLCS and a similar specification as Equation 1, with SES_i whether any household member was a retailer starting before June 2016.

[15] I chose to exclude those who start doing self-employed retail after June 2016, because it was not clear whether they did so knowing about the changed working conditions, and the link between spatial exposure and likelihood of doing $caguwa$ could have been different. The results are the same keeping them in control or dropping them

Next, I examine whether the effect on income is driven by an effect on earnings for the affected retail jobs, and not from another occupation that retailers could be doing. To do this, I leverage my triple-difference strategy and apply it to job-level data, with one observation per job-spell:

$$\begin{aligned} Y_{i,j,d,t} =& \alpha + \beta_1 post_t \times DE_{d(i,t-1)} \times SES_j \\ & + \beta_2 post_t \times DE_{d(i,t-1)} + \beta_3 post_t \times SES_j + \beta_4 DE_{d(j,t-1)} \times SES_j \\ & + \beta_5 post_t + \beta_6 DE_{d(i,t-1)} + \beta_7 SES_j + \beta_8 X_{i,j,d,t} + \gamma_d \times \delta_{rur_l} + trimester_t + \varepsilon_{i,j,d,t} \end{aligned} \tag{3}$$

With SES_j whether a job is in self-employed retail with a start date before the shock. I study daily wages for all job spells of the year and for respondents' most time-consuming job of the week. I also study hourly wages, which I observe only for jobs that the respondent is still working at during the interview week. I thus study hourly wages for all jobs still done at the time of the interview and for the main job of the week. Next, I study hours worked during the week for the same two categories. I also analyze still working at a job to avoid sample selection on these hourly variables, which could happen if part of the population is exiting jobs more rapidly than another.

Armed with results on the impact of the shock on the self-employed's earnings and income, I then investigate adaptation strategies: migration and sectoral reallocation, similar to Topalova [2010] although at an individual, and not region or industry, level. I exploit the same triple difference strategy and use inter, intra-district, and return migration as my outcomes. Then, I study different patterns of reallocation. I first look at the supply of labor: I study inactivity and unemployment, the overlap and duration of all jobs held during the year, and the total number of all jobs and paid jobs per week and year for the active population. Finally, I investigate occupational choice: I look at the categories of employment for the main job of the week, estimating linear probability models on working as a self-employed, wage, and unpaid family worker both on and off-farm, as well as having a formal job, working in retail or working in the broader category of sales, without retail. I repeat this exercise not considering only the main job of the week, but all jobs performed this week, with the same results, in Table 51 of the Appendix.

4 Results

4.1 Income and hours worked

First, I examine results on the whole population of self-employed workers living in a $caguwa$-exposed zone and working in retail prior to the shock. The coefficients associated with $Post \times SES \times ZDE$ denote the additional effect on self-employed retailers' trend in that outcome - the effect on the self-employed retailer premia - of living in areas 1 standard deviation[16] more exposed to $caguwa$, relative to the trend for retailers living in less exposed zones. From Table 1, we see that these retailers experienced slower personal income growth: income grew 6.3% slower for self-employed retailers retailers living in an area 1 sd. more exposed to $caguwa$ trade all things equal (col. (1)). This effect is even larger for income by hours worked during the

[16] around +0.07% in the ratio of caguwa workers over active population from a mean of 0.03%, keeping in mind that the measure is a lower bound for actual caguwa activity

	log(inc.)	log(tot hours)	log(hourly inc.)	log(cons.)
Post × SES × ZDE	-0.063*	0.036*	-0.096***	0.001
	(0.04)	(0.02)	(0.04)	(0.02)
Post × SES	0.051	0.037	0.018	-0.041*
	(0.05)	(0.02)	(0.05)	(0.02)
Post × ZDE	0.004	-0.002	0.004	0.060***
	(0.01)	(0.01)	(0.01)	(0.01)
SES × ZDE	0.037	-0.022*	0.063***	-0.078***
	(0.02)	(0.01)	(0.02)	(0.01)
R-squared	0.479	0.161	0.404	0.236
N	29980	53684	29969	27961
District-urban FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round).
F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.
Samples: for (1) and (3), all jobs with non-null earnings. For (2), all jobs. For (4): all households.

Table 1: Individual-level income and hours worked, across all jobs

week (col. (3)), which can be explained by the fact that these more exposed retailers also work significantly more: hours worked grew 3.6% faster for retailers living in more exposed areas than for retailers living in less exposed ones (col. (2)). The shock that we saw in imports figures seems to have been transmitted to these sellers' income. Interestingly, the shock does not seem to impact household consumption, indicating that intrafamilial mitigation mechanisms might be at play. To go deeper into my findings and ascertain that the income decrease does come from a retail job, I go from this individual-level analysis to a job-level one, estimating Equation 3 on workers' main jobs of the week[17].

From the coefficient on $Post \times SES \times ZDE$ in Table 2, we see that self-employed main jobs of the week (henceforth, jobs, as results are similar for all jobs) in retail located in districts more exposed to $caguwa$ trade by 1 sd., all else equal, saw their earnings grow 8.5% slower. This is amplified by hourly earnings, who undergo an even larger negative effect (col. (2)). We can look more deeply at what precisely drives the effects on self-employed retailers using the business module of the survey, administered to the subsample of self-employed workers of the IHLCS. Retailers in more exposed areas are not seeing their earnings grow slower primarily because of increased costs (col. (4)) but because of relatively decreasing sales (col. (3)). This indicates two things: although we know that unit prices for used clothing have increased, from the imports and CPI data, retailers have been buying less of it rather than increasing expenses. Second, sales have grown slower: either some of this unit price increase has been passed through to customers, or prices stayed constant and quantity sold decreased - both phenomena likely to be at play, given the documented impact both on import volumes and local clothing prices in urban zones, and accounts in other countries that retailers can split bales amongst themselves [Mesa, 2021]. However, this negative profit effect does not translate into more hours worked at these jobs, either in levels (col. (5)) or in variation (col. (6)), and this is not due to

[17]For the sake of clarity, I only focus on main jobs of the week, but results on all jobs are all qualitatively similar and of similar significance levels

	log(earnings)		*Self-emp. profits*		*Hours this week*		*Selection*
	Daily	Hourly	Turnover	Non-labor expenses	Hours	Log hours	Kept job
Post × SES × ZDE	-0.085**	-0.102**	-0.131***	-0.093	0.124	0.011	-0.001
	(0.04)	(0.04)	(0.04)	(0.08)	(0.71)	(0.02)	(0.00)
Post × SES	0.018	-0.072	-0.000	-0.162	3.452***	0.109***	0.002
	(0.07)	(0.08)	(0.09)	(0.15)	(1.14)	(0.04)	(0.00)
Post × ZDE	0.011	0.005	0.122***	0.152***	0.007	-0.001	-0.001
	(0.01)	(0.01)	(0.03)	(0.05)	(0.27)	(0.01)	(0.00)
SES × ZDE	0.069***	0.085***	0.018	-0.033	-0.675	-0.027**	0.000
	(0.02)	(0.03)	(0.03)	(0.05)	(0.45)	(0.01)	(0.00)
R-squared	0.467	0.392	0.292	0.205	0.237	0.144	0.005
N	23638	23619	5212	3999	53429	53429	53459
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: (1) - (2): all jobs with non-null earnings. (3)-(4): all self-employed jobs. (4)-(6): all jobs

Table 2: Job-level earnings, hours worked and abandon likelihood

selection in who keeps their job and who leaves it (col. (6)).

From this table I conclude, first, that the effect of the shock is driven by a negative effect on retailers' earnings from retail, and not through another job entering in the individual income aggregation. Second, the effect is persistent: the IHLCS round lasted until October 2017, 16 months after the shock, and the effect on the main job of the week is still significant. Finally, although there are negative effects on their hourly earnings that translate into their income, retailers do not leave their jobs, nor do they reduce hours worked at them, contrary to expectations and standard labor supply theory.

Interpreting the magnitude of the results In Table 1, the $Post \times SES \times ZDE$ coefficients indicate that in areas 1 s.d. more exposed to $caguwa$ trade, the income gap (resp. hourly income gap) between retailers and non-retailers grew 6.3% slower (resp. 9.6%) than in less exposed areas. I first turn to a brief discussion of the magnitude of such coefficients, before turning to identifying assumptions.

A simplistic way that the import tariff increase would transmit to the difference in retail premia across exposed states, assuming no buyer or seller power on the part of $caguwa$ retailers and no spillover to non-$caguwa$ retail, would be first through an increase in prices at wholesalers' warehouses lowering unit profit for $caguwa$ retailers. In turn, retailers' income would decrease proportionately to the share of $caguwa$ in retail, leading to a retail premia decrease and a decrease in the difference between retail premia from exposed states to non-exposed states, which is what the $Post \times SES \times ZDE$ coefficient identifies, under our assumptions. To speak to whether the 10% decrease in the difference in retail premia matches the context, I would need estimates of the bale price increase at wholesalers' warehouses (Δp), the importance of costs in $caguwa$ sellers' profits ($\frac{c}{\pi}$, the size of $caguwa$ in more exposed states' retail sectors R, and the difference in retail premia growth between more and less exposed states Y. Although I lack, in the current version of this paper, the data to speak to these parameters, I can benchmark some. Governmental estimates[18] indicate that the price of used clothing imports resulted in a 30% unit price increase for wholesalers, who would transmit that increase to $caguwa$ retailers in case of perfect pass-through. The share of such retailers in the whole retail sector, in the top 10% most exposed districts, could be as high as 12,5% (Establishment Census). Finally, in raw data, we can see that the retail premia in earnings did not grow as fast in exposed areas than in non-exposed areas, resulting in a semi-elasticity coefficient that would be of higher magnitude. Setting our Δp to be 3/10 (perfect pass-through assumption) and R to be 1/8, $\frac{c}{\pi} \times \frac{1}{Y}$ would need to be around 13/10 for the triple-difference coefficient to be 0.1, which is credible knowing $\frac{1}{Y} > 1$ and that $\frac{c}{\pi}$ is not bounded by 1.

Discussion of identifying assumptions The assumption behind our triple difference model is that, for each level of exposure, if not for the policy, the trends in growth of retail premium would have been parallel. If something is modifying the trend in the retail premium specifically for more exposed states that is not the policy, then that would be a threat to identification. This could be the case, for example, if in areas more exposed to the policy, the retail markets were also larger, leading to more spillovers from $caguwa$ retail to non-$caguwa$ there than in less exposed states. For example, used clothing price increases could allow new clothing retailers to increase the price of their clothing, making them better off and mitigating my negative coefficient on earnings. $caguwa$ sellers could also have more outside options in markets in which other type of clothing retailers thrive, making reallocation easier in more exposed areas, and again pushing my coefficient toward the null. I argue that this is not likely to be a sizeable threat, first because $caguwa$ represents at best 1/8th of the retail sector, and a much lower share of the overall workforce: spillover effects are not likely to impact my results significantly, given the very localized quality of that trade. Also, for the workforce to reallocate more easily toward non-$caguwa$ retail in priority, it would have to be the second best option for workers in $caguwa$. However, that is not the case: if we look at secondary jobs held by self-employed retailer, they are mostly outside of retail **??**. Still, I do test for the possibility that the size of retail sector relative to $caguwa$ is affecting my results by changing my spatial index to be $\frac{caguwa}{retail}$ in subsection A.2, with similar results. I show in the later section that these coefficients are not driven by selection in who migrates, leaves employment altogether or this particular job.

4.2 Reallocation channels

Our results on income and wages point to a persisting negative impact of the shock on retailers' income growth, partly compensated for by an increased growth of their working hours though not necessarily within retail employment. I will thus examine where these hours are reallocated, and with what consequences on the total labor supply. As is standard in the literature, I will also test that my estimates are not biased by selective migration patterns, which could happen if, for example, affected retailers are relocating to zones where average earnings are lower.

Table 3 reports results from estimating Equation 1 on reallocation decisions: the probability of having no job this week, total hours per job and average job duration during the year - respectively $\sum_{j=1}^{JobsWeek} \frac{hours_j}{JobsWeek}$ and $\Sigma_{j=1}^{JobsYear} \frac{months_j}{JobsYear}$ - total number of paid and overall jobs, per week and year. An important result in column (1) is that those affected by the policy are neither more nor less likely to be inactive or unemployed

[18] Strategy For The Transformation Of Textile, Apparel And Leather Sectors in Rwanda, MINICOM 2022

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × SES × ZDE	0.002	0.969	0.242***	0.020*	-0.008	-0.004	-0.021
	(0.01)	(0.72)	(0.08)	(0.01)	(0.01)	(0.01)	(0.02)
Post × SES	-0.000	2.195**	0.477***	-0.034**	-0.093***	-0.118***	-0.127***
	(0.01)	(0.88)	(0.10)	(0.02)	(0.02)	(0.02)	(0.03)
Post × ZDE	0.000	-0.145	-0.029	-0.011***	-0.005	0.004	0.001
	(0.00)	(0.32)	(0.04)	(0.00)	(0.01)	(0.01)	(0.01)
SES × ZDE	0.006	0.534	0.286***	-0.025***	-0.060***	-0.049***	-0.093***
	(0.00)	(0.45)	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)
R-squared	0.049	0.240	0.356	0.233	0.328	0.234	0.234
N	61001	42087	71766	71766	71766	66232	61001
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals (1-7)

Table 3: Reallocation - intensive margin

during the interview week. This, as mentioned in Section 1, contrasts with findings of unemployment or inactivity resulting from trade-induced negative earnings shock in richer countries, but fits the insights one would have about the self-employed population that is affected by the import tariff shock. Looking to explain the source of our positive coefficient on total hours worked per week in the previous section, we see that the average duration of employment (col. (3)), or the extent to which two jobs performed during the year will overlap or cover inactivity spells, is growing faster than in non-affected areas. Workers are remaining in jobs for longer periods or time. An increase in jobs overlap and in total hours worked within the week, as in Table 1, results in either an increase in the number of paid jobs worked within the week or in more hours worked at each of these jobs: we see that paid jobs have significantly grown faster for affected workers (col. (4)), while the coefficient on total hours per job (col. (2)) is positive but non-significant. The biggest channel for self-employed workers' reallocation patterns flowing a shock thus seems to be an increase in both the number of jobs held this week, but not this year, and an increase in duration of these jobs - more overalapping of jobs in a context of multiple job holding.

I turn to the investigation in occupational choice in Table 4. I am mostly interested in the nature of the main job of the week, although table Table 51 in the Appendix explores the nature of all jobs performed this week, with similar results. "Persistence" denotes the likelihood that one's main job of the year is their main job of the week, exploring the likelihood of changing main job as a result of the shock. W(f) and W(nf) are respectively, wage farm and non-farm employment. As a result of the shock, retailers in more exposed areas pre-shock are not more likely to change their main job of the week: although they could increase hours in other occupations, they are not doing so to the extent that their main occupation changes (col. (1)n cik!, (5)), which is important given the significant negative impacts of the shock on their retail wages. This result, however, dissimulates flows from unpaid family work (col. (4)) and non-farm wage work (col. (3)) and into farm wage employment (col. (2)) and sales outside of self-employed retail (col. (7)). This shift to wage work is important in that it is conditional on being able to access salaried employment, and thus, on having good employment prospects outside of self-employed retail work. It is thus not straightforward that work-

	Persistence	Main job of the week					
		W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × SES × ZDE	-0.015	0.012***	-0.022***	-0.009	-0.018	0.010	0.003*
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Post × SES	-0.006	-0.011	-0.024**	-0.007	-0.005	0.028	0.004**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.00)
Post × ZDE	0.016***	-0.009***	0.020***	0.008***	0.022***	-0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SES × ZDE	0.037***	0.004	-0.030***	0.005	0.004	0.063***	-0.005***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
R-squared	0.250	0.124	0.285	0.190	0.247	0.424	0.010
N	66232	66131	66131	66131	66232	71766	71766
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round).
F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals (1-7)

Table 4: Reallocation - main job week

	Migrant	Infra-distr. move	Return migrant
Post × SES × ZDE	-0.000	0.004	-0.005
	(0.01)	(0.01)	(0.00)
Post × SES	-0.010*	0.009	-0.000
	(0.01)	(0.01)	(0.00)
Post × ZDE	0.010**	0.003	0.005***
	(0.00)	(0.00)	(0.00)
SES × ZDE	-0.005	0.007	-0.001
	(0.00)	(0.01)	(0.00)
R-squared	0.064	0.064	0.068
N	66232	66232	66232
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round).
F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals (1-3).

Table 5: Migration

ers leaving unpaid family work as a main occupation are those reallocating to farm wage jobs, as we will detail in the time allocation framework. Importantly, those affected by the shock do not experience differential trends in taking up a formal main job (col. (5)), which also contrasts with a trade shock literature that mostly finds informality to be a common response to negative earnings shocks in developing countries, such as McCaig and Pavcnik [2018], Ponczek and Ulyssea [2021], Bas and Bombarda [2023] among many others.

Finally and in concordance with this literature [Topalova, 2010, Dix-Carneiro and Kovak, 2019, Borusyak et al., 2022], we find no migration response. These results have to be qualified in the light of recent debates [Borusyak et al., 2022] as they do not necessarily mean that migration is not a potential reallocation response: if the shock entails negative earnings prospects everywhere for affected segments of the population, it simply means that there is no advantage in moving.

5 Theoretical framework

In this section, I build a simple theoretical framework to aid in thinking about my results. I begin with a simple model of time allocation between leisure, retail, and other jobs. Motivated by my imperfect reallocation results and by qualitative evidence of the used clothing supply chain, I introduce input constraints on potential jobs. The model formalizes a setting in which a decrease in hours worked would not automatically follow a decrease in hourly wages from an occupation: by introducing production constraints into our retailer time allocation program, we can thus explain the lack of response to the tariff shock, in terms of hours worked in retail and occupational choice. I then discuss the implications of having better or worse employment options outside of self-employed retail. After presenting suggestive evidence that there are gendered differences in the quality of available outside options, I check the framework's predictions by studying the change in men's and women retailers' trajectories.

I begin with a basic setup: our agent has time $\bar{T}$ to allocate between leisure and work: retail (r) or another job (o), respectively paying wage w_r or w_o. The remaining time that they have can be considered leisure, or housework (such as unpaid family work in our occupational choice table). The agent maximizes utility from consuming a unitary good with a price of 1, and leisure:

$$\begin{gathered} \underset{c,l,j}{max}\, U(c,l) \;\; s.t.\, c = w_j(\bar{T} - l) \\ c \geq 0,\; l \geq 0\;,\;\; j \in (r,o) \end{gathered} \tag{4}$$

In that unconstrained setting, the highest-paying occupation will be chosen and the agent will only work there so that the ratio of marginal utilities over their respective prices will be equal:

$$(c*, l*) \;\; tq \;\; U_c(c,l) = \frac{U_l(c,l)}{w_j} \tag{5}$$

This intuition does not match both our static result of frequent multiple job holding, and our dynamic result that workers do not abandon their downgrading retail job altogether. If workers are not allocating all of their working time to one job only, it must be that the amount of work that they can put into one occupation is constrained. Hence, I incorporate the context described in section 1. Sellers buy bales of used clothing in bulk at a given period, and before the next arrival, it is unsure whether they can refurnish their stocks once they have sold everything. I introduce this in the model as a constraint on inputs, similar to the framework delineated in Hardy and Kagy [2020]. If agents can only buy $\bar{\iota}$ quantity of used clothing per period (45 kgs in [Brooks, 2012]), with p the mean unit price of clothing, they can only sell $p \times \bar{\iota}$ and gain maximum total retail wages $\pi \times \bar{\iota} = \bar{y}$, $\pi = p - C$, with C the mean cost of one piece of clothing, each period. I thus limit the consumption derived from retail to $\bar{y}$. This assumes that retailers are price takers for their bale and that they cannot build inventory, consistent with sellers working at open stalls and with the qualitative literature. As we know less about the outside option, o, we draw from the standard assumption in Shishko and Rostker [1976] that labor in o is constrained to a quantity $\bar{L}$, which for example fits most casual wage farm work that we see as a frequent reallocation destination. Finally, we assume that individuals always start by working at their highest-paying job. The optimization program thus becomes

$$\underset{c,l,j}{max}\, U(c,l), \;\; s.t.\; c \leq w_j(\bar{T}-l) \;\; , 0 \leq c \leq \bar{y}, \;\; l \;\; \geq 0 \text{ if } w_r > w_o$$
$$0 \leq \bar{T}-l \leq \bar{L}, l \geq 0 \text{ if } w_o > w_r \tag{6}$$

If retail is a lucrative option and $w_r > w_o$, as is the case before the shock (Figure 3) then resolution depends on whether $\bar{y}$ binds or not. If does not, then as usual, $(c*, l*) \;\; st \;\; U_c(c,l) = \frac{U_l(c,l)}{w_r}$.
If $\bar{y}$ is binding ($c^* > \bar{y}$), then the agent will work until reaching the constraint: $(\bar{c}, \bar{l}) = (\bar{y}, 1 - \frac{\bar{y}}{w_r})$. They will then consider working at their outside option o for extra consumption, solving:

$$\underset{c,l}{max}\, U(c,l) \;\; s.t.\; c = w_o(\bar{l}-l) + \bar{c} \;\; , \;\; \bar{l} \geq l \geq 0 \;\; , \;\; \bar{l} - l \;\; \leq \;\; \bar{L} \tag{7}$$

We assume that $\bar{L} > \bar{l}$: as the agent has already worked in r, they do not have enough time for the labor constraint on o to be binding. Two potential o labor supply responses follow:

1. If w_o is not high enough, $(\bar{c}, \bar{l})$ will be a corner solution and there will be no work in o.
2. If w_o is high enough, as $w_o < w_r$, the new equilibrium is $(c*_o, l*_o)$ s.t. $U_c(c*_o, l*_o) = \frac{U_l(c*_o, l*_o)}{w_0}$. The agent will consume less and work less than the unconstrained optimum $(c*, l*)$: $c_o < c^*, l_o > l^*$, because w_o pays less and the opportunity cost of leisure decreases.

That time allocation framework in the first period implies two mechanisms. First, lower wages in retail, by making the opportunity cost for leisure go down, make the $\bar{y}$ constraint less likely to bind, or if still binding, make it so that agents reach it using more work, ending up with less $\bar{l}$. Second, if opportunities outside of retail o are low (low $\frac{w_o}{w_r} < 1$), it is more likely that if $\bar{y}$ is binding, $(\bar{c}, \bar{l})$ would still be preferable to $(\bar{c} + c_2, \bar{l} - L_2)$ and no work would be done in the other job. Hence, all other things equal, if retail is still the most lucrative option (that is if workers start by allocating time to r), lower retail wages will make it less likely that they decide to also allocate time to o. For a given level of r wages, lower opportunities outside of retail (a lower $\frac{w_o}{w_r} < 1$ ratio) will also make workers less likely to take another paid employment o.

We now turn to a situation in which, as in our context, a tariff shock makes retail less profitable. The tariff increase, through bale prices increasing and some tariff pass-through, increases unit clothing prices, as can be seen with the CPI, with negative impacts on demand that make hourly earnings decrease - else the price increase would have been implemented already. We denote $\pi = (p - C)$ the profit made on one piece of clothing in period 1, corresponding to wages $w_{r,1} = \pi \times nb$ with nb the amount of clothes sold in one efficiency hour ε. One can summarize the effect of tariff τ as $w_{r,2} = (1-\gamma)w_{r,1} = ((1+\theta\tau)p - (1+\tau)C) \times (1-\Delta)nb$ with τ the initial tariff, θ the tariff pass-through rate, prices p and C costs in period 1, and Δ the horizontal shift in demand corresponding to the new unit price $((1+\tau\theta)p$. The weight of a bale is still fixed to $\bar{\iota}$, so a retailer can only sell $(1+\tau\theta)p \times \bar{\iota}$ and make total retail wages $((1+\tau\theta)p - (1+\tau)C)\bar{\iota} = \pi\bar{\iota} + \tau(\theta p - C) = \bar{y} + \tau(\theta p - C)$. I have assumed that sellers are price-takers, which causes the pass-through rate to also be exogenous. I assume

1st best binding ($\nearrow$ with w of the 1st best)	*Retail preferred* ($\frac{w_o}{w_r} < 1 - \gamma$)		*Other job preferred* ($\frac{w_o}{w_r} > 1 - \gamma$)		
Binding (switch to 2nd best)	$\mathbf{h_r} \nearrow, \mathbf{h_r} \times \mathbf{w_r} \rightarrow$		$\mathbf{h_o} \nearrow, \mathbf{h_o} \times \mathbf{w_o} \nearrow$		
	$L^* > \bar{L}$	$L^* < \bar{L}$	$c^* > \bar{y}$	$c^* < \bar{y}$	
	Impossible	$\mathbf{h_o} \rightarrow, \mathbf{h_o} \times \mathbf{w_o} \rightarrow$	$\mathbf{h_r} \nearrow, \mathbf{h_r} \times \mathbf{w_r} \rightarrow$	$\bar{y}^1$ *binding* $\mathbf{h_r} \rightsquigarrow, \mathbf{h_r} \times \mathbf{w_r} \searrow$	$\bar{y}^1$ *not binding* $\mathbf{h_r} \searrow \mathbf{h_r} \times \mathbf{w_r} \searrow$
Not binding	$\varnothing \mathbf{h_o}$		$\varnothing \mathbf{h_r}$		
	$\bar{y}^1$ *binding* $\mathbf{h_r} \rightsquigarrow, \mathbf{h_r} \times \mathbf{w_r} \searrow$	$\bar{y}^1$ *not binding* $\mathbf{h_r} \searrow, \mathbf{h_r} \times \mathbf{w_r} \searrow$	$\mathbf{h_o} \nearrow, \mathbf{h_o} \times \mathbf{w_o} \nearrow$		

Notes: h_r, h_o hours in retail/other occupation. $h_{r/o} \times w_{r/o}$ daily earnings from that occupation.$\rightsquigarrow$: uncertain effect $\nearrow$ increase, $\searrow$ decrease, $\rightarrow$ stable, $\varnothing$ 0 hours worked in retail/other. Explanation in the Appendix.

Table 6: Summary of potential responses to a negative earnings shock in my time allocation framework

that the total earnings that sellers get from selling a whole bale is fixed (p = $\frac{C}{\theta}$): unit price p and pass-through θ adjust to the new τ to guarantee the same competitively-set earnings from selling a whole bale to a seller than before, and therefore $\bar{y}$ does not move.

In that case, what job will be undertaken first depends on the gap between w_r and w_o. $\frac{w_o}{w_r} > 1 - \gamma \iff w_o > (1-\gamma)w_r$: all else equal, for a small enough gap between the two prospects, an agent will now start by the labor-constrained other option. They will turn to o first, solving:

$$\underset{c,l}{max}\, U(c,l) \;\; s.t.\; c = w_o(\bar{T} - l) \;\; 0 \leq c,\; 0 \leq \bar{T} - l < \bar{L} \tag{8}$$

1. If $\bar{L}$ is binding: $L^* > \bar{L}$, $(\bar{c}, \bar{l}) = (w_o \times \bar{L}, \bar{T} - \bar{L})$
   And the agent considers working in retail for extra consumption:

   $$\underset{c,l}{max}\; U(c,l) \;\; s.t.\; c = (1-\gamma)w_r \times (\bar{l} - l) + \bar{c} \;\; 0 \leq c \leq \bar{y}\;,\; \bar{T} - \bar{L} \geq l \geq 0 \tag{9}$$

   $\bar{y}$ will be less likely to bind and will constrain the number of hours worked less before: wages are lower, making work in retail less attractive, and the agent has less time because they have already worked elsewhere.

2. If $\bar{L}$ does not bind, then the agent chooses (c^*, l^*), an equilibrium with less consumption and more leisure than with r as w_r was higher.

If $\frac{w_o}{w_r} < 1 - \gamma$, agents will allocate time to retail first, $\bar{y}$ will be less likely to bind, and if still binding, will be attained through more work than before. This simplistic framework nevertheless brings forward important predictions. We summarize them in Table 6 and detail the mechanisms behind each prediction in the Appendix.

Looking more in-depth into the two cases for which effects on hours is ambiguous (r best option - $\bar{y}$ not binding - $\bar{y}$ binding at first period and o best option - $\bar{L}$ binding - $\bar{y}$ not binding -$\bar{y}$ binding at first period), we can delineate these two agents' optimization programs : For an agent that begins with r and makes an unconstrained choice,

$$\max_{c,l} U(c,l) \ \ s.t. \ c = w_r(1-\gamma)(\bar{T}-l) \ , 0 \leq c \leq \bar{y}, \ 0 \leq \bar{T}-l < \bar{T} \tag{10}$$

With solution $(c_*, l_*) \ \ st \ \ U_c(c,l) = \frac{U_l(c,l)}{w_r(1-\gamma)}$

$$\max_{c,l} U(c,l) \ \ s.t. \ c = w_r(1-\gamma)(\bar{l}-l) + \bar{c} \ , 0 \leq c \leq \bar{y}, \ 0 \leq \bar{l}-l < \bar{T} \tag{11}$$

The solution is the same, $(c_*, l_*) \ st \ U_c(c,l) = \frac{U_l(c,l)}{w_r(1-\gamma)}$ but agents already have consumption from their first o job spell. In the case of no corner solution, agents will then choose an amount of leisure proportional to their fixed time. Because those who started with o have less time remaining, their hours worked in retail will decrease more and are thus more elastic to the wage decrease. For two agents, 1 and 2 with different outside options o so that $\frac{w_{o,1}}{w_{r,1}} < 1-\gamma < \frac{w_{o,2}}{w_{r,2}} < 1$, the framework predicts that

1. For agent 1, retail will still be chosen first. Because of the wage decrease, labor is less attractive, but that also means that the constraint $\bar{y}$ takes a longer amount of labor to be reached: daily earnings in retail will fall, but less than hourly earnings because the agent is working additional hours that they could not work before - whether they compensate for the hours that they are not working anymore because of the wage decrease is unknown. Because wages in retail are lower, it is more likely that only one paid occupation will be worked, with a decrease in hourly and, to a lesser extent, daily aggregate income. The model thus predicts a decrease in the number of jobs held, and a decrease in hourly income with a smaller decrease in nominal income, because of an ambiguous effect on retail working hours.

2. For agent 2, because the best option changes, income losses are mitigated through higher involvement in the other occupation o. Because the agent has more time to allocate to o, labor will be constrained to $\bar{L}$ and some work will still be done in r. Earnings from retail fall as well as hours, with higher elasticity to the wage decrease than for agent 1, more than one paid job is worked, and income losses are lesser than for agent 1.

To justify the construction of this model, I check these predictions relative to outside options and reallocation patterns using two populations with varying levels of outside options: men and women. Armed with descriptive statistics and insights from the gender gap in self-employment and wage employment literature focused on low-income countries, I argue that the outside option and bargaining power difference between men (m) and women (w) can be summarized as $\frac{w_{o,w}}{w_{r,w}} < 1-\gamma < \frac{w_{o,m}}{w_{r,m}}$, leading to differential reallocation responses and notably, to hours worked in retail being less elastic to wage decreases in retail for women than for men (or even, elasticities of contrasting signs). These different reallocation responses are precisely what our results disentangled by gender show.

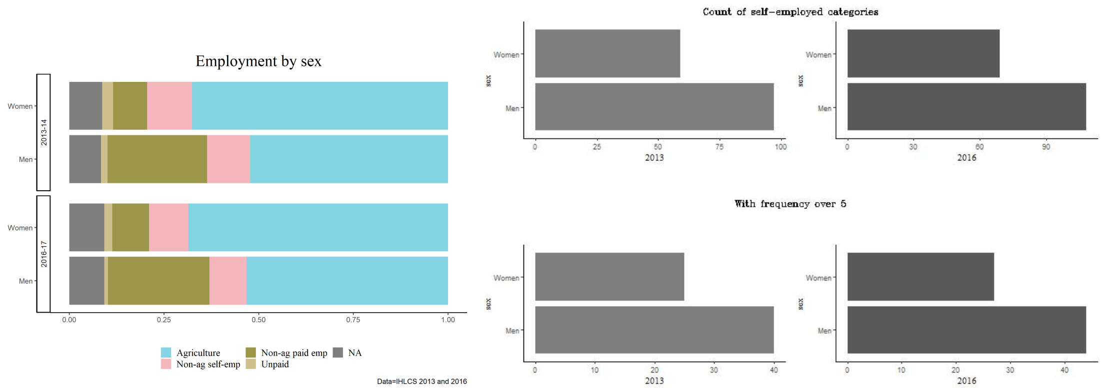

Figure 6: Type of and number of self-employment categories declared by sex (2013-2016)

5.1 Descriptive evidence on gendered outside options in the labor market

Insights from the literature on gender-dependent market power Two facts describe the working environment in which most working women of the developing world operate: a universal over-representation in self-employment, and yet, higher income gender gaps in self-employment gaps there than in any other working status [Heath et al., 2015]. I explore the causes for this gap providing descriptive evidence of women's lack of salaried employment opportunities, and higher within-industry concentration in self-employed occupations, following closely the argumentation in Hardy and Kagy [2020]. Relative to my framework, I conclude that women have a lower level of outside options in retail than men: $\frac{w_{o,w}}{w_{r,w}} < \frac{w_{o,m}}{w_{r,m}}$.

First, I argue that self-employed women having fewer outside employment options than men leave them having relatively less market power, and therefore less profits, in the labor markets they operate in, following the intuition set by Hardy and Kagy [2020]. Political science accounts of used clothes markets in other sub-Saharan African countries, such as Mozambique in Brooks [2019], mention product segmentation - women selling women's clothes - and similar labor markets such as the garments market in Ghana [Hardy and Kagy, 2020] also feature customer segmentation - women shopping from women. With either of these characteristics, the fact that women operate in more crowded markets will make a negative earnings shock weigh more on women - which we observe in our earnings regressions.

Then and in conformity with the framework's predictions, a relative lack of outside options could induce a lower ability to exit toward other occupations - a mechanism illustrated in Sharma [2023] in the case of salaried textile workers in Brazil, with men exiting the profession relatively more when wages decrease exogenously. To support this channel, I first present descriptive statistics, showing that self-employed women operate in fewer industries (cross-industry concentration) and that the industries that they do operate in are more crowded (within-industry concentration), relative to self-employed men, closely following Sharma [2023].

Descriptive evidence on gendered within- and cross-industry concentration I present job-spell level descriptive statistics, closely following Hardy and Kagy [2020] in their argumentation that women operate in more crowded industries than men.

The structure of employment differs greatly by gender, which is primarily due to lower access to paid non-agricultural employment (Figure 6). As stated in Heath et al. [2015], the higher prevalence of self-

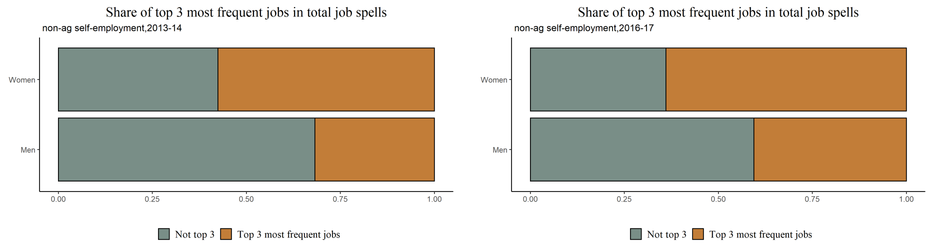

Figure 7: Share of self-employment obs held in top 3 occupations, by sex

employment among women in developing countries can be partly explained is explained partly by hiring discrimination preventing them from entering non-farm wage work. In the context of Rwanda, there is a comparable share of men and women in non-agricultural self-employment job spells. However, when looking at the variety of these job spells, in terms of the number of ISIC3 classifications declared (Figure 6), it appears that women operate in fewer occupations than men, and even more so when only looking at occupations where more than 5 women or men say they operate. The fact that a lower number of industries provide suitable jobs is characterized in Sharma [2023], in the case of salaried work, as a higher cross-industry concentration for women.

In our setting, while self-employed men outside of agriculture declared almost 100 occupations (40 with more than 5 men declaring to work in that sector) in 2013, only 55 (respectively 25) industries were cited by women (Figure 6). This result is constant across time.

Beyond being kept in a few sectors, the industries women do work in are relatively more crowded. Looking at the number of people declaring a to work in a given ISIC3 sector in Figure 7, we can see that more than 50% of women's non-agricultural self-employed job spells are concentrated in 3 industries only[19], while men face less polarized self-employment labor markets. As a result, in 2013, men operated in sectors where 783 other people worked, on average (2013), versus 556 for men, and in 2016, these numbers were respectively 858 and 577.

The consequence of this discrepancy in within and cross-industry crowding is, first, that men's earnings react relatively less to shocks - adverse in our case, but also to positive shocks in the case of Hardy and Kagy [2020]. Men in the self-employed retail sector are making more profits than women: although unfortunately, the IHLCS data lacks information on total capital use, Figure 8 also suggests that, for a similar level of expenses, they are generating more turnover than women. Given this initial situation, it is thus likely that they either have more customers and are operating at fuller capacity, or are able to charge more prices, because of that differential crowding and of product or customer segmentation - two plausible channels that our data does not allow us to investigate, but could mitigate the impact of a negative shock.
Secondly, this gender difference in the availability of suitable occupations implies that a given impact level has

[19]These industries are, in order, retail sales via stalls and markets, retail sales not in stores, stalls or market, and wholesale of food, beverages, and tobacco, with retail sales of food, beverages, and tobacco also a predominant industry in 2016.

more persistence on women's income. With fewer outside options, owing either to geographical or amenities preferences or norms of "acceptable occupations" for women [Sharma, 2023], women will not reallocate as quickly. In the event that women suffer a larger shock on their earnings (lower $1 - \gamma$ in the framework) than men, which follows from the higher concentration, a lower reallocation response such as the one I shed light upon is all the more telling as to the outside options available to them.

After presenting descriptive evidence supporting considering women as having lower outside options than men, I then turn to heterogeneity results and check my model's predictions. In Appendix B, I explore two other potential channels that my results could have picked up: composition effects in skill and education driving negative results for women, the role of being the sole breadwinner, or living with a husband - a proxy for intra-household bargaining power. Overall, interacting with these explanatory variables does not change the sign and significance of our main coefficients of interest, the impact of the shock on the whole exposed retail workers population, and the additional effect on women, and the interaction with the new variables is never statistically significant.

6 The role of outside options: results on heterogeneity by gender

As in the first result section, I first investigate job-spell level earnings and individual income, discussing gendered impacts on livelihoods before turning to reallocation patterns.

Table 7 shows gendered effects of the shock on weekly earnings and hourly earnings at the job level from Equation 3. We have two ways of interpreting the results. First, $Post \times SES \times ZDE$ is the effect of being a man retailer in a zone 1 s.d. more exposed to $caguwa$ trade, and $Post \times SES \times F \times ZDE$, denotes the additional effect for women's trends. Alternatively, the difference between $Post \times SES \times F \times ZDE$ and $Post \times SES \times ZDE$ is the comparison of the trends of retail premia for women, from exposed areas to non-exposed areas. Because $caguwa$ is an occupation in which women are over-represented, women could also be disproportionately affected by the shock, leading to a gender composition effect which is netted out when comparing the trends for women retailers across zones.

When separating by gender in columns (1) and (2), it appears that the weight of the relative earnings decrease fell almost exclusively on women, with their job-level daily earnings growing less by 14% (18.9% for hourly earnings), while the coefficients for men's earnings in more exposed areas, $Post \times SES \times ZDE$ are not significant at traditional levels. Not only are women retailers in most exposed areas the only ones suffering slower earnings growth relative to less exposed zones ($Post \times SES \times F \times ZDE$ - $Post \times SES \times ZDE$), but the divergence also intensifies when looking at hourly earnings (col. (2)).

The impact of the tariff shock is thus gendered in two ways: first, earnings grow slower in more exposed zones, but especially so for women. Second, effects on women relative to men are more negative when considering the main job of the week, suggesting that men are reallocating toward other occupations during the year. Effects on hourly earnings are also stronger than effects on daily earnings, indicating that women could be working relatively more hours to mitigate their daily losses, in conformation with the simple framework of time allocation. We investigate this possibility in col. (3)-(4).

We see that the gap between the impact on daily and hourly wages is partly driven by the fact that women

	Earnings		*Hours worked*		*Selection*
	Daily	Hourly	Hours	Log. hours	Kept Job
Post × SES × F × ZDE	-0.140**	-0.189***	3.480**	0.060	-0.003
	(0.06)	(0.07)	(1.38)	(0.04)	(0.00)
Post × SES × ZDE	-0.009	0.002	-1.799*	-0.019	0.001
	(0.05)	(0.06)	(1.05)	(0.03)	(0.00)
Post × SES	-0.055	-0.191*	4.800***	0.155***	0.005*
	(0.10)	(0.11)	(1.82)	(0.06)	(0.00)
Post × SES × F	0.140	0.236*	-2.733	-0.090	-0.006*
	(0.13)	(0.14)	(2.31)	(0.07)	(0.00)
Post × F	0.040	0.028	-0.245	-0.012	0.000
	(0.03)	(0.03)	(0.38)	(0.02)	(0.00)
Post × F × ZDE	-0.001	-0.013	0.129	0.002	0.001
	(0.02)	(0.02)	(0.43)	(0.02)	(0.00)
Post × ZDE	0.014	0.011	-0.040	-0.002	-0.001
	(0.01)	(0.01)	(0.33)	(0.01)	(0.00)
SES × F	-0.338***	-0.360***	-2.470*	-0.025	0.002
	(0.08)	(0.09)	(1.38)	(0.05)	(0.00)
SES × F × ZDE	0.164***	0.174***	-0.167	0.028	0.002
	(0.04)	(0.05)	(0.93)	(0.03)	(0.00)
SES × ZDE	-0.010	-0.001	-0.347	-0.039*	-0.001
	(0.04)	(0.04)	(0.76)	(0.02)	(0.00)
F × ZDE	-0.040**	-0.034**	-0.692**	-0.020*	-0.001
	(0.02)	(0.02)	(0.32)	(0.01)	(0.00)
R-squared	0.468	0.394	0.238	0.144	0.005
N	23638	23619	53429	53429	53459
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round).
F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.
Sample: (1)-(2): all main jobs of week with non-null earnings. (3)-(5): all main jobs of week.

Table 7: Daily and hourly earnings

	log(Weekly Y)	Tot. hours	log(weekly Y/hour)
Post × SES × F × ZDE	-0.096*	0.069*	-0.165***
	(0.06)	(0.04)	(0.06)
Post × SES × ZDE	-0.004	-0.001	-0.003
	(0.05)	(0.03)	(0.05)
Post × SES	-0.024	0.066*	-0.071
	(0.07)	(0.04)	(0.08)
Post × SES × F	0.114	-0.052	0.136
	(0.09)	(0.05)	(0.09)
Post × F	0.051*	-0.007	0.067**
	(0.03)	(0.02)	(0.03)
Post × F × ZDE	-0.019	-0.003	-0.009
	(0.02)	(0.01)	(0.02)
Post × ZDE	0.012	-0.001	0.008
	(0.01)	(0.01)	(0.02)
SES × F	-0.225***	-0.036	-0.202***
	(0.06)	(0.03)	(0.06)
SES × F × ZDE	0.125***	0.011	0.145***
	(0.04)	(0.03)	(0.04)
SES × ZDE	-0.033	-0.025	-0.017
	(0.03)	(0.02)	(0.03)
F × ZDE	-0.002	-0.014	-0.011
	(0.02)	(0.01)	(0.02)
R-squared	0.479	0.162	0.405
N	29980	53684	29969
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals with non-null earnings ((1) and (3)), and all individuals with a job in the interview week (2).

Table 8: Income - gender heterogeneity

are working relatively more hours in affected jobs, driving these jobs to become their main jobs of the week (column (2)). If a man's main job of the week is in retail, the hours he works at that job will decrease by 1.799 hours relative to workers with a main job in retail in less exposed areas. By contrast, women with a main job in retail in more exposed areas will increase hours worked by 1.681 hours on average (the difference between the coefficients for $Post \times SES \times ZDE$ and $Post \times SES \times ZDE \times F$) compared to self-employed women retailers in less affected areas. The coefficients are not statistically significant when we study the logarithm of hours worked (col. (4)): I put both coefficients because, first, the p-value on our gendered coefficient on col.(4) is around 15%, indicating that something could be happening still, but also because the model put forward delivers predictions in terms of levels. Additionally, the explanatory power of our level model seems to be higher, consistent with the fact that there do not seem to be unreasonably high values in hours worked. Finally, col. (5) shows the absence of gender-dependent trends in the likelihood of still exercising an affected job, which could lead to selection in the sub-sample of jobs for which we have hour data if, for example, men leave affected jobs more often than women. While women increase hours worked in the negatively affected occupation, men decrease them, indicating different abilities to adjust to a shock.

In order to tie these results with individual, real-life consequences for self-employed women, Table 8 estimates impacts on weekly income at the individual level: SES now designates having worked in self-employed retail with a start date before June 2016, as in Equation 2. While weekly income only decreases slightly for women retailers as compared to men retailers in exposed areas (col. (1)) - hourly income decreases much more (col. (3)). Maintaining the same weekly income gap is done at the cost of working more hours for women, and these hours are worked in the affected jobs, as shown in Table 7. These adjacent facts suggest that faced with a decrease in earnings, self-employed retail women work more hours in the affected jobs to mitigate negative impacts, while men reallocate time away from these occupations, which fits the predictions of the framework delineated in prior sections.

6.1 Reallocation channels

The results on earnings and income paint a picture of both differential impact and persistence of shocks on self-employed workers in developing countries. While men and women both suffer a decrease in earnings, women's relative decrease is larger. Additionally, only women's earnings persist to be relatively smaller even during the interview week, sometime after the shock (up to 17 months), pointing to different adaptation strategies and leading to divergence in earnings and income as time passes after the policy. While men draw away from declining jobs, not only do women stay, but they become more and more invested in them in terms of working hours. Examination of income patterns reveals that affected women invest more time in these jobs to maintain total income relative to their men counterparts, at the expense of longer working hours. These findings are striking in light of standard labor theory: in response to an hourly wage decrease, hours worked should decrease and even more so for affected women for whom the relative decrease was larger. They point to limited reallocation capacity, leading to these increased working hours. While our results on total hours worked and earnings in and out of retail fit the simplistic framework that we have put forward, it is policy-relevant to examine further the occupational choices that men and women are making behind this reallocation of their working hours. I thus will focus the rest of my investigation on the mechanisms behind these theory-divergent results. First, I will explore further differences in adaptation strategy along several intensive and extensive dimensions, looking specifically at how men reallocate to draw away from affected jobs and in what ways women are not following their strategy. We have seen that there is no gender-dependent trend in leaving affected jobs altogether. Rather, men seem to be maintaining income relative to retailers in less affected areas, but working less and diminishing earnings from their affected retail jobs. Whether they redistribute time away from this job into jobs they already hold or take on new occupations, signals different reallocation mechanisms and the fact that women seem not to be doing the same entails policy implications. To explore these responses, I investigate trends on several dimensions of the intensive margin, following the results examined in the first strand of results.

Results from Table 9 reveal striking heterogeneity behind the labor supply results in Table 3. In contrast with this table, only affected retailers who are women, and not all affected retailers, are increasing the hours they work per job (col. (2)), through an increase in total hours worked coupled with a decrease in the number of jobs worked per week and year (cols. (6-7)), which given the lack of results on paid jobs, indicates a decrease in the likelihood of being an unpaid worke. The result on paid jobs per week from Table 3 seems only to be close to significace for men (col. (4), p-value 10.1%), who seem to thus be decreasing the number of hours worked in affected retail jobs, while not abandoning these occupations (Table 2), but are maintaining income, hours (col. (2)) and months worked (col. (3)) by diversifying and potentially acquiring another paid job (col. (4)). In contrast, women that were affected by the shock seem to be adapting, in line with

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × SES × F × ZDE	0.013	2.574*	0.178	-0.007	0.002	-0.046*	-0.037
	(0.01)	(1.38)	(0.14)	(0.02)	(0.03)	(0.02)	(0.03)
Post × SES × ZDE	-0.004	-0.615	0.118	0.024	-0.008	0.022	0.003
	(0.01)	(0.97)	(0.10)	(0.01)	(0.02)	(0.02)	(0.03)
Post × SES	0.003	2.772*	0.547***	-0.021	-0.113***	-0.118***	-0.145***
	(0.01)	(1.59)	(0.15)	(0.03)	(0.04)	(0.03)	(0.05)
Post × SES × F	-0.005	-1.094	-0.075	-0.025	0.029	-0.000	0.022
	(0.01)	(1.83)	(0.20)	(0.03)	(0.04)	(0.04)	(0.05)
Post × F	-0.004	-0.270	-0.396***	0.031***	0.057***	0.004	0.084***
	(0.00)	(0.48)	(0.07)	(0.01)	(0.01)	(0.01)	(0.01)
Post × F × ZDE	-0.005	0.698	0.071	-0.008	-0.021**	0.010	-0.017
	(0.00)	(0.48)	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)
Post × ZDE	0.002	-0.423	-0.056	-0.006	0.006	-0.001	0.009
	(0.00)	(0.39)	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
SES × F	0.012**	-0.214	-0.508***	0.056**	0.165***	0.001	0.158***
	(0.01)	(1.00)	(0.12)	(0.02)	(0.03)	(0.03)	(0.03)
SES × F × ZDE	0.005	-0.368	0.353***	0.015	0.003	0.024	-0.043*
	(0.01)	(0.86)	(0.11)	(0.01)	(0.02)	(0.02)	(0.02)
SES × ZDE	0.001	0.984	0.157**	-0.033***	-0.065***	-0.059***	-0.079***
	(0.01)	(0.70)	(0.08)	(0.01)	(0.02)	(0.01)	(0.02)
F × ZDE	0.010***	-0.983***	-0.562***	-0.011**	0.011**	-0.030***	0.055***
	(0.00)	(0.36)	(0.05)	(0.00)	(0.01)	(0.00)	(0.01)
R-squared	0.051	0.240	0.361	0.234	0.330	0.235	0.236
N	61001	42087	71766	71766	71766	66232	61001
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals (1-7), except for (2) which is all individuals with at least a job in the interview week.

Table 9: Intensive labor supply

our job-level estimates and our model, by increasing the number of hours they work at a job during the week but decreasing the number of jobs they work per week (col. (7)). Exploring whether men take on new occupations or substitute time away into already held jobs leads us to uncover diverging trends in how workers reallocate their time: rather than diversifying as men do, taking new jobs, women's time is polarized toward pre-existing, declining jobs, leading them to let go of some of their unpaid occupations. In contrast with the existing literature on impacts of trade shocks on workers, there does not seem to be unemployment response, either on the part of all exposed workers or only for women (col. (1)) here either.

In Table 10, I explore which jobs women are abandoning. Although I focus on the main job of the week results are constant across all jobs, including those that individuals work beyond their main job of the week, as shown in Table 52 in the Appendix.

First and speaking to the literature on responses to trade shocks in developing countries, we notice the absence of an informality response for both men and women retailers. Contrary to Ponczek and Ulyssea [2021] or McCaig and Pavcnik [2018], changes in returns to informal jobs - characterized here as wage jobs with no fixed contract or self-employed jobs that are not registered to the Rwanda Revenue Authority, sector or district administration - do not lead to changes in the likelihood of holding a formal job. In our case, women choose to make up for the lost income not by switching jobs, but by reallocating time away from other jobs to their negatively affected retail job. Looking at our occupational choice results, it appears that women are drawing

	Persistence	*Main job of the week* W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × SES × F × ZDE	-0.033*	0.006	-0.006	-0.031***	0.028	-0.013	-0.002
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)
Post × SES × ZDE	0.022*	0.006	0.006	0.007	-0.014	0.017	0.004
	(0.01)	(0.00)	(0.01)	(0.00)	(0.02)	(0.01)	(0.00)
Post × SES	0.031	-0.001	-0.007	-0.013	0.003	0.006	0.007*
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.00)
Post × SES × F	-0.000	-0.024*	-0.001	0.051***	0.006	0.033	-0.005
	(0.03)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.00)
Post × F	-0.015**	0.017***	0.008	-0.071***	-0.002	0.000*	0.006***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Post × F × ZDE	0.007	-0.002	0.004	0.012**	-0.002	0.000**	0.000
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Post × ZDE	-0.006	-0.004**	-0.007	0.002	0.002	-0.000	-0.001
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
SES × F	-0.028	0.046***	0.103***	-0.032**	-0.090***	-0.139***	0.003
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)
SES × F × ZDE	0.029**	-0.014***	0.021**	0.012**	-0.006	0.028**	-0.000
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
SES × ZDE	0.011	0.006**	-0.048***	0.000	0.007	0.047***	-0.005***
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
F × ZDE	-0.050***	0.003*	-0.022***	-0.052***	-0.013***	-0.000	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.186	0.075	0.234	0.170	0.215	0.432	0.010
N	71766	71665	71665	71665	71766	71766	71766
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level. Sample: all individuals (1-7)

Table 10: Occupational choice - main job week

away from unpaid family member jobs (col. (4)).

I also study gendered migration patterns in Table 50. There are no inter or intra-district migration responses, although women are less likely to perform return migration which is usually done for loss of employment or marriage purposes, potentially suggesting binding budget constraints, in line with our other results.

The gap between men and women's responses to a common, although not equal, decrease in earnings is illustrative of differential adaptation capacities and consequential in terms of hourly income and occupational choice. In line with predictions from the simple framework put forward in prior sections, with literature interested in self-employment in developing countries and with suggestive descriptive evidence from my Rwandan databases, I attribute these diverging adaptation paths to women's outside options being lower out of the self-employed job spells they are kept into, leading them to stay in downgrading occupations, maintaining income at the cost of their unpaid family work. Although we see no consequence of this unpaid family work abandon on household consumption in Table 8, the fact that these were not lucrative occupations could be suggesting consequences elsewhere, notably for household children - an important follow-up avenue.

7 Robustness checks

Robustness checks are presented in Appendix B. I first check that the effects picked up by the heterogeneity analysis are not those of a different skill composition across genders, or of different financial burdens, further differentiating my estimating equations by a dummy for having a school diploma or a dummy for being the sole breadwinner of the household. Neither of these indicator variables change the results, first-stage or interaction with gender.

I also use two alternative spatial indexes. The first changes the numerator: as the $caguwa$ variable is determined by the enumerator's choice to specify that a given seller sells used clothes, it is a lower bound for true $caguwa$ activity. Moreover, in areas with low prevalence of $caguwa$ sellers, the choice of a few enumerators to not specify $caguwa$ could lead to a false zero exposure being attributed to a district. I consider the prediction on invariant characteristics of being a $caguwa$- establishment: the procedure is detailed in the data section and has good predictive power for actual $caguwa$ establishments. Considering this spatial index in subsection A.3 does not change the direction and overall significance of the results. Alternatively, I change the denominator and use standardized $\frac{caguwa}{retail}$ - the number of workers in the retail sector rather than the number of workers in the district - to account for the size of the retail sector in a given district. The index can be thought of as a measure of the impact of the shock on retail sectors, rather than a measure of the impact on the district as a whole. I find that while earnings, income, and reallocation results are unchanged, women do not follow significantly different trajectories than men in terms of hours reallocation. Retailers are affected differently in more exposed areas compared to less exposed retailers, but the reallocation patterns become more similar between genders. As a consequence, the gendered effect ($Post \times SES \times ZDE \times F$) disappears. The result supports our main hypothesis, the outside option channel: the results suggest that the districts in which trajectories were most different between men and women were those with a high $\frac{caguwa}{active\_population}$ and a low $\frac{caguwa}{retail}$ ratio, areas with both prevalent used clothing trade and big retail sectors. As stated in section 1, for men operating in $caguwa$, retail - and especially retail as wage-earners - is an outside option, while for women, it is not. For a given level of $caguwa$ prevalence, having a smaller retail sector - leading to a larger $\frac{caguwa}{retail}$ ratio - means lower quality of outside options for men relative to women. As a result, men and women should have more similar reallocation trajectories, which the results on hours not being significant while still of the right direction illustrate.

Finally, in order to check the stability of the results and check that one high-density state is not influencing all of them, I discretize the spatial exposure variable, isolating the 10% most isolated states, which are shown on the map. Results have similar significance levels and directions that the main specification.

8 Conclusion

In this paper, I use an administrative census of formal and informal firms and job-level survey data to compare trends in earnings and income following a trade policy-induced price shock on a good bought and re-sold by self-employed workers. My results point to the specific margins available to the self-employed and underexplored by the literature: rather than an unemployment or informality response to this negative earnings shock, self-employed workers adjust quantities bought to maintain expenses, pass some of the policy through to customer prices, and adjust the time spent at this and their other jobs to mitigate income losses. Impact studies of trade shocks in countries with high self-employment prevalence such as most African countries, should allow for self-employed specific adaptation margins, ideally with job-level data as these margins are exerted across different jobs in the same time peroid.

I rationalize these self-employment specific responses in a time allocation model. It predicts different reallocation patterns conditional on the quality of available outside options, which I test by looking at trajectories for men and women. I test the model's prediction and uncover striking gender heterogeneity in how self-employed workers respond to shocks, along two dimensions: profit losses are borne primarily by women, suggesting a larger impact, and the impact vanishes with time only for men, indicative of longer persistence and limited reallocation capacity of women. While men are reallocating time away from affected jobs to other paid occupations, women are doing the opposite, polarizing their time in affected retail jobs by abandoning unpaid family jobs. I put forward a gender-specific lack of outside options and the fact that women operate in more crowded industries as a potential channel behind my results, provide descriptive evidence to speak to that hypothesis and explore other possible mechanisms in the Appendix. The abandonment of unpaid family member jobs, especially as it does not affect household-level consumption, indicates that the ceased activities were in-house non-lucrative jobs. It suggests that they were bringing utility either to women themselves, or other household members like children, and entails empowerment consequences beyond gendered adaptation strategies to seemingly gender-neutral trade policy. Reallocating away from unpaid jobs also suggests binding consumption constraints making women more dependent on their paid job, even though it is getting less and less lucrative because of the trade shock. Policies aimed at helping the most vulnerable segments of the population adapt to trade policy are all the more crucial in low-income countries where self-employment is prevalent.

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	log(inc.)	log(tot hours)	log(hourly inc.)	log(cons.)
Post × SES × Exp.	-0.238*	-0.011	-0.207	-0.017
	(0.13)	(0.06)	(0.13)	(0.07)
R-squared	0.478	0.161	0.403	0.233
N	30080	53821	30069	28031
District-urban FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 11: Income and hours, individual level - discrete spatial exp.

	log(earnings)		*self-emp. sample*		*Hours this week*		*Selection*
	Daily	Hourly	Turnover	Non-labor expenses	Hours	Log hours	Kept job
Post × SES × Exp.	-0.428***	-0.388**	-0.302	0.445	-0.495	-0.011	0.000
	(0.16)	(0.16)	(0.18)	(0.34)	(2.47)	(0.08)	(0.01)
N	23729	23710	5220	4006	53566	53566	53596
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 12: Earnings, hours worked and selection - discrete spatial exp.

A Robustness checks - other specifications

A.1 Alternative spatial index: discrete $caguwa$ (top 10% districts)

A.1.1 Income and earnings

A.1.2 Migration

A.1.3 Reallocation

	Earnings		*Hours worked*		*Selection*
	Daily	Hourly	Hours	Log. hours	Kept Job
Post × SES × F × Exp.	-0.700**	-0.939***	12.066**	0.182	-0.015
	(0.29)	(0.31)	(5.41)	(0.17)	(0.01)
Post × SES × Exp.	-0.008	0.175	-8.175*	-0.108	0.010
	(0.25)	(0.27)	(4.48)	(0.13)	(0.01)
R-squared	0.468	0.393	0.237	0.144	0.005
N	23729	23710	53566	53566	53596
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 13: Earnings, hours worked and selection - gender heterogeneity - discrete spatial exp.

	log(Weekly Y)	Tot. hours	log(weekly Y/hour), week
Post × SES × F × Exp.	-0.503**	0.221	-0.738***
	(0.23)	(0.14)	(0.24)
Post × SES × Exp.	0.093	-0.136	0.250
	(0.20)	(0.11)	(0.22)
R-squared	0.479	0.161	0.404
N	30080	53821	30069
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 14: Income and hours, individual level - gender heterogeneity - discrete spatial exp.

	Migrant	Infra-distr. move	Return migrant
Post × SES × F × Exp.	0.017	0.037	-0.039
	(0.04)	(0.06)	(0.03)
R-squared	0.079	0.064	0.060
N	66410	66410	66410
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 15: migration - discrete spatial exp.

	Migrant	Infra-distr. move	Return migrant
Post × SES × Exp.	-0.006	-0.000	-0.015
	(0.02)	(0.03)	(0.01)
R-squared	0.079	0.064	0.059
N	66410	66410	66410
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 16: Migration - gender heterogeneity - discrete spatial exp.

		Main job of the week					
	Persistence	W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × SES × Exp.	0.011	0.036*	0.027	-0.053**	0.030	-0.001	0.007
	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.01)
N	71956	71854	71854	71854	71956	71956	71956
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 17: Reallocation - main job week - discrete spatial exp.

	Main job of the week					
	W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × SES × F × Exp.	0.021	0.018	-0.141***	0.119*	-0.029	-0.010
	(0.04)	(0.05)	(0.04)	(0.07)	(0.09)	(0.01)
Post × SES × Exp.	0.024	0.015	0.035*	-0.055	0.011	0.015
	(0.03)	(0.05)	(0.02)	(0.06)	(0.07)	(0.01)
R-squared	0.075	0.232	0.167	0.212	0.424	0.011
N	71854	71854	71854	71956	71956	71956
District-urban FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 18: Reallocation - main job week - gender heterogeneity - discrete spatial exp.

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × SES × Exp.	0.007	-2.005	0.909***	0.153***	0.062	0.069	-0.019
	(0.02)	(2.36)	(0.28)	(0.04)	(0.06)	(0.06)	(0.07)
N	61159	42188	71956	71956	71956	66410	61159
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 19: Reallocation - intensive - discrete spatial exp.

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × SES × F × Exp.	0.020	10.998**	0.398	-0.103	-0.041	-0.190*	-0.170
	(0.04)	(5.12)	(0.56)	(0.09)	(0.10)	(0.10)	(0.13)
Post × SES × Exp.	-0.005	-9.466**	0.614	0.235***	0.113	0.207**	0.122
	(0.02)	(4.38)	(0.43)	(0.07)	(0.09)	(0.08)	(0.11)
R-squared	0.048	0.243	0.358	0.233	0.329	0.234	0.235
N	61159	42188	71956	71956	71956	66410	61159
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 20: Reallocation - intensive - gender heterogeneity - discrete spatial exp.

	Wage	Unpaid fam	Formal	Retail	Sales, no ret.
Post × SES × Exp.	0.080***	-0.052*	0.042	0.006	0.015
	(0.03)	(0.03)	(0.04)	(0.04)	(0.01)
R-squared	0.174	0.190	0.209	0.612	0.616
N	71956	71956	71956	71956	71956
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 21: Reallocation - this week - discrete spatial exposure

	Wage	Unpaid fam	Formal	Retail	Sales, no ret.
Post × SES × F × Exp.	0.040	-0.143***	0.116	-0.110	-0.008
	(0.07)	(0.05)	(0.07)	(0.08)	(0.03)
Post × SES × Exp.	0.064	0.044*	-0.040	0.078	0.019
	(0.06)	(0.02)	(0.07)	(0.06)	(0.02)
R-squared	0.176	0.193	0.212	0.615	0.616
N	71956	71956	71956	71956	71956
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 Exp: district in the top 10% most exposed districts to caguwa trade. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 22: Reallocation - this week - gender heterogeneity - discrete spatial exposure

	log(inc.)	log(tot hours)	log(hourly inc.)	log(cons.)
Post × SES × ZDE	-0.098**	0.027	-0.120***	-0.016
	(0.04)	(0.02)	(0.04)	(0.02)
R-squared	0.478	0.161	0.404	0.233
N	29980	53684	29969	27961
District-urban FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 23: Income and hours, individual level - first stage - retail denominator

A.2 $caguwa/retail$

A.2.1 Income and earnings

A.2.2 Migration

A.2.3 Reallocation

	log(Weekly Y)	Tot. hours	log(weekly Y/hour), week
Post × SES × F × ZDE	-0.086	0.021	-0.109
	(0.07)	(0.04)	(0.08)
Post × SES × ZDE	-0.039	0.018	-0.054
	(0.06)	(0.03)	(0.07)
R-squared	0.479	0.162	0.404
N	29980	53684	29969
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 24: Income and hours, individual level - gender heterogeneity - retail denominator

	log(earnings)		*self-emp. sample*		*Hours this week*		*Selection*
	Daily	Hourly	Turnover	Non-labor expenses	Hours	Log hours	Kept job
Post × SES × ZDE	-0.183***	-0.207***	-0.179***	0.058	0.392	0.036	-0.001
	(0.05)	(0.05)	(0.06)	(0.11)	(0.82)	(0.03)	(0.00)
N	23638	23619	5212	3999	53429	53429	53459
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 25: Job-level earnings, hours and selection - retail denominator

	Earnings		*Hours worked*		*Selection*
	Daily	Hourly	Hours	Log. hours	Kept Job
Post × SES × F × ZDE	-0.169*	-0.188*	1.960	0.024	-0.003
	(0.09)	(0.10)	(1.73)	(0.05)	(0.00)
Post × SES × ZDE	-0.084	-0.100	-0.635	0.030	0.001
	(0.08)	(0.08)	(1.44)	(0.04)	(0.00)
R-squared	0.468	0.393	0.238	0.144	0.005
N	23638	23619	53429	53429	53459
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 26: Earnings, hours worked, selection - gender heterogeneity - retail denomiator

	Migrant	Infra-distr. move	Return migrant
Post × SES × ZDE	-0.003	0.001	0.001
	(0.01)	(0.01)	(0.00)
R-squared	0.063	0.064	0.041
N	66232	66232	66232
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 27: Migration - first stage - retail denominator

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × SES × ZDE	0.001	0.467	0.313***	0.046***	-0.005	0.008	-0.028
	(0.01)	(0.74)	(0.08)	(0.01)	(0.02)	(0.02)	(0.02)
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 28: Reallocation - intensive - first stage - retail denominator

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × SES × F × ZDE	0.009	1.719	0.096	-0.006	-0.007	-0.048	-0.042
	(0.01)	(1.66)	(0.16)	(0.03)	(0.04)	(0.03)	(0.04)
Post × SES × ZDE	-0.004	-0.578	0.257**	0.051**	0.001	0.039	-0.002
	(0.01)	(1.39)	(0.13)	(0.02)	(0.03)	(0.03)	(0.04)
N	61001	42090	71766	71766	71766	66232	61001
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 29: Reallocation - intensive - gender heterogeneity - retail denominator

		Main job of the week					
	Persistence	W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × SES × ZDE	0.003	0.019***	0.003	-0.020**	0.018*	0.016	0.002
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 30: Reallocation - main job week - first stage - retail denominator

	Main job of the week					
	W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × SES × F × ZDE	0.000	0.003	-0.063***	0.022	0.008	-0.002
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.00)
Post × SES × ZDE	0.019**	0.001	0.020**	0.003	0.010	0.003
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)
District-urban FEk	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 31: Reallocation - main job week - gender heterogeneity - retail denominator

	Wage	Unpaid fam	Formal	Retail	Sales, no ret.
Post × SES × ZDE	0.021**	-0.017*	0.018	0.006	0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
R-squared	0.174	0.190	0.211	0.612	0.616
N	71766	71766	71766	71766	71766
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 32: Reallocation - this week - retail denominator

	Wage	Unpaid fam	Formal	Retail	Sales, no ret.
Post × SES × F × ZDE	-0.001	-0.062***	0.025	0.005	0.002
	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
Post × SES × ZDE	0.023	0.023**	0.001	0.002	0.003
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
R-squared	0.177	0.194	0.213	0.615	0.617
N	71766	71766	71766	71766	71766
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district caguwa/retail sector ratio, t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 33: Reallocation - this week - gender heterogeneity - retail denominator

	log(inc.)	log(tot hours)	log(hourly inc.)	log(cons.)
Post × SES × ZDE	-0.068*	0.046**	-0.114***	0.012
	(0.04)	(0.02)	(0.04)	(0.02)
R-squared	0.479	0.162	0.405	0.236
N	29980	53684	29969	27961
District-urban FE	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 34: Income and hours, individual level - first stage - $caguwa$ predictor

	log(Weekly Y)	Tot. hours	log(weekly Y/hour), week
Post × SES × F × ZDE	-0.099	0.044	-0.138**
	(0.06)	(0.04)	(0.07)
Post × SES × ZDE	-0.008	0.021	-0.034
	(0.05)	(0.03)	(0.05)
R-squared	0.480	0.162	0.406
N	29980	53684	29969
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 35: Income and hours, individual level - gender heterogeneity - $caguwa$ predictor

A.3 Alternative spatial index: $caguwa$ predictor

A.3.1 Income and earnings

A.3.2 Migration

A.3.3 Reallocation

	log(earnings)		*self-emp. sample*		*Hours this week*		*Selection*
	Daily	Hourly	Turnover	Non-labor expenses	Hours	Log hours	Kept job
Post × SES × ZDE	-0.098**	-0.125***	-0.146***	-0.167**	0.392	0.022	-0.001
	(0.04)	(0.04)	(0.05)	(0.08)	(0.75)	(0.02)	(0.00)
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 36: Job-level earnings, hours worked and selection - $caguwa$ predictor

	Earnings		*Hours worked*		*Selection*
	Daily	Hourly	Hours	Log. hours	Kept Job
Post × SES × F × ZDE	-0.157**	-0.181**	2.372	0.029	-0.002
	(0.07)	(0.08)	(1.47)	(0.05)	(0.00)
Post × SES × ZDE	-0.011	-0.024	-0.892	0.010	0.001
	(0.06)	(0.06)	(1.16)	(0.03)	(0.00)
R-squared	0.469	0.395	0.239	0.144	0.005
N	23638	23619	53429	53429	53459
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 37: Job-level earnings, hours worked and selection - gender heterogeneity - $caguwa$ predictor

	Migrant	Infra-distr. move	Return migrant
Post × SES × ZDE	0.001	0.005	-0.004
	(0.01)	(0.01)	(0.00)
R-squared	0.063	0.064	0.081
N	66232	66232	66232
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 38: Migration - first stage - $caguwa$ predictor

	Migrant	Infra-distr. move	Return migrant
Post × SES × F × ZDE	0.003	0.019	-0.017**
	(0.02)	(0.02)	(0.01)
Post × SES × ZDE	-0.002	-0.005	0.005
	(0.01)	(0.02)	(0.01)
R-squared	0.063	0.064	0.081
N	66232	66232	66232
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 39: Migration - gender heterogeneity - $caguwa$ predictor

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × SES × ZDE	0.002	0.636	0.228***	0.020	-0.013	-0.005	-0.026
	(0.01)	(0.76)	(0.08)	(0.01)	(0.01)	(0.01)	(0.02)
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 40: Reallocation - intensive - first stage - $caguwa$ predictor

	No job	Tot.hrs/job	Av. duration	Paid jobs/week	Paid jobs/y	Jobs/w	Jobs/y
Post × SES × F × ZDE	0.008	2.501*	0.217	-0.004	0.000	-0.049**	-0.044
	(0.01)	(1.51)	(0.15)	(0.02)	(0.03)	(0.02)	(0.04)
Post × SES × ZDE	-0.001	-0.943	0.093	0.022	-0.013	0.023	-0.000
	(0.01)	(1.13)	(0.11)	(0.02)	(0.02)	(0.02)	(0.03)
R-squared	0.051	0.242	0.362	0.234	0.330	0.236	0.237
N	61001	42010	71766	71766	71766	66232	61001
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 41: Reallocation - intensive - gender heterogeneity - $caguwa$ predictor

		Main job of the week					
	Persistence	W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × SES × ZDE	0.007	0.008**	0.004	-0.008	0.008	0.010	0.003**
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
District-urban FE	✓	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 42: Reallocation - main job week - first stage - $caguwa$ predictor

	Main job of the week					
	W(f)	W(nf)	Unp. fam.	Formal	Retail	Sales, no ret.
Post × SES × F × ZDE	0.008	-0.020	-0.030***	0.020	0.003	-0.001
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.00)
Post × SES × ZDE	0.004	0.015	0.008	-0.005	0.008	0.004
	(0.00)	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)
R-squared	0.075	0.235	0.171	0.216	0.436	0.010
N	71665	71665	71665	71766	71766	71766
District-urban F	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 43: Reallocation - main job week - gender heterogeneity - *caguwa* predictor

	Wage	Unpaid fam	Formal	Retail	Sales, no ret.
Post × SES × ZDE	0.015*	-0.006	0.005	-0.000	0.005
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
R-squared	0.175	0.190	0.212	0.613	0.616
N	71766	71766	71766	71766	71766
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 44: Reallocation - this week - *caguwa* predictor

	Wage	Unpaid fam	Formal	Retail	Sales, no ret.
Post × SES × F × ZDE	-0.003	-0.034***	0.024	0.003	-0.008
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Post × SES × ZDE	0.016	0.012*	-0.009	-0.002	0.009
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
R-squared	0.178	0.197	0.215	0.616	0.617
N	71766	71766	71766	71766	71766
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1, as predicted by a classifier. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 45: Reallocation - gender heterogeneity - this week

B Controlling for alternative hypotheses

Descriptive evidence suggests that behind the disproportionate impact of the shock and limited reallocation capacity of women could be the fact that women are excluded from several salaried and self-employed occupations, making them experience more crowded markets and relatively less outside options than men. To explore alternative explanations behind our results, I also consider different channels. For each potentially explanatory variable E, I introduce an interaction term with this variable in my main specification, Equation 2. I will look at whether this variable mitigates earnings and income losses - the coefficient on $Post \times SES \times ZDE \times E_i$ - and whether this variable has an additional effect for affected women - the coefficient on $Post \times SES \times ZDE \times E_i \times sex_i$, while checking that the original impact variables, $Post \times SES \times ZDE$ and $Post \times SES \times ZDE \times sex_i$, still show an impact of the policy. Similarly to the main results, columns (1), (3) and (5) differentiate by sex, while the rest only control for it, checking for the average impact of the measure. For clarity, all of the other coefficients of the quintuple regression are omitted from the tables. Appendix G gathers descriptive statistics on the two variables I test mechanisms on, having a diploma and having no other working member in one's household. Overall, women tend to be less educated than men, and they tend to belong to households with only dependents more often, though not over-proportionately so in retail.

Education and skill First, I consider whether women were more affected because they were less skilled than men, making them both less productive (impact on earnings) and less likely to find work elsewhere (impact on income). Table 46 presents the results from the inclusion of a dummy for having received any education in my estimation. The coefficients on the interactions of this dummy with other difference terms are not significant, indicating that having received education is not the mechanism governing gender effects. Although global and gendered impacts on earnings (col. 1-4) are still precisely estimated and similar to our main results, coefficients for impact on income (col. 5-6) become imprecisely estimated, owing to the quintuple difference specification, while the effect of diploma on that variable is still insignificant.

	Earnings				*Income*	
	All jobs		*Main job of the week*			
P × SES × ZDE	-0.037	-0.145***	0.036	-0.066	-0.019	-0.062
	(0.08)	(0.05)	(0.08)	(0.06)	(0.07)	(0.06)
P × SES × F × ZDE	-0.178*		-0.205**		-0.081	
	(0.09)		(0.10)		(0.09)	
P × SES × Diploma × ZDE	-0.068	0.028	-0.066	0.000	-0.005	0.000
	(0.10)	(0.06)	(0.10)	(0.07)	(0.09)	(0.07)
P × SES × F × Diploma × ZDE	0.178		0.152		0.026	
	(0.12)		(0.13)		(0.13)	
R-squared	0.35	0.34	0.44	0.43	0.38	0.38
N	58469	58469	23932	23932	30364	30364
District-urban FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to $caguwa$ at t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 46: Impact of having any education on earnings and income

Binding budget constraints Households with fewer income-earning members, conditional on total household size, put additional pressure on those who do earn an income. If there are compositional differences in who lives in such households, my estimates could be picking up this effect rather than differences in outside options and competitive environment. To explore this possibility, I investigate whether income losses are more important when an individual does not have another working member in their household. There does not seem to be an effect of that variable on earnings, or on income: average impact (columns 2 and 4) is still significant and negative. The estimates of interaction with the indicator for being the only working member of one's household are not significant, and although the coefficient on an additional effect on women sellers is not precisely estimated anymore, it is still negative.

Impact of living with a spouse I use a dummy for living with one's spouse or partner, in order to cover the differential effects this could have on empowerment depending on gender.

	Earnings				*Income*	
	All jobs		*Main job of the week*			
P × SES × ZDE	-0.086	-0.151***	-0.033	-0.096**	-0.061	-0.097**
	(0.06)	(0.04)	(0.06)	(0.05)	(0.06)	(0.05)
P × SES × F × ZDE	-0.096		-0.113		-0.050	
	(0.06)		(0.07)		(0.07)	
P × SES × No help=1 × ZDE	0.083	0.061	0.089	0.095	0.207	0.140
	(0.14)	(0.08)	(0.15)	(0.09)	(0.14)	(0.09)
P × SES × F × No help=1 × ZDE	-0.061		-0.004		-0.178	
	(0.16)		(0.17)		(0.16)	
R-squared	0.40	0.40	0.51	0.50	0.33	0.33
N	58469	58469	23932	23932	30364	30364
District-urban FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to $caguwa$ at t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 47: Impact of being the only working household member

C Descriptive statistics

	Men				**Women**			
	not SES		**SES**		**not SES**		**SES**	
	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd
Hours worked (weekly, per job)	28.19	28.37	36.53	37.12	22.74	22.25	27.45	28.77
	(20.59)	(21.77)	(25.89)	(27.26)	(15.48)	(17.00)	(21.43)	(24.72)
Earnings	7.04	7.12	7.98	8.25	6.60	6.75	7.33	7.72
	(1.11)	(1.04)	(1.63)	(1.61)	(0.97)	(0.89)	(1.55)	(1.41)
log_turnover	8.00	8.10	8.43	8.60	7.17	7.55	7.70	8.09
	(1.68)	(1.64)	(1.57)	(1.48)	(1.63)	(1.57)	(1.51)	(1.36)
log(non-L expend.)	6.55	6.46	6.58	6.52	5.82	5.89	5.80	6.20
	(2.05)	(1.97)	(2.08)	(1.95)	(1.98)	(1.95)	(2.12)	(1.91)
Tot. hours/week	30.32	29.88	42.70	42.10	23.01	22.79	31.13	31.24
	(23.83)	(24.14)	(26.06)	(25.22)	(18.36)	(19.38)	(21.82)	(23.27)
Hourly earnings	5.24	5.26	6.39	6.45	4.92	4.94	5.95	6.08
	(1.20)	(1.13)	(1.60)	(1.55)	(1.09)	(1.02)	(1.44)	(1.40)
Observations	29598	28449	977	1013	29446	29248	1674	1539

	Men				**Women**			
	not SES		**SES**		**not SES**		**SES**	
	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd	Pre mean/sd	Post mean/sd
log(week Y)	8.58	8.66	9.63	9.52	7.91	8.00	8.83	8.98
	(1.31)	(1.28)	(1.62)	(1.59)	(1.26)	(1.22)	(1.57)	(1.48)
Observations	8219	8172	550	564	5582	5950	724	705

	Earnings				*Income*	
	All jobs		*Main job of the week*			
P × SES × ZDE	-0.033	-0.128***	0.036	-0.067	0.004	-0.066
	(0.06)	(0.04)	(0.07)	(0.05)	(0.07)	(0.05)
P × SES × F × ZDE	-0.147**		-0.196**		-0.121	
	(0.07)		(0.08)		(0.09)	
P × SES × not_living_together=1 × ZDE	-0.108	-0.033	-0.109	-0.012	-0.077	-0.011
	(0.11)	(0.06)	(0.11)	(0.07)	(0.11)	(0.07)
P × SES × F × not_living_together=1 × ZDE	0.116		0.179		0.106	
	(0.13)		(0.14)		(0.15)	
R-squared	0.41	0.40	0.51	0.51	0.47	0.47
N	58469	58469	23932	23932	30364	30364
District-urban FE	✓	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to $caguwa$ at t-1. P: post (2016-2017 round). F: female. SES: ISIC2=retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 48: Effect change with respect to living with spouse

	Men				**Women**			
	not SES		**SES**		**not SES**		**SES**	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
migrant	0.05	0.05	0.04	0.04	0.04	0.05	0.04	0.04
move	0.21	0.20	0.17	0.16	0.14	0.13	0.13	0.14
return migrant	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.01
Observations	16306	16172	694	680	18102	17901	1123	1074

	Men				Women			
	not SES		SES		not SES		SES	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Tot. hrs/job (wk)	27.80	29.00	34.92	35.40	21.00	21.64	25.55	28.53
	(23.01)	(23.99)	(28.18)	(29.42)	(17.11)	(18.89)	(24.83)	(27.31)
log(Tot hrs/job)	2.88	2.92	3.05	3.04	2.67	2.67	2.64	2.74
	(1.07)	(1.07)	(1.18)	(1.21)	(0.95)	(0.97)	(1.23)	(1.26)
Job switching								
Sum mo. work	12.51	11.37	16.41	15.29	12.21	11.05	16.44	14.65
	(8.75)	(8.07)	(7.96)	(7.11)	(8.10)	(7.66)	(8.41)	(7.48)
paid jobs/w	0.56	0.55	0.93	0.93	0.33	0.36	0.76	0.74
	(0.60)	(0.58)	(0.56)	(0.50)	(0.51)	(0.51)	(0.58)	(0.57)
paid jobs/y	0.97	0.94	1.47	1.41	0.64	0.67	1.36	1.37
	(0.87)	(0.85)	(0.75)	(0.70)	(0.71)	(0.70)	(0.59)	(0.60)
Jobs/y	1.93	1.89	2.10	1.97	1.70	1.71	2.05	2.02
	(0.93)	(0.89)	(0.96)	(0.92)	(0.74)	(0.72)	(0.84)	(0.86)
Jobs/w	1.00	1.16	1.34	1.33	0.96	1.11	1.25	1.21
	(0.74)	(0.63)	(0.70)	(0.65)	(0.71)	(0.63)	(0.76)	(0.73)
Av. job dur.	6.89	6.54	8.35	8.43	7.52	6.81	8.22	7.67
	(4.27)	(4.28)	(3.26)	(3.33)	(4.33)	(4.29)	(3.27)	(3.35)
No job (wk)	0.24	0.26	0.06	0.07	0.25	0.27	0.15	0.15
	(0.43)	(0.44)	(0.24)	(0.25)	(0.44)	(0.44)	(0.35)	(0.36)
SES (wk)	0.05	0.04	0.74	0.74	0.06	0.04	0.61	0.61
	(0.22)	(0.20)	(0.44)	(0.44)	(0.23)	(0.20)	(0.49)	(0.49)
SE (wk)	0.11	0.09	0.75	0.75	0.08	0.07	0.61	0.62
	(0.31)	(0.29)	(0.43)	(0.44)	(0.28)	(0.25)	(0.49)	(0.49)
Wage (wk)	0.42	0.43	0.11	0.14	0.24	0.28	0.12	0.11
	(0.49)	(0.50)	(0.31)	(0.35)	(0.43)	(0.45)	(0.33)	(0.31)
Ind. f (wk)	0.31	0.29	0.32	0.34	0.20	0.22	0.17	0.19
	(0.46)	(0.46)	(0.47)	(0.47)	(0.40)	(0.42)	(0.38)	(0.39)
Formal (wk)	0.17	0.18	0.40	0.40	0.07	0.08	0.19	0.18
	(0.37)	(0.38)	(0.49)	(0.49)	(0.26)	(0.27)	(0.39)	(0.38)
mjw=mjy	0.62	0.61	0.74	0.76	0.65	0.63	0.69	0.71
	(0.49)	(0.49)	(0.44)	(0.43)	(0.48)	(0.48)	(0.46)	(0.45)
Main job of the week								
Self-emp	0.08	0.07	0.59	0.57	0.04	0.04	0.42	0.44
	(0.27)	(0.25)	(0.49)	(0.50)	(0.20)	(0.19)	(0.49)	(0.50)
Wage	0.35	0.37	0.08	0.11	0.17	0.21	0.07	0.07
	(0.48)	(0.48)	(0.27)	(0.31)	(0.37)	(0.41)	(0.26)	(0.25)
W(f)	0.10	0.11	0.01	0.04	0.09	0.12	0.05	0.05
	(0.29)	(0.32)	(0.11)	(0.20)	(0.29)	(0.33)	(0.22)	(0.22)
W(nf)	0.26	0.26	0.07	0.07	0.07	0.09	0.02	0.02
	(0.44)	(0.44)	(0.25)	(0.25)	(0.26)	(0.29)	(0.13)	(0.12)
Indep. f	0.23	0.22	0.20	0.21	0.17	0.19	0.12	0.13
	(0.42)	(0.41)	(0.40)	(0.41)	(0.37)	(0.39)	(0.33)	(0.34)
Unp. fam.	0.09	0.08	0.06	0.04	0.36	0.29	0.23	0.21
	(0.28)	(0.28)	(0.23)	(0.20)	(0.48)	(0.45)	(0.42)	(0.41)
Unp. f	0.08	0.08	0.06	0.04	0.35	0.28	0.23	0.21
	(0.28)	(0.27)	(0.23)	(0.20)	(0.48)	(0.45)	(0.42)	(0.41)
Unp. nf	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01
	(0.07)	(0.06)	(0.00)	(0.05)	(0.11)	(0.11)	(0.06)	(0.07)
Formal	0.15	0.17	0.34	0.33	0.07	0.08	0.16	0.15
	(0.36)	(0.37)	(0.48)	(0.47)	(0.25)	(0.27)	(0.37)	(0.36)
SES	0.03	0.02	0.57	0.56	0.03	0.02	0.42	0.43
	(0.18)	(0.15)	(0.49)	(0.50)	(0.16)	(0.15)	(0.49)	(0.50)
Observations	16306	16172	694	680	18102	17901	1123	1074

Table 49: Descriptive statistics - occupation and reallocation

	Migrant	Infra-distr. move	Return migrant
Post × SES × F × ZDE	0.007	0.015	-0.017**
	(0.02)	(0.02)	(0.01)
Post × SES × ZDE	-0.005	-0.004	0.004
	(0.01)	(0.01)	(0.01)
Post × SES	-0.011	-0.018	0.001
	(0.01)	(0.02)	(0.00)
Post × SES × F	0.001	0.045**	-0.002
	(0.01)	(0.02)	(0.01)
Post × F	-0.000	-0.002	-0.001
	(0.00)	(0.01)	(0.00)
Post × F × ZDE	0.005	-0.014**	0.007**
	(0.01)	(0.01)	(0.00)
Post × ZDE	0.007	0.009	0.002
	(0.00)	(0.01)	(0.00)
SES × F	-0.005	0.029**	0.003
	(0.01)	(0.01)	(0.00)
SES × F × ZDE	-0.007	-0.016	-0.002
	(0.01)	(0.01)	(0.00)
SES × ZDE	-0.001	0.014	0.001
	(0.01)	(0.01)	(0.00)
F × ZDE	0.000	0.011***	-0.003**
	(0.00)	(0.00)	(0.00)
R-squared	0.064	0.064	0.068
N	66232	66232	66232
District-urban FE	✓	✓	✓
Trimester FE	✓	✓	✓

* p<0.10, ** p<0.05, *** p<0.01 ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 50: Migration responses

D Migration responses

E Reallocation responses - employment during the week

F Explanation for each mechanism in Table 6

1. If an agent's first best is still retail ($\frac{w_o}{w_r} < 1-\gamma$), the agent solves

$$\max_{c,l} U(c,l) \;\; s.t.\; c = w_r(1-\gamma)(\bar{T}-l)\;, 0 \leq c \leq \bar{y},\; 0 \leq \bar{T}-l < \bar{T} \tag{12}$$

r and o hours and earnings responses to the decrease in r wages will now depend on whether $\bar{y}$ is binding.

   (a) if $c_r^* > \bar{y}$, then the agent will work $\frac{\bar{y}}{(1-\gamma)w_r}$ hours to earn $\bar{y}$, which constitutes an increase in hours worked for stable earnings from r. If they decide to enter the second occupation, $\bar{L}$ will still not be binding, as they have even less remaining time than in period 1 ($\frac{\bar{y}}{(1-\gamma)w_r} > \frac{\bar{y}}{w_r}$) and the same consumption.

   (b) if $c_r^* < \bar{y}$, then the agent will work so that $U_c(c,l) = \frac{U_l(c,l)}{w_r(1-\gamma)}$. Earnings from retail are lower than in period 1 in any case, but the evolution of hours depends from whether retail work was constrained at first.

      - If r was constrained, then the effect whether the constraint being relaxed increases labor in retail more than the decrease induced by the drop in wages.
      - If not, then hours will decreased from one unconstrained equilibrium to another if wages decrease, consistent with standard labor supply theory.

2. If an agent's highest-paying job is now o ($\frac{w_o}{w_r} > 1-\gamma$), then as we know that they were not bound by $\bar{L}$ on the first period, hours worked and earnings from o increase.

   (a) If $\bar{L}$ is still not binding, the agent will abandon r and work only in o, with an equilibrium with more leisure than the unconstrained optimal starting with r in 1st period.

   (b) If $\bar{L}$ is binding, agents will work $\bar{L}$ before turning to r.

	Wage	Unpaid fam	Formal	Retail	Sales, no ret.
Post × SES × ZDE	-0.007	-0.004	-0.018	0.003	0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Post × SES	-0.021*	-0.010	0.004	0.028*	0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Post × ZDE	0.007**	0.005*	0.022***	0.000	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
SES × ZDE	-0.016***	0.001	-0.005	0.024***	-0.005*
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
R-squared	0.424	0.272	0.249	0.622	0.626
N	66232	66232	66232	66232	66232
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 51: Reallocation - all jobs this week

	Wage	Unpaid fam	Formal	Retail	Sales, no ret.
Post × SES × F × ZDE	0.008	-0.030***	0.033*	-0.011	-0.005
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Post × SES × ZDE	0.007	0.010*	-0.018	0.009	0.006
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Post × SES	0.004	-0.018	0.019	0.026	0.003
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Post × SES × F	-0.053**	0.039*	-0.011	-0.006	-0.009
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)
Post × F	0.032***	-0.061***	-0.001	0.000	0.007***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Post × F × ZDE	-0.003	0.007	-0.003	0.000	0.006**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Post × ZDE	-0.009*	0.003	0.002	0.000	-0.005**
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
SES × F	0.184***	0.021	-0.115***	-0.087***	-0.015**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
SES × F × ZDE	-0.004	0.006	-0.002	0.005	0.006
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
SES × ZDE	-0.035***	-0.006	-0.005	0.020**	-0.009**
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
F × ZDE	-0.016***	-0.055***	-0.012***	0.000	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.177	0.196	0.214	0.616	0.617
N	71766	71766	71766	71766	71766
District-urban FE	✓	✓	✓	✓	✓
Trimester FE	✓	✓	✓	✓	✓

* $p<0.10$, ** $p<0.05$, *** $p<0.01$ ZDE: Z-score district exposure to caguwa at t-1. post: (2016-2017 round). F: female. SES =retail × self-emp. × start date < 06/2016. SE clustered at the IHLCS cluster level.

Table 52: Occupational responses - employment during the week - gender heterogeneity

	Men				Women			
	not SES		SES		not SES		SES	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
diploma	0.44	0.45	0.44	0.50	0.40	0.43	0.39	0.44
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.49)	(0.49)	(0.50)
no_help	0.06	0.07	0.09	0.09	0.09	0.10	0.12	0.15
	(0.23)	(0.26)	(0.28)	(0.28)	(0.29)	(0.30)	(0.33)	(0.36)
Observations	16507	16317	493	535	18393	18133	832	842

Table 53: Statistics on education and household help

	Men				Women			
	not SES		SES		not SES		SES	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post
last_daily_profits	33579.67	18426.41	10543.41	12282.10	3522.78	5007.04	4889.58	5980.88
	(1288037.05)	(207879.34)	(32670.64)	(73203.87)	(25025.15)	(25255.85)	(16577.75)	(16657.80)
log_last_profit	7.51	7.76	7.98	8.25	6.72	7.21	7.33	7.72
	(1.65)	(1.61)	(1.63)	(1.61)	(1.62)	(1.56)	(1.55)	(1.41)
last_daily_turnover	42502.92	24156.08	15153.35	18179.36	5529.77	7319.47	6689.78	8419.75
	(1408004.29)	(214108.44)	(39473.84)	(66263.79)	(29952.70)	(34679.00)	(22545.33)	(22669.22)
log_turnover	8.00	8.10	8.43	8.60	7.17	7.55	7.70	8.09
	(1.68)	(1.64)	(1.57)	(1.48)	(1.63)	(1.57)	(1.51)	(1.36)
last_daily_non_labor_exp	736.95	277.78	4273.63	5453.82	128.87	113.36	1694.62	2254.13
	(42723.37)	(6638.32)	(16308.00)	(52110.61)	(3147.97)	(4058.81)	(12776.49)	(13810.41)
log_nonLexp	6.55	6.46	6.58	6.52	5.82	5.89	5.80	6.20
	(2.05)	(1.97)	(2.08)	(1.95)	(1.98)	(1.95)	(2.12)	(1.91)
Formal	2.60	2.55	2.50	2.39	2.82	2.85	2.78	2.70
	(0.69)	(0.96)	(0.63)	(0.90)	(0.42)	(0.64)	(0.51)	(0.71)
Observations	29598	28449	977	1013	29445	29248	1672	1539

Table 54: Statistics on individual businesses

- If $\bar{y}$ is still binding, agents work more both in o and r, maintaining nominal earnings from retail and aggregate income.
- If $\bar{y}$ does not bind, the evolution of hours in r depends on whether $\bar{y}$ was binding in first period:
  i. If $\bar{y}$ was not binding, then hours and earnings from r decrease as labor in r is even less attractive now than before, and the agent already has income from o.
  ii. If $\bar{y}$ was binding, then as the constraint is lifted but w_r decreases, it is ambiguous which effect dominates on hours, although earnings from r decrease.

G Additional descriptive statistics

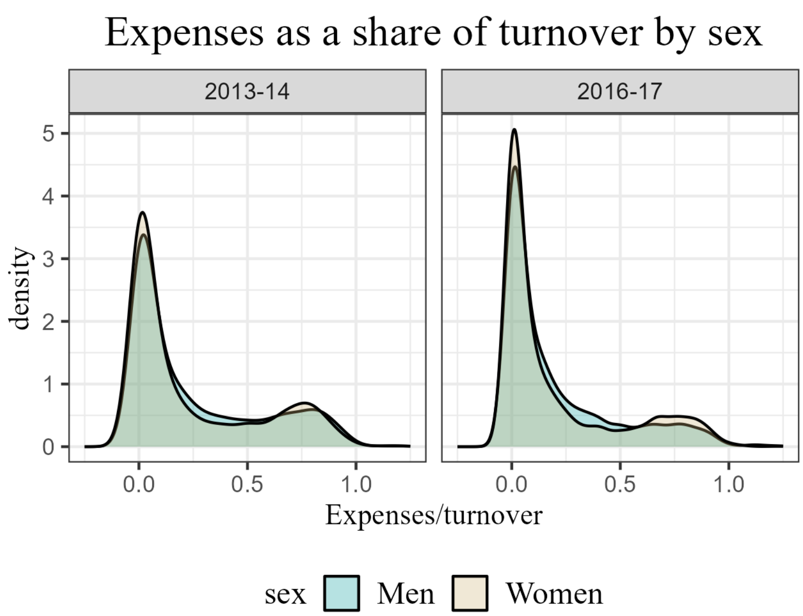

Figure 8: Turnover/expenses