Slack and Economic Development*

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Abstract

Slack – the underutilization of factors of production – varies systematically with economic development. Using novel and detailed measures of the utilization of labor and capital from a large representative sample of firms in rural and urban Kenya, we show that utilization is increasing in firm size, market access, and economic activity. We present a model of firm capacity choice where indivisibility in at least one input is a key driver of slack. We embed the model in spatial general equilibrium, with features characteristic of low-income settings – including many small firms and high transport costs – and show that it rationalizes both the endogenous emergence of slack in steady-state and elastic aggregate supply curves. We empirically validate model predictions using reduced-form estimates of the general equilibrium effects of cash transfers from a large-scale RCT in Kenya. The parsimonious model replicates much of the experimental evidence, predicting a large real multiplier of 1.5, driven by expansion in low-utilization sectors and firms, and limited average price inflation. Counterfactual analyses indicate that multipliers are likely to be meaningfully smaller in lower slack settings, such as urban areas. We use the model to revisit the estimation of spatial spillovers in clustered RCTs and uncover non-trivial 'missing intercept' effects on income and inflation. Additionally, we innovate methodologically by pre-registering key elements of model estimation and validation. The findings suggest that input indivisibilities and slack are key features of developing country settings, and are quantitatively important for macroeconomic dynamics and policies.

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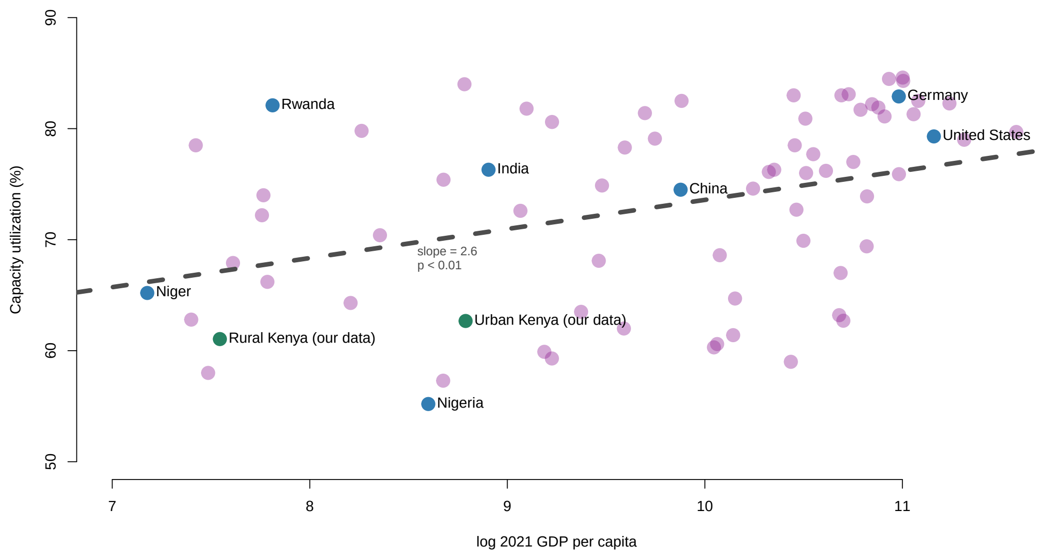
1 Introduction

At least since Lewis (1954), there has been a longstanding hypothesis regarding the pervasiveness of capacity underutilization – or slack – in developing economies. Contemporary data from standardized surveys of formal enterprises confirm a robust cross-country correlation of GDP per capita with overall capacity utilization (Figure 1). For instance, utilization in the United States is more than 20% higher than in Nigeria or Sierra Leone.[1] All else equal, these economies would thus be at least 20% more productive if they utilized their factors of production with the same intensity as the U.S. In contrast to the cyclical slack arising from sticky prices or matching frictions that feature prominently in macroeconomic theory (Keynes, 1936), steady-state capacity underutilization thus appears to be a notable feature of developing economies, with the potential to partially explain differences in living standards across countries. However, despite the influential early work calling attention to it, the relationship of development and slack appears to be a largely underappreciated stylized fact in contemporary development economics.

Figure 1: Capacity utilization across the world



Notes: This figure presents overall capacity utilization across countries in the most recent month/quarter/year where data is available (as of November 2023). Data for rural and urban Kenya (in green) is from our novel survey data described in section 2.1, all other observations are from Trading Economics and Moody's Analytics (2023), which aggregate data on capacity utilization from national statistics agencies across countries. Most national surveys relate to manufacturing firms, while the Kenyan data covers a broad range of sectors. Utilization rates are lower if we restrict our data to Kenyan manufacturing firms.

Slack has potentially important implications for macroeconomic dynamics and the effect of macroeconomic policies. If increasing utilization is possible without requiring additional factors of production, slack implies highly elastic aggregate supply curves at least over some range (Michaillat and Saez, 2015). It may thus provide an amplification mechanism leading to larger fiscal and transfer multipliers in developing economies. Egger et al. (2022), for instance, experimentally estimate a real local transfer multiplier of 2.5 in rural Kenya using a large-scale randomized cash transfer. They argue that a substantial fraction of the overall increase in output cannot be explained by increases in inputs of production and therefore likely reflects increased utilization (or productivity) of these factors. If slack is a general feature of low- and middle-income economies, macroeconomic policy in these settings may thus need to take it into account.

Yet despite the stark cross-country empirical patterns noted above and theoretical hypotheses about slack, there remains limited systematic empirical evidence at the micro-level, nor a coherent theoretical micro-foundation for how slack might arise in developing economies and persist in steady-state (Gollin, 2014). This article seeks to begin filling in these gaps.

[1] Capacity utilization is commonly defined as "the ratio of the actual level of output to a sustainable maximum level of output or capacity" (Corrado and Mattey, 1997, p.152). Kim and Winston (1974) also point out lower capital utilization in developing countries.

We first document substantial slack using novel data from representative surveys of enterprises in both rural and urban markets in Kenya. We measure capital utilization by collecting detailed data of the hours of operation of key equipment, labor utilization by discreetly observing employees' activity at work, and overall utilization through survey questions on capacity, detailed measures of customer and order flows, and by eliciting the firm-level marginal costs of expanding productive activity. Consistent with the cross-country evidence, we document extensive variation in utilization rates across space, firms, and sectors.

This dataset allows us to uncover three new stylized facts about slack in a developing economy. First, slack is more prevalent in small firms, and in particular in microenterprises with just a single owner-employee. Second, there is more slack in sectors with inputs that are plausibly more "lumpy" – including personal services, food processing, and artisanal manufacturing where employees can serve only one customer at a time, and where underutilization primarily comes in the form of waiting for customers with workers (and equipment) staying idle. And third, 'thinner' markets, including remote, rural, and low market-access regions, all exhibit systematically lower utilization.

Motivated by these facts, we develop a structural spatial model of capacity utilization in general equilibrium. The key new friction in the model is indivisibility constraints in input choices. If firms can only hire (at least) one of their inputs in indivisible units and face a fixed cost for doing so, they may be forced to 'overinvest' in capacity beyond what their optimal input choice would be in a continuous setting. In two typical examples from our Kenyan setting, a shop owner has to decide whether to spend the entire day at the market or spend the day working on the farm (due to transport time and costs of splitting the day between the two locations), even if there is not enough demand to require the shop being open for the full day. In grain milling – the most prominent type of manufacturing and food processing in the study context – entrepreneurs have to purchase at least one milling machine, even if demand within the village is insufficient to fully utilize the mill. Importantly, these input choices, and the resulting capacity underutilization, are optimal given the technological constraints entrepreneurs face: for instance, if sellers could coordinate better online, they might be able to reduce idle time waiting for customers at the market, and similarly, if there was a more effective rental market for inputs, smaller milling machines were widely available, milled grains became easier to transport, or markets became more integrated, then firms' levels of utilization might also increase.[2] This economic micro-foundation thus stands in contrast to earlier alternative theories of underutilization in developing countries based on hypothesized "surplus labor" (Lewis, 1954), or cultural factors that lead to idleness.

In the model, input indivisibilities take the form of "integer constraints", meaning input amounts are constrained to come from the set of integers – i.e., firms can only hire in increments of 1.0 full labor-units.[3] These constraints are more likely to bind for small firms: intuitively, the step up from one worker to the second is much larger proportionally than from the 50th to the 51st. In fact, the most discrete choice (and largest 'integer') is the decision of whether to enter into entrepreneurship at all – or, in practice, to enter for the day or season. We model this entry choice by entrepreneurs setting expected returns equal to an endogeneously determined outside wage (in agriculture). Integer constraints are also more relevant in low-productivity and low market-access settings where local demand is relatively low and firms are more likely to stay small and get stuck below full capacity. The model is thus able to qualitatively match some of the key empirical stylized facts. Importantly, these factors are typical of many low- and middle-income country settings, where a majority of people in the world live. To illustrate, 90% (76%) of firms in the rural (urban) setting we study have a single owner-employee, and the vast majority of customers walk to their closest market, effectively restricting potential market access to a relatively local neigh-

[2] Bassi et al. (2022) argue that enterprises in urban and peri-urban Uganda are able to overcome indivisibilities in input choices by sharing lumpy capital between many firms. Our empirical setting is different from theirs. They focus on three manufacturing sectors: carpentry, metal fabrication and grain milling operating, whereas our data covers a representative set of firms in all sectors, which are overall much smaller. Their firms have 4.9 employees on average, ours 1.2. Our rural setting is also more remote than the peri-urban economy studied by Bassi et al. (2022). In this environment, it is not practical for firms multiple villages apart to share a single machine, or for workers to work two part-time jobs across multiple locations. Indeed, only 27 firms (less than 0.2%) in our sample rent in any machines, and only 0.04% of machine working hours are rented in. As such, we see our work as complementary to Bassi et al. (2022) in investigating the macroeconomic implications of input indivisibilities in environments where they cannot be overcome.

[3] We focus on indivisibilities in labor, which is by far the most important input for firms in our study setting (with an average capital to annual output ratio of just 0.17). Our model could easily be adapted to account for indivisibilities in capital as well.

borhood. Given the predominance of small firms and high transportation costs, indivisibility constraints may also have quantitatively important aggregate consequences for developing economies.

When embedded in a two-sector spatial general equilibrium model with endogenous entrepreneurship and hiring, we show that indivisibility constraints have important implications for aggregate supply: when monopolistically competitive firms are below capacity, they meet additional demand by simply increasing output. When they hit a constraint, however, they increase prices until upgrading to the next unit of the indivisible factor is preferable. In general equilibrium, this leads to convex aggregate supply curves. In low demand or productivity settings where slack is high, local supply is thus relatively elastic as firms' supply increases primarily by increasing utilization. As more firms hit capacity constraints, they begin raising prices, until supply eventually becomes vertical when all firms' inputs are fully utilized. Even at full utilization, however, indivisibilities lower aggregate productivity due to a form of "misallocation" relative to the standard model where all inputs are continuous: with lumpy inputs, firms' marginal revenue products cannot be exactly equalized.

In the model, these dynamics only apply to locally traded, differentiated goods such as local services (e.g. food stalls, tailors, and barber shops) and on-demand manufacturing such as grain milling, carpenters, or vehicle repair. In the tradable sector, firms are price takers in the world market, implying they make full use of their capacity to serve a potentially infinite foreign demand. An increase in transfers from abroad increases utilization in the non-tradable sector, wages rise and labor reallocates from the tradable sector (primarily agriculture in our setting) to the non-tradable sector (in line with experimental evidence from large-scale cash transfers, e.g. Egger et al., 2022; Banerjee et al., 2023a).

The model generates important insights and predictions for macroeconomic dynamics in developing economies. Aggregate supply in economies with many small firms and low demand or market access can increase relatively freely in response to demand shocks. This generates large real multipliers in response to fiscal policy or external transfers. More broadly, the reservoir of many small, underutilized firms may act as an amplification mechanism for productivity growth in other sectors (e.g., exports). In this setting, demand-side interventions may be more effective at raising aggregate output than supply interventions (echoing other recent work, see Goldberg and Reed, 2023). Crucially, however, this mechanism is not unbounded. As firms begin hitting capacity constraints, inflation sets in. Real multipliers therefore decrease with increased size of the demand shock and are lower in higher-utilization areas such as busy urban markets. Our analysis also quantifies the importance of labor mobility for the elasticity of aggregate supply, another key point in the early work on slack (Lewis, 1954). A large reservoir of available labor in agriculture reallocating to the non-tradable sector helps mute inflationary pressures, maintaining the effectiveness of demand-side interventions.

We then apply the model to the context of a large externally financed unconditional cash transfer program in Siaya County, Western Kenya (Egger et al., 2022) that injected 15% of GDP into treated villages. We do so transparently and innovate methodologically by pre-registering the model structure, estimation approach, the data moments we target in the calibration, and the out-of-sample predictions we validate the model with prior to model estimation. (Miguel, 2021).[4] While registering pre-analysis plans (PAPs) has become the norm in some fields of economics, and especially in development economics, this is one of the first applications of a PAP in macroeconomics (to our knowledge). First, we calibrate the model to the baseline economy, leveraging newly collected data on household-firm linkages across space in addition to comprehensive enterprise and household censuses and survey data on households and firms in Western Kenya. A unique feature of the dataset is its high spatial resolution. We match enterprises to owner households in the census, allowing us to populate the full bilateral matrix of trade, capital, and profit flows across small spatial units (towns, villages, and weekly markets). We also observe spatial shopping patterns which we use to estimate gravity and transport costs. To rationalize underutilization of labor inputs, the model assumes that firms need to compensate workers for their labor effort in addition to a lump sum wage payment. We discipline this cost of utilization by matching the share of firms that report being able to expand supply at close to zero marginal cost.[5]

[4]AEA Trial Registry AEARCTR-0013210. See https://www.socialscienceregistry.org/trials/13210

[5]Reassuringly, the calibrated effort cost is in line with recent micro-experimental estimates of the opportunity cost of time for micro-

Second, we validate the model by replicating the implementation of the RCT in Egger et al. (2022) within the model, and comparing its predictions against the pre-specified empirical reduced form estimates of the effects of the cash transfers from the RCT.[6] The estimated model matches the aggregate empirical facts in Egger et al. (2022) well. It generates a large real multiplier of 1.5 with limited 1.3% inflation.[7] In addition, new empirical evidence is quantitatively in line with the model's underlying mechanisms: (1) output responses to cash-induced demand shocks are substantially larger in small firms, and in sectors with less divisible inputs and thus lower utilization, (2) inflation is larger in the 'thickest' markets, and (3) wages rise overall, and there is sectoral reallocation out of agriculture.

The validated model allows us to quantify how the aggregate impacts of cash transfers vary (1) with the transfer size: larger transfers lead to moderately declining real multipliers; and (2) with regional targeting: multipliers are larger in rural, remote, high-slack regions compared to urban, high-utilization regions. We quantify the importance of these channels by simulating counterfactual transfers in environments with more typically urban characteristics: lower transport costs to large markets, less movement in and out of agriculture, and the ability to overcome integer constraints by working part-time (which could be related to lower transport costs between home and markets). Intuitively, each of these counterfactuals yields higher inflation rates and lower real multipliers in response to cash transfers, highlighting that input indivisibility constraints in small firms and remote markets are a quantitatively significant friction for developing country settings with meaningful implications for the macroeconomy.

Lastly, we use the structural model to quantify the full distribution of real income impacts of the cash transfer program. While recipients of the cash grants uniformly gain from receiving the transfer, non-recipients might plausibly be hurt by rising inflation rates, or could gain from income flowing through economic interactions into their hands. Such ambient effects, which affect the entire study population including the control group, constitute a SUTVA violation, a problem known as the "missing intercept" (Wolf, 2023). The predominant approach for addressing this empirically is to consider both direct, as well as indirect treatment exposure within a suitably defined neighborhood when estimating treatment effects. Egger et al. (2022) do so by experimentally varying treatment intensity, and estimate spillovers by including nearby cash transfers in spatial radii bands in their regressions. Another approach in the literature is to use sufficient statistics that yield measures of 'exposure' derived from a structural model (Adao et al., 2019; Franklin et al., 2024; Borusyak et al., 2024). We assess to what degree such strategies can overcome the missing intercept problem by implementing these empirical strategies within our calibrated model geography. In the model, we find evidence of a meaningful positive missing intercept. Non-recipients gain from increased enterprise profits and wages, and these effects outweigh losses to non-recipients due to higher inflation rates. A simple treatment regression would understate the impacts of such a randomized cash transfer program by about 40%. State-of-the art spatial econometric designs can combat this problem, but may miss 20% of the total income gain.[8] Focusing on the distribution of real income impacts, our estimates also imply that the cash transfer program studied by Egger et al. (2022) increased real income for nearly every village and town in the study area. Indeed, less than 1% out of 852 villages in the study area saw modest real income declines, while the most fortunate village gained more than 60% of baseline real income.

We contribute, first, to a long literature on the constraints faced by firms in low- and middle-income countries, leading to an excess mass of small firms. On the supply side, these range from transaction costs and search frictions in the labor market (Abebe et al., 2020; Foster and Rosenzweig, 2022), contracting frictions and trust (Ar-

entrepreneurs (Agness et al., 2023).

[6]The NGO GiveDirectly transferred unconditional cash transfers to randomly selected villages in Western Kenya. Treatment saturation varied across sublocations, which are administrative units containing between 5-15 villages; section 4.1 has more details.

[7]The empirically estimated multiplier in Egger et al. (2022) is 2.5 and the model-generated multiplier falls within the relatively wide confidence interval of the empirical estimate. This is noteworthy considering the model only incorporates one friction and abstracts from many other frictions proposed in the literature on macroeconomic multipliers (e.g. nominal rigidities). Empirically, Egger et al. (2022) estimate inflation of 0.2% on average, and 0.4% in the most intense transfer period. Below, we argue why these empirical estimates may have somewhat underestimated the overall extent of inflation.

[8]The missing intercept problem also arises for inflation, with 40-65% of inflation remaining unexplained by different measures of spatial exposure. Intercept issues are more severe for inflation because consumers are able to substitute across markets which limits the ability of firms to raise prices in any one location, leading to spillovers across a larger geographic area (although overall price inflation remains low).

row, 1972), credit constraints (de Mel et al., 2008), to imperfect rental markets for capital (Bassi et al., 2022). On the demand side, they include low standardization in products (Bassi et al., 2023), search frictions of consumers (Ramos-Menchelli and Sverdlin-Lisker, 2022; Vitali, 2023), and access to export markets (Atkin et al., 2017). Indivisibilities of inputs, in combination with credit constraints and financial frictions, have featured in this literature primarily as a source of under-investment in profitable technologies and poverty traps (Buera et al., 2014; Banerjee et al., 2019; Kaboski et al., 2022; Balboni et al., 2022). We show that even in the absence of financial frictions, and in static equilibrium, input indivisibilities may lead to over- or under-investment in productive capacity, and act as a driver of lower aggregate productivity through underutilization of these investments.

Bassi et al. (2022) study rental markets for machines in Uganda and document how firms in peri-urban settings are able to deal with indivisibilities by effectively sharing capital. In contrast, our paper focuses on the macroeconomic consequences of not being able to overcome lumpiness in environments where remoteness and low demand makes sharing not practical or technologically impossible. We further show that indivisibilities are particularly binding for small firms and derive the aggregate consequences of many small firms and single person micro-enterprises for economic development. We argue that slack due to indivisibility constraints may exacerbate or amplify the macroeconomic impact of these other frictions.

Second, we provide a new micro foundation for the emergence of slack in the macroeconomy and its implications for aggregate supply, particularly pertaining to low- and middle-income economies. Slack has typically been modeled as arising either cyclically due to sticky prices (Keynes, 1936; Kuhn and George, 2019), disequilibrium forces (Barro and Grossman, 1971, 1974), collusive norms (Banerjee et al., 2023b), or resulting from search and matching frictions leading to steady-state unemployment (Lucas and Prescott, 1974; Diamond, 1982; Mortensen, 1982; Pissarides, 1985; Michaillat and Saez, 2015). We show that slack can emerge in steady state when inputs are lumpy, particularly when firms are small and market access and productivity are relatively low. These features are highly relevant for most poor economies around the world, and thus slack appears important to understand macroeconomic dynamics and the impacts of economic policies or interventions in these settings. The model also connects to the literature on how capacity constraints can generate convex supply curves (Boehm and Pandalai-Nayar, 2022; Cavallo and Kryvtsov, 2021).

Third, these new micro-foundations can rationalize the large real demand multipliers in poor economies that have been documented in at least some of the relatively limited empirical work on the topic (Sadoulet et al., 2001; Gerard et al., 2021; Banerjee et al., 2023a; Galego Mendes et al., 2023; Gassmann et al., 2023). Methodologically, we contribute to a literature that estimates cross-sectional multipliers within a monetary union using natural experiments (Nakamura and Steinsson, 2014), and a nascent literature quantifying spillover effects and aggregate impacts of policy interventions by using at-scale randomization combined with structural modeling (Akcigit et al., 2021; Franklin et al., 2024), thus at least partially bridging the gap between micro and macro development economics research (Muralidharan and Niehaus, 2017; Buera et al., 2023).

And fourth, we relate to a long literature on factor misallocation (Hsieh and Klenow, 2009; Baqaee and Farhi, 2020), and its role in understanding differences in productivity across space. We show that input indivisibilities in small firms contribute to misallocation (i.e., divergent marginal revenue products across firms) for two reasons. First, underutilization of lumpy inputs in general equilibrium implies that marginal revenue products of input factors vary because some firms fully utilize these factors while others do not. Second, even when all firms are operating at full capacity, firms cannot exactly equalize marginal products due to discreteness in their choice of input quantities unlike in the continuous case. The results also provide an additional mechanism contributing to the large observed rural-urban gaps in productivity (Gollin et al., 2014), namely, differences in firm input utilization across space.

In the remainder of the paper, we present novel insights on slack in Kenya (section 2), present a model of integer constraints to rationalize these findings (section 3), quantify the model using detailed spatial microdata (section 4), and derive predictions for macroeconomies characterized by low capacity utilization (section 5), while the final section concludes.

2 Motivating evidence

To motivate the analysis, we combine several sources of original enterprise data in Kenya specifically designed to measure firm capacity utilization. We then use these data to document four stylized facts on slack in an LMIC context.

2.1 Measuring capacity utilization

Sampling strategy. We collect measures of capacity utilization for 5,380 non-agricultural enterprises located in rural Kenya and Nairobi. Collecting data from these two settings, with features that, respectively, are typical of rural and urban markets in Kenya – and Sub-Saharan Africa more broadly – helps determine whether the trends we document are specific to rural areas or hold more generally. In both settings, we draw a representative sample of firms from enterprise censuses collected by the research team.

Specifically, enterprise data was collected from four distinct locations: (i) enterprises operating within rural homesteads, (ii) enterprises operating within rural villages, (iii) enterprises operating within rural market centers, and (iv) enterprises operating within urban (Nairobi) market centers. These locations exhibit a wide range of market access, from rural homesteads considered the most remote – and unlikely to receive major foot traffic – to enterprises in busy market centers in Nairobi, which see large numbers of passers-by and potential customers.

Data for enterprises operating in rural homesteads and villages comes from surveys conducted as part of a longer-term follow-up (the "second endline") to the Egger et al. (2022) study. In 2019, an enterprise census was conducted in the Egger et al. (2022) study area, comprising 653 rural villages in Siaya County, a relatively poor and densely populated area in Western Kenya (more details on the study area geography are in Section 4.1 and Figure 5). The census captured the universe of all non-agricultural enterprises operating in study area villages. Data for rural markets comes from a census conducted in 2024 in all 71 markets in Siaya County that operate at least weekly. These censuses captured 14,793 enterprises: 5,945 (40%) operated from homesteads and 2,095 enterprises (15%) operated within rural villages, while 6,753 enterprises (45%) operated within rural markets. 6,077 enterprises were then chosen to be surveyed, sampled from the censuses stratified by operating location. The main analysis includes 4,721 of these enterprises that were still in operation around the time of the survey. The data thus aims to be representative of all non-agricultural private sector production within Siaya County.[9] The order in which villages were visited was randomized. Visits to market centers were made on the weekly market day, and during times of the day when markets were most likely to be busy. This means we are capturing periods when these rural markets are likely to be busiest and thus when we are presumably less likely to be able to detect slack capacity.

In contrast, Nairobi is a major metropolitan city with a population of over 4.4 million people (according to the 2019 Kenyan census). We study four urban markets in Nairobi, each of which is large (1400-5500 total vendors, compared to an average of 95 in rural markets). These markets (Muthurwa, Gikomba, Toi, and Kawangware) are all major markets that local collaborators indicated were common shopping locations and represent a meaningful share of urban consumer expenditure. Importantly, and unlike in the rural area, the data from these markets do not represent the universe of enterprises operating in Nairobi: they exclude firms not operating in daily market centres, such as most formal firms, most manufacturing firms, and firms that are not consumer-facing.

These markets do not have specific market days, and are instead busy on each day of the week. Survey enumerators collected data in Nairobi across two weeks in November and December 2023. Upon arriving at a market, enumerators first walked through the market, dividing up the market into sections for each enumerator and generating an estimate of the number of enterprises an enumerator was expected to cover. Enumerators would then go through their section of the market, recording the business type for each enterprise on their tablet. Each enumerator's tablet was programmed to randomly select a number of enterprises that they were expected to be able to complete within one visit to the market (20 surveys per day). When the tablet indicated that an enterprise was selected for surveying, the enumerator would seek to conduct a survey and collect the measures of slack capacity.

[9] Appendix E provides more details on the enterprise data and sampling strategy.

Table 1: Summary statistics by location

Variable	Overall rural	Homestead	Village	Rural market	Urban market
No. censused	14793	5945	2095	6753	12108
No. surveyed	4721	1343	881	2497	659
Firm size	1.16	1.09	1.15	1.22	1.35
Average revenue (USD PPP)	5327	3520	4512	7259	25159
Customers per hour	1.06	0.82	1.47	1.06	0.86
Sectoral composition					
Share in retail	0.39	0.45	0.28	0.36	0.65
Share in food	0.35	0.34	0.41	0.34	0.27
Share in manufacturing	0.06	0.08	0.05	0.04	0.0
Share in hospitality	0.02	0.0	0.03	0.03	0.02
Share in transport	0.04	0.0	0.05	0.07	0.01
Share in food processing	0.04	0.04	0.11	0.03	0.01
Share in personal services	0.11	0.08	0.07	0.13	0.04
Utilization measures					
Capacity utilization	0.61	0.6	0.61	0.63	0.63
Ratio of worst to best week sales	0.37	0.35	0.39	0.37	0.37
Share with 0 MC	0.37	0.31	0.29	0.4	0.03
Capital utilization	0.64	0.6	0.63	0.68	0.7
Labor utilization	0.47	0.39	0.48	0.62	0.85

Notes: Data for rural homesteads and villages comes from a 2019 enterprise census and a 2021-22 enterprise survey in 653 villages in Siaya County in the Egger et al. (2022) study area. For rural markets, the data is from a 2024 census and survey of all 71 markets that operate at least weekly within Siaya county. Data for urban markets is from a 2023 census and survey of four busy urban markets in Kenya's capital Nairobi. Statistics representing averages across firms are weighted using survey weights within categories: i) rural homesteads, ii) rural villages, iii) rural markets, and iv) urban markets. Rural categories (i-iii) are then weighted by their share of all firms in the census. Firm size refers to the number of workers, including the owner (if working). Revenues are annualized based on monthly recall.

In total, the census captured 12,108 enterprises across four urban markets, of which we surveyed a representative 659 enterprises.

Summary Statistics. Table 1 presents firm summary statistics for non-agricultural enterprises across the four different locations. Table 2 presents statistics differentiated by sector.

The rural areas we study are primarily agricultural: 78% of consumption expenditure in these areas is on food, agriculture is the predominant sector, and 70% of all revenues accrue to farmsteads. The non-agricultural economy is largely retail and service-based. Retail, food vendors, transport services, hospitality, and personal services make up 90% of total revenue. Even what we classify as 'manufacturing' is better thought of as artisanal production similar in terms of firm structure and operation to a local service. The most common type of manufacturing enterprise are carpenters and welders, who operate on-demand (Table 2). In food processing – predominantly in the form of grain milling – operators typically grind small quantities of maize to service private customers' weekly demand. Across sectors, the rural setting is characterized by high transportation costs (typically, individuals walk a non-trivial distance to their closest market), low overall demand, and many small firms: 90% have no employees (i.e., the only labor input is from the self-employed owner), 6% have one employee, and only 4% have two or more (Figure A.1, Panel A).

Firms in Nairobi markets are also small, and even more concentrated in retail and services. In the Nairobi markets in our sample, there were essentially no artisanal manufacturers or food processors. A defining feature of these markets is that they include many similar enterprises that are spatially concentrated. For instance, there are an average of 519 food vendors, and 14 barbers located within the same market (compared to 16 and 3 in weekly rural markets). Firms in urban markets are only somewhat larger than those in the rural markets that we study: 76% have no employees, 17% have one employee, and 7% have two or more employees (Figure A.1, Panel B), highlighting that there is a large mass of small informal firms even in typical urban markets in LMIC. That said, the urban market firms we surveyed report far higher annual revenue than the rural market firms, with a difference of 4.7 times more revenue on average.

Measures of capacity utilization. In addition to standard enterprise outcomes, the surveys collected several measures of slack, measured in the same way across Nairobi and rural areas. Appendix E.5 gives a more detailed

Table 2: Sectoral patterns in production and utilization

Sector	Number of Firms	Revenue share	Firm size	Average revenue (USD PPP)	Customers per hour	Movable capital to revenue ratio	Utilization index	Share with 0 MC	Most common firm type
Hospitality	394	0.01	1.97	8423	1.04	0.06	0.28	0.31	restaurant
Food	6618	0.28	1.17	11475	1.34	0.04	0.21	0.20	food stall
Retail	11538	0.63	1.21	14631	0.87	0.03	0.11	0.16	small grocery stall/store
Transport	575	0.01	1.13	6003	0.70	0.17	0.10	0.21	motorcycle taxi
Food Processing	530	0.01	1.24	5481	1.07	1.86	0.01	0.35	grain mill
Personal Services	1585	0.04	1.25	6397	0.61	0.15	-0.31	0.39	tailor
Manufacturing	605	0.01	1.41	5069	0.31	0.35	-0.53	0.45	carpenter
Overall	21845	1.00	1.22	11593	1.00	0.17	0.08	0.21	food stall

Notes: Data is from 5,380 ”endline 2” enterprise surveys in rural homesteads, villages, and markets in Siaya County and four urban markets in Nairobi (more details in Appendix E.1). When calculating the number of firms, We drop 5056 firms from the census, for which sector information is missing. Statistics representing averages across firms within a sector are weighted using survey weights within categories: i) rural homesteads, ii) rural villages, iii) rural markets, and iv) urban markets. Rural categories (i-iii) are then weighted by their share of all firms in the census, while we weight rural vs. urban areas at 70% vs. 30% to reflect the share of Kenya’s population living in rural areas in 2023 (World Bank). Firm size refers to the number of workers, including the owner (if working). Revenues are annualized based on monthly recall. Movable capital includes vehicles, machines, equipment, furniture, and tools.

overview of how we construct these measures. To measure overall utilization, firms were directly asked about their capacity utilization in an analogous manner to the US Census of Manufacturing. Firms in our sample report an average utilization of 61% (63% in urban markets), relative to US rates that are typically around 80%.[10] Second, we asked firms about sales in their best week versus sales in their worst week last month; sales in the worst week are 37% of sales in the best week, indicating a substantial amount of intertemporal variation in utilization, which may also imply that factors are not being fully utilized for at least some of the time.[11] Third, we asked firms about the amount of (marginal) costs they would incur in order to increase their output by 10%. 40% of rural market firms report that they would incur zero additional costs to expand their output by 10%, while only 3% of firms in Nairobi report the same. This share is particularly high for firms in personal services (e.g. tailors) and manufacturing (e.g. carpenters) sectors, suggesting a substantial fraction of firms operating below their capacity constraint.

In addition to characterizing the overall utilization of inputs, we also examined labor and capital utilization specifically. We measured labor utilization by conducting discreet public observation of enterprise workers for a random subset 429 firms in rural areas, and all 659 firms in Nairobi. After completing surveys, enumerators would remain in a public area near the enterprise for an hour to wrap up the survey. During this process, they observed the enterprise and, when observable, noted whether workers at the firm were engaged in any productive activities. Less than 50% of the observed time in rural villages (62% in rural markets) was spent on productive activities, versus 85% of time in Nairobi markets, indicating a substantial amount of idle time. These figures are comparable to those found by Bassi et al. (2022) in grain mills, carpentry and welding businesses in urban markets in Uganda.[12]

Surveys asked firms that operate machines and equipment about their utilization of this capital as well. This applied to 47% of firms, particularly those in the manufacturing and food processing sectors. First, firms listed all machines, equipment, and tools that they employed. For the three most frequently used, respondents then reported how many hours they were in operation during the last work day. A typical example are grain mills, a common type of (food processing) firm (see Figure A.2 for a distribution of grain mill operating hours). Machines used by firms within our sample only operate roughly 70% of the time; this level of under-utilization holds both in rural markets and in Nairobi.[13] While this does suggest considerable idle capacity for capital as well, the

[10] Firms from all sectors were asked about their capacity utilization, whereas the US number only comprises manufacturing firms. If we restrict our sample to enterprises classified as manufacturing, we find an even lower average utilization rate of just 54%.

[11] In a setting where the hypothetical production at full capacity may be difficult for survey respondents to quantify, sales in the best week over the last month may also be a more reliable lower-bound on production capacity.

[12] We also collected employees’ self-reported time use (including idle time) over a randomly chosen hour during their last working day. These survey-based measures were not correlated with our more objective measures of utilization based on enumerator observations, but which we only observe for a small subset of firms. We therefore exclude labor utilization from our main index. Our findings remain robust to including it (see Figure A.5).

[13] While various “dependencies” – such as the need for electricity in a setting where outages are more common compared to high-income countries – may contribute to lower capital utilization, the utilization of machines is 63% when we restrict attention to rural firms that do not

capital to (annual) revenue ratio is low in this setting, at 0.17 on average. It is highest in food processing and manufacturing, at 1.86 and 0.35 respectively. Even assuming relatively high rental and depreciation rates, the capital share in production is thus relatively low, implying that capital is unlikely to be the quantitatively most important driver of overall patterns of under-utilization.

2.2 Stylized facts on slack

We next document four stylized facts about slack. In this section, we focus on a standardized index (mean zero, standard deviation of 1) of the different measures of slack discussed above. High values of this "utilization index" imply low rates of slack.[14]

First, as shown in the introduction, we find more slack in poor economies. Countries with higher GDP are utilizing more of their capacity. And, we find that this relationship also holds when comparing the urban enterprises to the rural enterprises we surveyed within Kenya, in line with a large literature documenting rural-urban gaps in development. That we would find this relationship was not obvious *a priori*. If, for instance, credit constraints prevented firms from investing in productive capacity, we may expect utilization of existing factors of production to be *higher* in poorer settings. While many factors may contribute to average differences in capacity utilization between high and low income economies, this strong empirical relationship motivates a deeper micro-level investigation into these patterns.

Turning to this study's Kenyan data, the second stylized fact is that smaller firms on average have more slack than larger firms. This holds whether we characterize smaller firms by their productive capacity, which we measure by their sales during the best week in the last month[15] (Figure 2a) or by whether firms hire any employees (panel b). Utilization rises steadily as productive capacity increases, by 0.2 standard deviations for each log unit increase in maximum revenue in our data, and is lowest in firms with no paid employees. These patterns hold even when we include firm location (homestead, village, rural market or urban market) fixed effects and firm sector fixed effects.[16] Small and owner-operated microenterprises are of course different in many ways from larger firms. Yet not all factors would obviously predict this pattern. For instance, smaller firms might be easier to manage and face fewer principal-agent problems, making it easier to optimally assign tasks and leading to the reverse pattern from the one we observe. Conversely, their opportunity cost of slack may be lower, e.g., if they use some of their idle time for childcare (Delecourt and Fitzpatrick, 2021). We argue below that small firms are more likely to face binding indivisibilities in the use of inputs.

Third, we find that firms in sectors most likely to require lumpy inputs are those where we see the highest levels of slack (Table 2), namely, manufacturing, personal services, and food processing. Manufacturing and food processing are both likely to require capital investments that may be indivisible. Grain mills, for instance, are the predominant form of food processing. Each village typically has only a single such milling machine, attended by a single employee or owner and households typically grind only a few days worth of maize (the most common grain) at a time because maize flour is much more perishable than dried maize. This effectively limits the market access of each mill to the village (see next stylized fact) leading to large variation in the hours at which mills are operational each day, with a mean of 6 hours (see Figure A.2). Similar to food processing, common manufacturing firms, such as producers of crafts, carpenters, welders, or vehicle mechanics operate largely "on-demand" and require at least one person to attend to the shop. Capital stocks are low overall in these firms, and most own only a small number of lumpy capital inputs; for instance, the average number of

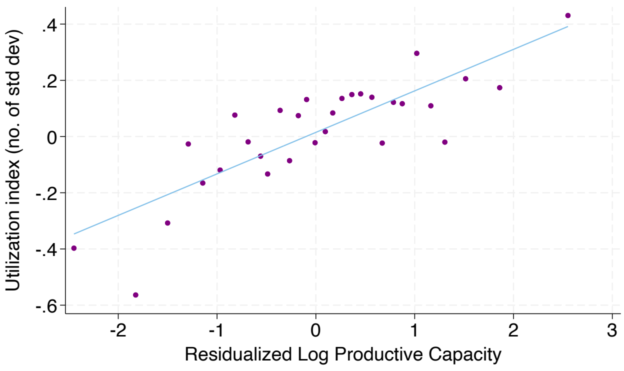
report an electrical connection, indicating that power outages and related factors are not solely driving these results.

[14]We do not include self-reported labor utilization in the index, since employees' self reported time use did not match our directly observed time use for the same workers in a cross-validation. The main findings remain robust to including labor utilization in the index (see Appendix Figure A.5.

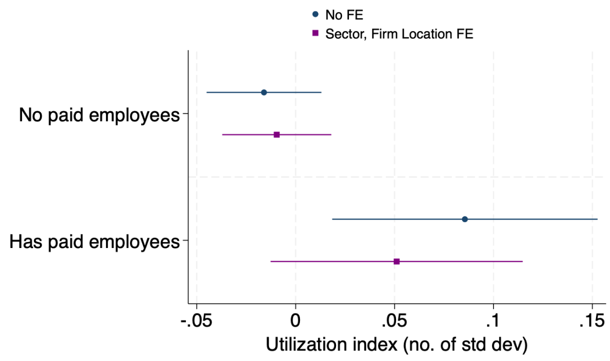
[15]We use revenue in best week as a measure of underlying firm size to minimize a mechanical correlation between revenue and utilization. The correlation remains robust to using the firm's productive capacity, defined as the hypothetical maximum revenue firms would be able to achieve using their existing factors of production at full capacity. We opt for the 'best week sales' as our primary (lower bound) measure of productive capacity, as hypothetical quantities are challenging to elicit in this setting.

[16]Bassi et al. (2023) study time-use within firms in a representative sample of three sectors in Uganda: carpenters, welders, and grain milling. They also report significant amounts of employee idle time, which also decreases with firm size. As firms in their setting are somewhat larger than our sample overall, they are able to show that the steady increase in utilization continues for firms up to 10 employees.

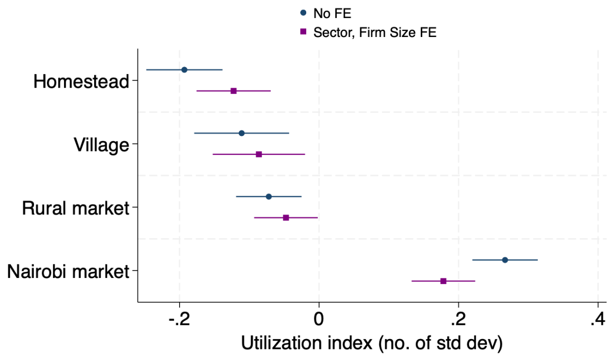
Figure 2: Stylized facts about slack



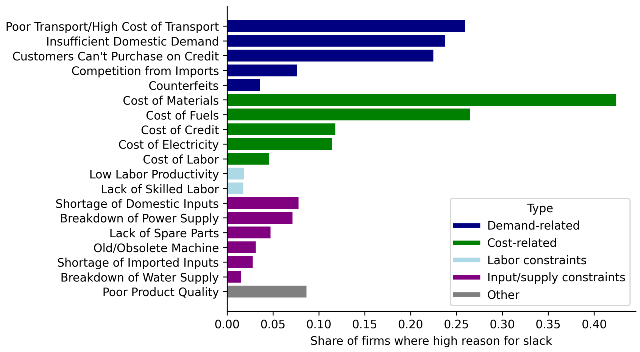
(a) Utilization index by productive capacity



(b) Utilization index by firm size



(c) Utilization index by firm location



(d) Self-reported reasons for slack

Notes: This figure depicts stylized facts about slack using a"utilization index" of all the utilization-related measures: operating capacity, the ratio of best to worst week sales, the fraction of time machines and equipment were operational, and the probability that a firm reports zero marginal costs to increase production by 10%. A higher value of the utilization index implies less slack. These measures are standardized following Anderson (2008) so that magnitudes are interpretable as standard deviations. As noted in the text, we exclude labor utilization from the index because direct observations are only available for a small random subsample, and because self-reported idle labor was uncorrelated with the more objective direct observations of labor utilization made by field enumerators, leading us to doubt its validity. However, results are robust to including labor utilization in the index, see Appendix Figure A.5. Panel (a) reports a binscatter plot showing that firms with higher revenue potential (measured as the best week over the last 4 weeks to approximate underlying productivity and residualized by sector and firm location) have higher utilization or lower slack. Panel (b) presents means of the utilization index by whether firms hire any paid employees, both unconditional (no fixed effects) and with firm location (homestead, rural village, rural market, and urban market) and sector fixed effects, and shows that firms with no paid employees have more slack than those with paid employees. Panel (c) shows means of the utilization index by firm location, both unconditional (no fixed effects) and when controlling for sector and firm size (no paid employees, $\geqslant$ 1 paid employee) fixed effects; firms in more central locations have less slack. Panel (d) reports firms' stated reasons for under-utilization following an open-ended questionnaire. Firms' responses are grouped by broad category, with demand and cost-related reasons featuring prominently. Observations are weighted using inverse sampling probabilities, and we weight rural vs. urban areas at 70% vs. 30% to reflect the share of Kenya's population living in rural areas in 2023 (World Bank). N=5,380. See also Figure A.4, where we replicate these figures and patterns with an indicator for whether an enterprise reports zero marginal cost for expanding production by 10%, the statistic we rely on when fitting the structural model.

machines and tools owned by manufacturing enterprises is 2.4. For personal services (such as tailors, salons or barber shops) the indivisibility is primarily on the labor side. Typically, a single employee will wait for customers. On average, personal service enterprises serve only 0.6 customers per hour, staying idle for a significant fraction of their open hours (as compared to a still relatively modest 1.3 and 0.9 customers per hour in food and retail businesses, respectively). This is consistent with indivisibilities contributing to slack capacity, and variation in demand being the primary driver of capacity utilization at least over some range.

Perhaps surprisingly, the highest utilization sectors in our Kenyan setting are hospitality (primarily restaurants) and food (primarily raw and prepared food stalls). As restaurants are likely busiest during particular times of the day, there is significant downtime in this sector even in wealthy economies. However, this demand may be more predictable than in other sectors, making it easier to optimize opening times and appropriate staffing. Moreover, since the food share of total consumption in our setting is approximately 70%, markets for these sectors may also be "thicker" in rural Kenya than they are in other sectors, a fact that we show next is also related to slack.

Fourth, we document substantially less slack in "thicker" markets and those characterized by greater access to customers. We characterize market access in terms of a) location, b) season, and c) time of day. In terms of location, slack is highest for firms operated from homesteads, followed by villages and rural markets (Figure 2c). Firms operating in Nairobi markets – where population density (and thus market access) is substantially higher – have the highest utilization across multiple measures. These patterns hold even when controlling for firm size and sector fixed effects, suggesting that this is not simply due to firms sorting by location. It holds also despite the fact that firms in these busy urban markets face much more competition for customers, with many similar firms clustered near to each other in the market. These facts motivate our spatial approach to modeling market access, entry, and competition among firms within the same location in what follows.

We complement the analysis of how slack relates to market access by looking at patterns of utilization across the time of year (Figure A.3a), and by hour of day (Figure A.3b) in the Appendix. Seasonality is a prominent feature in agriculture-dominant developing country settings. In Western Kenya, there are two main harvest seasons, the one after the so-called 'long rains' from July to August, and after 'short rains' from November to December. While our surveys did not cover the full calendar year, there is suggestive evidence that utilization in rural markets is higher after the harvest in January when households are likely to have higher levels of cash-on-hand, and lower during the lean or growing seasons (February to May), though confidence intervals are wide. There is also variation in utilization throughout the market day: Figure A.3b documents a small utilization peak in the early morning, and a significant drop-off after 4 pm. Taken together, these facts support the interpretation that variation in demand over time, similar to market access across locations, is systematically related to capacity utilization.

To summarize, we have shown so far that slack varies systematically with levels of economic development, and that it is associated with factors that are often present in low and middle income economies: many small firms, lumpy inputs, and low market access due to high transportation costs. These findings are corroborated by the fact that when we asked firms directly as to the reasons for why they operated below capacity, 45% of firms report at least one factor related to constrained demand, with transportation costs mentioned by 26% of respondents (Figure 2d). Conversely, comparatively few firms mention supply constraints (18%) or the cost of credit (12%). However, 59% mention costs of intermediate inputs such as materials, fuels and electricity as a reason for under-utilization. This highlights the possibility that expanding utilization carries a marginal cost which may result in firms choosing an optimal amount of idle time for workers and capital when faced with insufficient demand – a channel that will feature in our model.

Motivated by these facts, we next introduce an integer constraint as a new friction in a spatial general equilibrium model, capturing the idea that small firms can only make lumpy investments. We then use this model to explain how slack may emerge endogenously in general equilibrium, and to develop the aggregate implications of slack for economic productivity and for the effect of macroeconomic policies.

3 Model

In this section, we describe how indivisibility or "integer" constraints can give rise to slack in general equilibrium. The starting point is a standard two-sector model with monopolistic competition in non-tradeables and only one input factor - labor. The key innovation of the model is the presence of indivisibilities in labor input choice in non-tradeable services. In line with our stylized facts and the discussion in section 2.2, one can think of this sector as encompassing all non-agricultural firms in the Kenya study setting, including local services as well as on-demand manufacturing and local retailers. Producers in this sector can only hire workers in indivisible integer units (e.g., hire one full worker for a unit of time, or two workers, and so on). This simple constraint can rationalize substantial under-utilization in general equilibrium and open the door for potentially large multipliers of demand-side policy, as we show below. To streamline the discussion, we first present a single location version of our model. We outline the setup and solve for equilibrium wages, prices, and quantities. Afterwards, this structure is embedded in a standard spatial general equilibrium model.

3.1 Demand

The model is static. There are two sectors, traded agriculture and non-traded services. Consumers earn income I and have Cobb-Douglas preferences over agriculture X and a bundle of services Y:

$$U = X^{1-\alpha} Y^{\alpha}$$

where Y is itself a CES aggregate of differentiated varieties $\omega \in \Omega$ with elasticity of substitution θ:

$$Y = \left(\int_{\Omega} y(\omega)^{\frac{\theta-1}{\theta}} d\omega \right)^{\frac{\theta}{\theta-1}}$$

Demand for each variety ω satisfies

$$D(p(\omega)) = \alpha I P^{\theta-1} p(\omega)^{-\theta} \equiv \zeta p(\omega)^{-\theta} \tag{1}$$

where αI is the total budget spent on local services and $P \equiv \left(\int_{\omega} p(\omega)^{1-\theta} d\omega\right)^{\frac{1}{1-\theta}}$ is the ideal price index of the local service sector. To ease notation, we define $\zeta \equiv \alpha I P^{\theta-1}$ and denote the welfare-relevant cost of living index for the representative household by $P_U = \left(\frac{P}{\alpha}\right)^{\alpha} \left(\frac{P_x}{1-\alpha}\right)^{1-\alpha}$.

3.2 Supply

Agriculture. We assume a simple model of agricultural production. Agricultural products X are competitively produced using a decreasing returns to scale production function using labor N_X, hired at price w_X:

$$X = \tilde{A} N_X^{\beta}$$

with $\beta < 1$. $\tilde{A}$ represents composite agricultural technology consisting of a TFP parameter A and a fixed supply of land Λ, so that $\tilde{A} \equiv A \Lambda^{1-\beta}$. The economy is a small open economy so that agriculture is freely traded with the rest of the world at the numeraire price of $P_X = 1$. Agricultural labor demand is equal to $N = \left(\frac{\beta \tilde{A}}{w_X}\right)^{\frac{1}{1-\beta}}$.

Non-tradeable services and manufacturing. This sector is subject to the key innovation of the model: indivisibility constraints in input choice. We focus on indivisibilities in labor which is by far the most prominent input in the study context, while noting that our argument extends to indivisibilities in capital. An endogenous mass of firms M with heterogeneous productivity φ drawn from a distribution G produce according to the value-added production function:[17]

$$y(\varphi) = \varphi \min\{e, n\}, \qquad n \in \mathbb{N}. \tag{2}$$

where n denotes labor input and e denotes *effort* or labor services. Take a barbershop for example. In order for a haircut to take place, a worker needs to staff a store (n), potentially wait for customers to arrive, and once they arrive perform a task (e).

Two properties of this production function are worth discussing. First, its functional form gives rise to a natural *capacity constraint* ($e = n$), where further effort does not yield more output. Once all workers are fully utilized, there is no room to expand production without additional hiring (Fagnart et al., 1999; Boehm and Pandalai-Nayar, 2022).

Second, the key novelty we introduce are *integer constraints*. Effort e can be employed at any desired quantity, but labor can only be hired at indivisible full integer values, $n \in \mathbb{N}$. This captures a key characteristic of most labor

[17] In the interest of parsimony we state production in value-added terms, which abstracts from the role played by intermediate goods in the production process. These could be included in a straightforward way with little change to the core mechanisms of the model.

markets across the world, where workers are locked into their current activity for a full day, week, or month, and cannot be hired at arbitrarily small time intervals.[18] There are two plausible explanations for how this arises. First, in many occupations it is difficult for workers to multitask because of geographical or logistical constraints. Second, a prominent feature of on-demand services is the unpredictable arrival of demand: many retail stores cannot predict at what exact time customers arrive and so staff the store throughout the day in order to be ready once demand materializes.[19]

Firms in the non-tradeable sector are monopolistically competitive, observe their productivity φ, and choose their price p and labor capacity n to maximize profits given the residual demand curve in (1).

$$\max_{p,n} D(p)\left(p-\frac{\nu}{\varphi}\right)-w_Y(n-1) \quad \text{s.t} \quad D(p)\leqslant \varphi n, n\in\mathbb{N} \tag{3}$$

where ν is the exogenous cost of effort and w_Y is the endogenous cost of hiring a full unit of labor. We assume that the owner of a firm simultaneously acts as its first employee – without additional hired labor, the hiring cost for such an owner-operated firm is $w_Y(n-1)=0$. Such firms still need to pay ν for each marginal unit of production, which can be thought of as an opportunity cost of effort for the owner. Firms with additional hired labor, $n>1$, pay both hiring cost and exactly compensate workers for the opportunity cost of providing effort ν. This compensation structure is in line with the fixed plus piece-rate labor contract often observed in developing countries (Foster and Rosenzweig, 2022).

Firms solve this profit maximization problem by jointly choosing how many workers to hire and what price to charge. If feasible given the chosen level of capacity n, the profit-maximizing price of a monopolistically competitive firm with productivity φ and marginal costs ν/φ is to charge a constant CES markup over marginal costs, yielding *unconstrained* prices p_u, quantities y_u, and profits π_u:

$$p_u(\varphi,n)=\frac{\theta}{\theta-1}\frac{\nu}{\varphi},\quad y_u(\varphi,n,\zeta)=\zeta\left(\frac{\theta}{\theta-1}\frac{\nu}{\varphi}\right)^{-\theta},\quad \pi_u(\varphi,n,\zeta)=\frac{\zeta}{\theta}\left(\frac{\theta}{\theta-1}\frac{\nu}{\varphi}\right)^{1-\theta}-w(n-1)$$

where u-subscripts denote unconstrained firms. This production schedule is only feasible if it does not violate the chosen level of capacity n. If this optimal price turns out to be low enough, however, it can induce demand that is so high that every worker works at full capacity and cannot possibly produce enough. In particular, as $y_u(\varphi,n,\zeta)>\varphi n$, the firm becomes *constrained* as it cannot produce its desired quantity without violating the capacity constraint. In this case, the best the firm can do is to increase its markup so that it sells exactly everything it can produce:

$$p_c(\varphi,n)=\zeta^{1/\theta}(\varphi n)^{-1/\theta},\quad y_c(\varphi,n,\zeta)=\varphi n,\quad \pi_c(\varphi,n,\zeta)=\zeta^{1/\theta}(\varphi n)^{\frac{\theta-1}{\theta}}-\nu n-w(n-1)$$

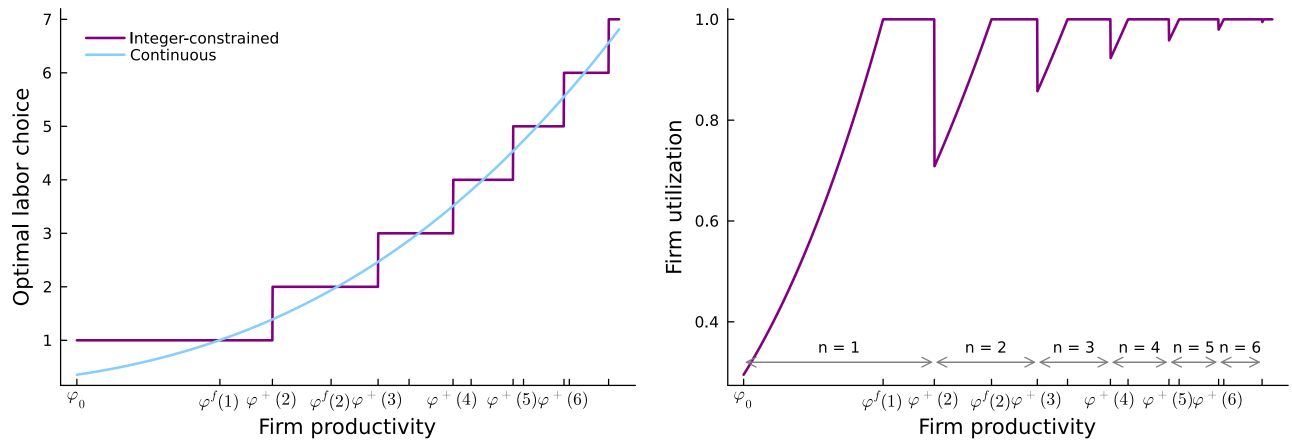
This production schedule (denoted with c-subscripts to indicate constrained firms) features prices that react to demand conditions ζ: as demand goes up, a constrained firm raises prices to lower demand accordingly and remain at full capacity utilization.

The solution to the joint problem of choosing capacity and prices takes the form of a cutoff rule. The condition $y_u(\varphi,n,\zeta)>\varphi n$ defines a *full capacity cutoff* $\varphi^f(n,\zeta)$ for each level n of $\mathbb{N}$, which is the productivity level at which the monopolistic firm charging constant markups operates exactly at capacity, $y_u(\varphi^f(n,\zeta),n,\zeta)=\varphi^f(n,\zeta)n$. A firm with productivity below $\varphi^f(n,\zeta)$ is unconstrained, a firm above becomes constrained and increases its

[18]Gig economy labor markets may be an exception to this, but are not yet relevant to the division of labor in rural or urban Kenyan markets. We revisit the exact nature of the indivisibility in detail below.

[19]A similar argument holds for capital. Most firms in our setting employ only a few specific tools or machines. The market for such tools or machines may not offer finely differentiated products tailored to the small scale of microenterprises, especially since many machines are likely themselves imported from countries with larger average firm sizes.

Figure 3: Capacity and utilization decisions of integer-constrained firms



(a) Labor choice

(b) Optimal utilization

Notes: Schematic hiring and utilization decisions of firms with different productivity levels φ in partial equilibrium for a given wage w_Y and demand level ζ. Panel (a) contrasts the optimal labor choice decision for a firm subject to integer constraints (purple) to the benchmark case of continuous labor hiring (light blue). Integer-constrained firms over- or underinvest in labor, depending on their productivity level. Panel (b) plots the optimal labor utilization decision e/n for firms at different productivity levels φ. This choice features regions of underutilization, as well as prolonged ranges of operation at full capacity. Full utilization cutoffs $\varphi^f(n)$ as well as upgrade cutoffs $\varphi^+(n)$ are highlighted along the x-axis.

markups. This leads to profits conditional on capacity n:

$$\pi(\varphi, n, \zeta) = \begin{cases} \frac{\zeta}{\theta}\left(\frac{\theta}{\theta-1}\frac{\nu}{\varphi}\right)^{1-\theta} - w(n-1) & \text{if } \varphi \leqslant \varphi^f(n,\zeta) \\ \zeta^{1/\theta}\left(\varphi n\right)^{\frac{\theta-1}{\theta}} - \nu n - w(n-1) & \text{else} \end{cases}$$

The optimal choice of n is defined by *upgrade cutoff* values $\varphi^+(n,\zeta)$ at which point the firms upgrades from $n-1$ to n, i.e. $\pi(\varphi^+(n,\zeta), n, \zeta) = \pi(\varphi^+(n,\zeta), n-1, \zeta)$.[20] Appendix section C.1 presents a detailed derivation.

Implications. Integer constraints lead to non-standard hiring and utilization decisions. Figure 3a compares the optimal hiring choice of an integer-constrained firm (in purple) to a benchmark case of continuous hiring (in blue).[21] Not surprisingly, the integer-constraint hiring schedule resembles a step-function: firms make a discrete jump to the next-highest value of n as soon as it's profitable to do so. This constraint leads firms within certain productivity ranges to hire more labor than under the continuous benchmark, while others hire less. Intuitively, both firms that in the benchmark case of continuous input choices would hire 1.9 or 2.1 workers, respectively, are now forced to hire exactly 2.0 workers due to integer constraints.

Panel 3b illustrates implications of integer constraints for utilization rates. It presents optimal firm utilization e/n for firms at different productivities φ. Starting from $n = 1$ at the left of the graph, firms with low productivity (below $\varphi^f(1)$) find it optimal to not fully utilize their only employee. These low-productivity firms have high marginal costs, charge a constant monopolist markup over marginal cost, which induces demand that is lower than what the firm could produce under full utilization. This underutilization is constrained-optimal for the firm. Of course, the firm would benefit if it could hire only exactly as much labor as it needs to produce this quantity,

[20] We can derive the values for the full capacity cutoffs φ^f in closed form: $\varphi^f(n,\zeta) = \left[\frac{\zeta}{n}\left(\frac{\theta}{\theta-1}\nu\right)^{-\theta}\right]^{\frac{1}{1-\theta}}$. The upgrade cutoffs φ^+ do not permit a closed-form solution, as finding the point where constrained profits at n equal unconstrained profits at $n+1$ requires solving a higher-order polynomial. However, as we show below, firms eventually become big enough to always be constrained. In this case, we can express upgrade cutoffs as

$$\varphi^+(n) = \left(\frac{\zeta^{1/\theta}\left[n^{\frac{\theta-1}{\theta}} - (n-1)^{\frac{\theta-1}{\theta}}\right]}{\nu + w_Y}\right)^{\frac{\theta}{1-\theta}}$$

[21] We provide the analytical solution to the continuous model in Appendix C.2

but in the presence of integer constraints, the best it can do is to hire $n = 1.0$ workers and have them sit idle for some of the time.[22] Further increasing productivity to $\varphi^f(1)$, firms become large enough so that workers are exactly fully utilized. Once this level is reached, however, firms do not immediately upgrade to the next-highest indivisible labor unit. Instead, there is a region between $\varphi^f(1)$ and $\varphi^+(2)$ where firms find it optimal to be at full capacity and react to further increases in productivity (or increases in demand) by varying their markup. These "full-capacity" regions are crucial to understanding overall price movements in response to changes in demand: while unconstrained firms do not marginally change their prices in response to a demand shock, firms at the constraint do. Moving along the productivity distribution, firms are eventually productive enough to find it optimal to upgrade and hire a second worker (denoted $\varphi^+(2)$ in Figure 3b), and utilization drops again. However, it does not drop as far as it had been with just a single employee. Similarly, after growing into another full-capacity region, the firm at some point hires a third worker and is even less underutilized, and so on.

This model captures the intuition that integer constraints bind most at "small integers": going from 0 to 1 worker (or from 2 to 3) is a relatively large jump, but moving from 50 to 51 is fairly close to the continuous benchmark. Hence, medium and large firms do not have to worry much about integer constraints, as indivisible units are small relative to their own scale of activity. However, integer constraints can be an important concern in small enterprises which represent the vast majority of enterprises in our study sample and in developing economies more broadly.[23]

Entry. Households are freely mobile between sectors and can choose between wage employment and starting a business. For households choosing wage employment, free mobility implies that agricultural and non-agricultural wages equalize: $w = w_Y = w_X$.[24] We denote the mass of households entering as entrepreneurs by M.

Prior to entry, households do not know their own productivity as entrepreneurs, and only know that it is distributed $\varphi \sim G$. Similar to Melitz (2003), entry depends on whether the benefit of entrepreneurship, namely, the expected profit, exceeds its opportunity cost w. We abstract from additional fixed costs to operating an enterprise since the data indicates very low capital shares (cf. Table 2). As a consequence, all households that enter also become active as entrepreneurs.[25] In equilibrium, households are indifferent between wage employment and entrepreneurship:

$$\int \pi(\varphi) dG(\varphi) = w.$$

3.3 Equilibrium.

Household income equals the sum of an exogenous transfer Δ, profits across both sectors, and earned labor income:

$$I = \Delta + \Pi_x + \Pi_y + wN_x + M \left(\underbrace{\int w(n(\varphi) - 1) dG(\varphi)}_{\text{wage payment}} + \underbrace{\int \nu e(\varphi) dG(\varphi)}_{\text{avg. effort payment}} \right) \tag{4}$$

[22]Or if owner-operators could work part-time in their enterprise, the remaining time could be used productively on other economic activities. In our empirical setting, people typically engage in multiple different activities throughout the year. For our model to be empirically relevant, all that is required is that there is a meaningful minimal step or indivisibility that is binding on labor supply designs.

[23]To see why this arises, notice that firms will never hire another worker while their current workers are unconstrained. As a result of this, the lowest possible utilization rate for a firm with n employees is $(n-1)/n$, so that slack decreases with firm size n.

[24]Note that workers in the non-agricultural sector also receive effort payments ν for every marginal unit they produce. We assume that this payment is chosen to offset their disutility from exerting effort, so that only the fixed component w determines which sector workers prefer. In Appendix section C.3, we present an extension of the model where agricultural work also requires effort payments of the same size. Our quantititative results are very similar across these two specifications.

[25]The difference with respect to Melitz (2003) is we set the sunk-cost of entry $f^e = w$ or one unit of labor resources. Additionally, we assume that entry labor is not only used to create the firm, but also becomes active in production. This implies that we calculate the expected profits from entrepreneurship by integrating over the unconditional productivity distribution. Below, we also consider an extension where households know their type as entrepreneurs prior to entry, which gives rise to selection.

where payments to labor in the service sector are the sum of wages paid to hired workers and effort compensation.

Equilibrium in this economy consists of an allocation of labor $\{N_X, N_Y, M\}$ and a vector of output and factor prices $\{P, w_X, w_Y\}$ such that given optimal behavior by firms, workers and consumers,

1. labor markets clear: $N = N_X + N_Y + M$.
2. the goods market clears in the service sector: $PY = \alpha I$.
3. sectoral wages equalize: $w_X = w_Y = w$.
4. households are indifferent between wage employment and entrepreneurship: $w = \mathbb{E}\pi(\varphi)$.
5. a choice of numeraire: $p_X = 1$.

In Appendix section C.1, we provide more detailed expressions of service sector aggregates as a function of the previously defined cutoffs for selection into entrepreneurship and each integer-level of employment $\{\varphi^+(n)\}_{n=1}^{\infty}$ and discuss how we solve for the equilibrium numerically.

Supply Curves. The macroeconomic implications of integer constraints and the resulting slack capacity can be understood by studying how they affect supply curves. The slope of this supply curve depends on the relative share of constrained versus unconstrained firms. At the micro level, the supply curves of unconstrained firms are flat because they charge constant markup prices. For constrained firms, demand shocks directly push up markups and prices. At the macro level, the share of constrained versus unconstrained firms additionally determines factor market tightness. If most firms are unconstrained, labor demand is less affected by a demand shock because firms can expand supply by increasing utilization. As demand grows, however, more firms will run into capacity constraints and will want to hire additional workers, raising wages and ultimately prices.

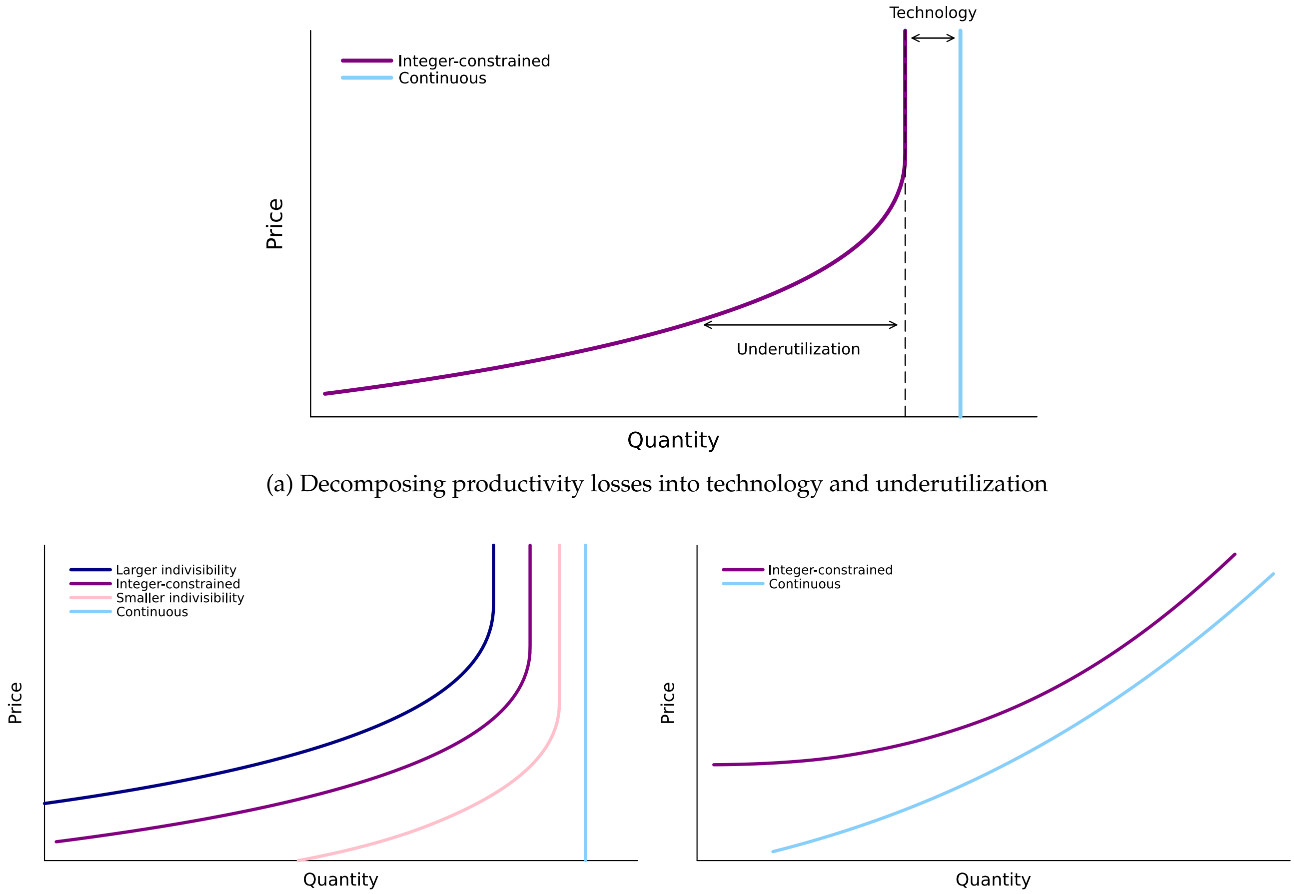
Figure 4a illustrates these dynamics by tracing out the local service sector supply curve induced by different levels of the transfer Δ. To highlight the role of integer constraints most clearly, we ignore sectoral labor reallocation between agriculture and services and entry into entrepreneurship for now.[26] Integer constrained supply curves (in purple) are convex in shape, with an initially flat region for low levels of demand. In this region, the economy can raise output without requiring much increase in prices. As demand rises, the economy runs out of underutilized labor leading to much larger required price increases to further expand supply. Eventually, all labor becomes fully utilized and the supply curve becomes fully vertical, as would be the case under a fully continuous hiring choice and a fixed supply of labor to the sector.

The benchmark supply curve under continuous hiring is depicted in light blue in panel (a). Again note that for this panel, we have abstracted from labor reallocation between sectors, rendering this a fully vertical curve with fixed output. Comparison to this continuous model reveals that integer constraints make an economy less efficient: at any given price level, the integer constrained economy produces less output than a continuous economy. We can decompose this efficiency loss into two parts: misallocation from a technological inability to hire the optimal amount of labor due to integer constraints, and underutilization of the hired labor. First, even in the full utilization limit to the right, the two supply curves do not coincide. With integer constraints, firms differing in productivity choose the same amount of labor, leading to a dispersion in marginal revenue products. Among the firms choosing to hire n workers, output could be increased by reallocating a marginal unit of labor effort towards higher productivity firms (Hsieh and Klenow, 2009). This form of misallocation is not present in the continuous version of the model. Second, at lower levels of demand, integer constraints lead to a potent second source of productivity loss: underutilization. Firms maximize profits by optimally not utilizing their inputs fully, which opens up a potentially large underutilization gap.

In principle, there is nothing special about the unit of indivisibility to be integers. One could imagine n to come from any discrete set $\mathcal{N} = \{s, 2s, 3s, ...\}$. For example, labor market regulation might necessitate that firms hire

[26] Formally, this implies assuming an exogenous mass of entrants M and that all agricultural consumption is imported $\Delta = X$.

Figure 4: Integer-constrained supply curves



(a) Decomposing productivity losses into technology and underutilization

(b) Varying sizes of the indivisibility

(c) Full model with agriculture and free entry

Notes: Schematic aggregate supply curves for the service sector in integer-constrained economies. Curves are traced out by varying the transfer parameter Δ and recomputing the equilibrium. Panel (a) contrasts an integer-constrained supply curve with the benchmark continuous model. To ease exposition, this economy does not feature labor reallocation across sectors or entry into entrepreneurship. The figure decomposes the output gap arising due to integer constraints into a technology gap (that does not vanish even in the full-capacity limit) and an underutilization gap. Panel (b) varies the "stepsize" of the indivisibility gap to labor being allowed to be hired in larger bundles (dark blue) or smaller bundles (light pink). Panel (c) presents the full model with labor reallocation between agriculture and services, as well as endogeneous entry into entrepreneurship.

labor for much longer time periods or in larger groups, e.g., our setup could model spousal hiring practises through n having to come from the set of even numbers, or information technology developments might enable a gig-economy where workers can more easily split tasks across different locations or firms. Figure 4b presents resulting supply curves coming from different units of indivisibility, denoted by s. In dark blue, we print the case of supply curves with a larger indivisibility constraint, i.e., labor having to be hired in bundles of $s > 1.0$. Not surprisingly, this further exacerbates both technology and underutilization gaps. On the other hand, the supply curve in pink can be thought of as introduction of part-time work, where the indivisibility drops to $s < 1.0$ and gets closer to the efficient continuous benchmark. The model asymptotes the continuous benchmark as we take the step size of the constraint towards zero. We return to this point in the quantitative exercise in section 5.5 below, which presents structural estimates of the size of the indivisibility in the rural Kenyan context.

The service sector supply curve shown in Figure 4a abstracts from agricultural production and firm entry. With these additional margins, increased demand can also be met by drawing workers out of agriculture into the service sector, as emphasized in Lewis (1954). This is shown in Figure 4c, which includes all general equilibrium forces of the model. As before, supply curves are much flatter for low levels of demand in the integer-constrained case. Regardless of the level of demand, supply without integer constraints also remains higher, consistent with the discussion of how integer constraints lower efficiency. The main difference with respect to the one-sector equilibrium depicted in Figure 4a is that, even for higher levels of demand, service sector supply remains relatively more elastic due to the availability of additional workers previously employed in the agricultural sector. As utilization rises, compensation in the services sector increases, leading workers to reallocate from agriculture to the service sector until agricultural wages rise to equal compensation across sectors.

Implications for Transfer Multipliers. This discussion of service sector supply curves indicates that supply for non-traded goods responds to increases in aggregate demand. To examine the response of aggregate supply to demand shocks and provide intuition for the multiplier dynamics implied by our model, we derive a simple expression for nominal income. Using $X = (1-\alpha)I$ (the agricultural good consumption share), market clearing for non-traded goods, and the household budget constraint in (4), we can derive nominal income as:

$$I = \frac{\Delta + \tilde{A}N_x^{\beta}}{1-\alpha}. \tag{5}$$

Differentiating (5), the transfer multiplier on nominal income can be expressed as:

$$\frac{dI}{d\Delta} = \frac{1}{1-\alpha}\left(1 + \beta\tilde{A}N_x^{\beta-1}\frac{dN_x}{d\Delta}\right). \tag{6}$$

This multiplier takes an intuitive form. Absent any sectoral reallocation of labor, $\frac{dN_x}{d\Delta} = 0$, it is simply equal to $\frac{1}{1-\alpha}$, where α represents the marginal propensity to consume an additional dollar of income on non-traded goods. The intuition follows standard Keynesian thinking: for each additional dollar of transfers, the household spends share α on service sector goods and share $(1-\alpha)$ on agricultural goods. The share α spent on non-traded goods comes back in the form of wages, profits and effort payments. Continuing this chain, the effect on nominal income in the absence of labor reallocation is

$$\frac{dI}{d\Delta} = 1 + \alpha + \cdots = \frac{1}{1-\alpha}.$$

With labor reallocation, the nominal multiplier is lower than $\frac{1}{1-\alpha}$ because spending on agricultural goods rises by less than with fixed labor, which in turn constrains nominal service sector spending. The effect on agricultural consumption is given by the transfer net of reallocation to the service sector.

$$\frac{dX}{d\Delta} = 1 + \beta\tilde{A}N_x^{\beta-1}\frac{dN_x}{d\Delta} < 1.$$

While there is no inflation in the agricultural sector, the responses in the service sector features an inflation component.

$$\frac{dY}{d\Delta}P + Y\frac{dP}{d\Delta} = \alpha\frac{dI}{d\Delta}. \tag{7}$$

Inflationary pressure arises because with additional income, households want to spend on goods from both sectors. While they are able to do so for tradeable goods, which can be imported at a fixed world price, increasing supply of non-traded goods either requires reallocation of labor from agriculture or exploiting existing underutilized labor in the service sector.

3.4 Spatial shopping economy

We next embed this production structure into a canonical multi-location spatial economy (Ahlfeldt et al., 2015). This allows the model to speak to the empirical stylized fact that locations with higher market access exhibit less slack on average.

There are L locations indexed by o, d. In the application considered below, origin destinations o are villages and shopping destinations d are markets. In each location, there is a mass of N_o of households. Since non-agricultural goods and services are not traded, consumers need to travel to shop at different markets around them. Agriculture X is freely traded and does not require travelling. In particular, we follow Ahlfeldt et al. (2015) and assume that each household c in location o who shops in location d receives indirect utility

$$u_{cod} = \frac{I_o}{P_d} \frac{z_{cod}}{D_{od}}$$

where I_o/P_d is real consumption, $D_{od} = \exp(\kappa\tau_{od} - \widetilde{\gamma}_d)$ is disutility from travel, τ_{od} is distance in kilometres between o and d, $\widetilde{\gamma}_d$ is a destination specific demand shifter, and $z_{cod} \sim \text{Frechet}(\sigma)$ is an idiosyncratic shock. Demand shifters γ_m capture a fixed preference for shopping at a given market, which we assume also include any love-of-variety effects.[27] Households observe prices in each location, draw their idiosyncratic shock z_{cod}, and decide where to shop. With shocks drawn from a Frechet distribution, we can express *expenditure shares* π_{od}, i.e., the share of total spending from location o that occurs at location d, as:

$$\pi_{od} = \frac{(P_d D_{od})^{-\sigma}}{\sum_{d'} (P_{d'} D_{od'})^{-\sigma}} \tag{8}$$

so that the total demand expenditure facing a location d is

$$E_d = \sum_{o'} \pi_{o'd} I_{o'}$$

An equilibrium in the spatial economy satisfies conditions 1 - 5 above in each location, as well as equation (8) in shares. The goods market clearing condition can now be restated as $P_o Y_o = E_o$. In this setup, we abstract from other notions of spatial equilibrium, such as labor mobility or migration. This is motivated by results from Egger et al. (2022), who do not report any significant migration or commuting responses to demand shocks, at least in the short- to medium-run period of up to approximately 2-3 years that they study.

3.5 Alternative microfoundations for slack

This paper focuses on the role of indivisibilities in generating slack in small firms in developing countries. There are, of course, other reasons why capacity might be underutilized in these contexts. We briefly describe some of the most plausible alternative microfoundations below and discuss to what extent these are consistent with the empirical evidence and stylized facts presented above.

Limited managerial capacity could lead to slack if firms are unable to optimise an organisationally complex series of tasks required for production (Leibenstein, 1966; Bloom et al., 2013). Similarly, idle capacity could be caused by the complementarity of many complex tasks in the production function, the failure of any one of which lead to lower productivity in the remaining tasks (Kremer, 1993; Jones, 2011). Note, however, that these theories would suggest that slack should be more prevalent in larger and more complex firms, contrary to the patterns presented above.[28] Few firms directly mention constraints on complementary inputs as a reason for slack.

Slack might also in part be the result of *market power and collusion*. Allen et al. (2000) argue that incumbents might have an incentive to build up capacity to deter entry of potential competitors, with unused capacity serving as a threat (see also Prescott, 1973). However, the markets we study commonly feature many firms of the same type operating side by side, with little evidence for barriers to entry.[29] More closely related to our context, Banerjee et al. (2023b) document food vendors in India forgoing profitable quantity expansions, which the authors attribute

[27] We multiply the CES aggregator by $M^{\frac{1}{1-\theta}}$ in the spatial model, where θ is the elasticity of substitution across varieties. Potential love of variety effects are thus held fixed at the level implied by the calibrated demand shifters $\widetilde{\gamma}_m$.

[28] Similarly, workers and machines might be idle for some time in response to unreliable power supply. This would predict that firms more reliant on electricity should report higher rates of slack. In Figure A.3c in the Appendix, we decompose the utilization index by the type of electricity a firm uses (if any), and do not find much evidence that firms reliant on the Kenyan national power grid have more slack than those using a generator or not using electricity at all.

[29] Market power may be a more plausible determinant of slack in a few sectors such as food processing, where there is often only one firm operating mill to grind maize.

to collusive behavior among the vendors. And Bergquist and Dinerstein (2020) show that agricultural traders in Kenya act consistently with a model of joint profit maximisation. In this setting, demand shocks could lead to large increases in supply without much increase in prices. To generate steady state slack, however, a model of retail collusion would likely also need some notion of indivisibility constraints, without which even collusive agents would have an incentive to cut any unused capacity.

Another microfoundation of slack could stem from *adjustment costs and cyclical demand*. Firms might build up capacity in order to accommodate high demand in good times (for example, the post-harvest season), which then sits idle in bad times. However, it is unclear why this would lead to more slack in the smallest firms, which likely should have the smallest adjustment costs to explore different options in the lean season. A slightly different explanation might be *volatile or uncertain demand*. If firms cannot accurately predict the level of demand, they build up capacity just to be ready in case demand is high so as to not miss periods of excess profits (Fafchamps et al., 2000). We note, however, that some models of investment under uncertainty would also predict the opposite, with firms investing less if the return to the investment is more uncertain (Dixit and Pindyck, 1994). We believe disentangling the interplay of demand uncertainty and slack to be a promising area for future work.

Lastly, a common approach in dynamic stochastic general equilibrium (DSGE) models in macroeconomics is to omit capacity constraints and instead model effective labor input as following a *convex cost curve*. Workers could in principle supply more labor, but doing so would incur an increasingly heavy cost. We see our model as providing a plausible microfoundation for such convexity: firms with underutilized capacity can increase output marginally at a constant cost ν, while larger increases require more labor, which is fixed. Hence, while we do not explicitly model labor costs as convex, the setup rationalizes such a shape and is broadly consistent with assumptions made in DSGE models.

4 Estimation and calibration

We next calibrate the model to the rural western Kenyan economy and simulate the impact of local demand shocks (in the form of cash transfers) in an environment of endogeneous slack. This quantification exercise leverages detailed microdata on firm capacity utilization, ownership, revenue and costs, as well as household consumption and spatial shopping patterns to characterize the economic geography of the study area.

The model quantification proceeds in three main steps. First, we calibrate the model to fit the baseline economy. Next, we simulate the effects of a large demand shock by recreating the spatially randomized inflow of cash in the Egger et al. (2022) RCT. Last, we validate model predictions against the Egger et al. results, which we treat as untargeted moments. Importantly, we do not fit the model to match any experimental treatment effects, in order to generate what we see as a true out-of-sample test of the model.[30] Finally, we use the fitted model to make counterfactual predictions about the macroeconomic impacts of cash transfers of different sizes and characteristics.

As a methodological innovation, we pre-specified parts of the structural calibration and validation approach with a pre-analysis plan (PAP) on the AEA trial registry (trial 13210).[31] This is intended to instill greater confidence that the untargeted moments that the model's predictions are judged against represent true out-of-sample performance, and not just the few – out of potentially very many – dimensions along which the model happens to perform favorably (see eg. Casey et al., 2012; Burlig, 2018). It is worth stating that we do not believe pre-specification to necessarily be desirable for all macroeconomic models and contexts. Rather we see our PAP as an exploratory early attempt at applying a widely-used method from other subfields of economics into more structural macroeconomics research.

In particular, we pre-specified the main equations of the integer-constraint microfoundation and the equilibrium

[30] Following the terminology of Schorfheide and Wolpin (2016), we reserve the treatment data as a hold-out sample. Prominent related examples of this strategy are Todd and Wolpin (2006) and Kaboski and Townsend (2011).

[31] There are just a few existing examples of pre-specified structural econometric analysis to our knowledge, including Bai et al. (2021) and Arcidiacono et al. (2024). Our pre-registration is more limited in scope as experimental results were already known from Egger et al. (2022).

conditions outlined in section 3, as well as a general strategy for how to identify key parameters. We also committed to a series of out-of-sample experimental moments against which to test the model's predictions. In a few instances, we subsequently decided to deviate from the PAP; Section C.5 in the Appendix provides a list of these deviations as well as a justification for our reasoning in each case.

Structural macroeconomic models are different in several dimensions from the reduced-form equations underlying much of empirical development economics, in which pre-analysis plans have become more widely accepted (Swanson et al., 2020). As a result, some elements of the analysis are deliberately only partially pre-specified. For one, the model is meant to explain and quantify a phenomenon – high rates of slack in developing countries – and not to assess the impact of a particular intervention. At the time of writing the PAP, all data collection had finished and the authors had conducted substantial descriptive analysis, including establishing the extent and main correlates of capacity underutilization as described in section 2. The model was written with (and inspired by) knowledge of these characteristics and patterns.

4.1 The Egger et al. (2022) RCT

We calibrate the model to represent the rural county of Siaya in western Kenya where the cash transfer experiment in Egger et al. (2022) took place, and where there is detailed data on population, demand, and production from before and after the experimentally assigned cash transfers. Here, we briefly describe the experiment, and the data sources used to calibrate the model to the experimental setting.

The cash transfer experiment. The NGO *GiveDirectly* provided large, lump-sum payments to poor households meeting a basic means test (having a grass-thatched roof) within the villages randomly chosen to receive the program. The cash transfers were large: USD 1,000 (nominal), about 75% of annual household consumption expenditure for recipient households. Households enrolled in the program received the cash transfer via mobile money as a series of three payments over eight months. In treated villages, cash transfers amounted to 15% of annual village level GDP on average.

The Egger et al. (2022) RCT used a two-level design in order to generate experimental variation in both a village's own treatment assignment, as well as in the number of surrounding villages assigned to treatment. Specifically, villages were randomly assigned to receive the NGO program (with all households meeting the eligibility criteria receiving the cash transfer), and the share of villages assigned to treatment was experimentally varied at the sublocation level, the administrative unit above the village. Sublocations contain 5-15 villages, and were assigned to high or low saturation status: in high saturation (low saturation) sublocations, two-thirds (one-third) of villages were assigned to treatment.

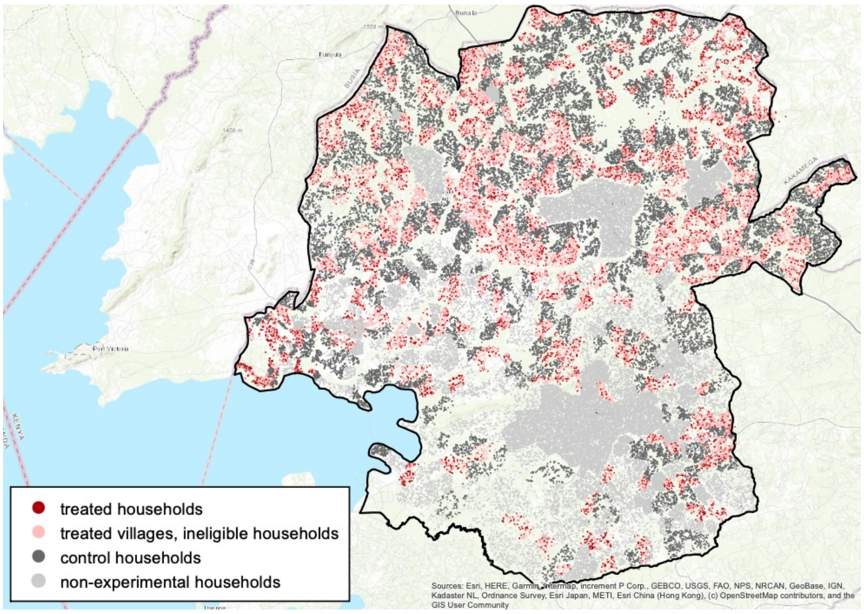
Population. At baseline in 2014, Siaya County was home to approximately 420,000 people living in roughly 100,000 households (Figure 5a). Around 70,000 people (17%) lived in five peri-urban towns – Siaya, Ugunja, Ukwala, Sigomere, and Sega Town – and these were excluded from the cash transfer experiment. The remainder lived in 847 rural villages with an average of 115 households per village. 653 of these villages took part in the Egger et al. (2022) RCT, and were censused at baseline in 2014. The census captured a total of 65,383 households and 66% of the population of Siaya County.[32] Population data for towns comes from the 2009 census (inflated to 2014 by average Kenyan population growth). Population estimates for the remaining villages is from additional surveys with village elders conducted in 2024 (see Appendix E for more details).

Demand. A second endline survey was collected approximately 5 to 7 years after cash transfers were distributed, and gathered detailed data on household expenditures among a representative 8,700 households in the 653 study villages. For each product category, households reported not only total spending, but also where

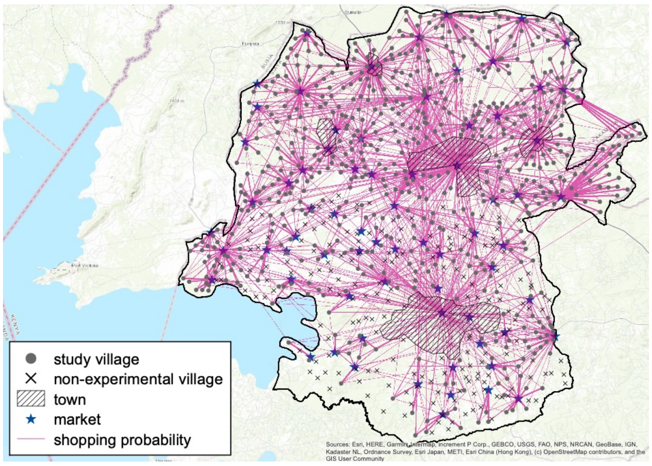
[32]Cash transfers amounted to 15% of annual village level GDP in the 50% of sample villages that were treated. Thus, the total program injected cash worth approximately 5% of Siaya county GDP (= 66% $\times$ 50% $\times$ 15%).

Figure 5: Data geography

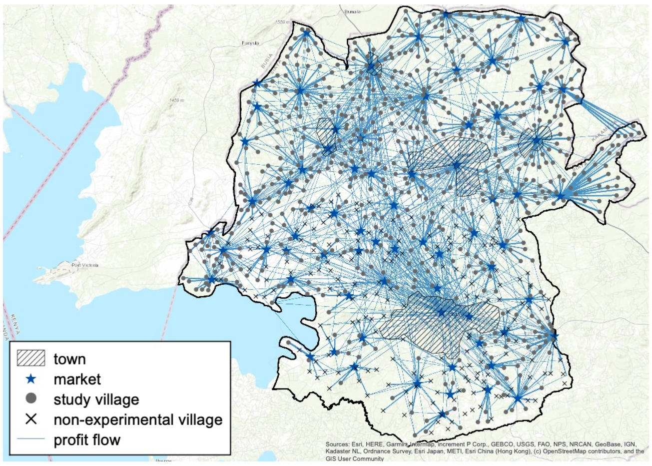
(a) Treatment assignment



(b) Shopping flows



(c) Profit flows



Notes: Maps depict Siaya County in western Kenya. Panel A shows all households: treated and control households are from GPS data collected during the baseline household census of Egger et al. (2022), while non-experimental sample households are randomly distributed within town and village boundaries. Panel B depicts expenditure shares from each of the 653 study villages to 71 weekly markets, collected from representative household surveys. Line thickness increases with spending share. Panel C depicts profit flows between markets and villages, calculated from representative enterprise surveys that collected information on owner residence location and profits. Section 4.1 has more details.

(i.e., in which market) they purchased these products. Figure 5b illustrates the resulting spending shares, linking each of the 653 villages to the 71 markets within Siaya County.[33]

Production. Agricultural production takes place primarily in household farmsteads, and 97% of households are engaged in some form of agriculture. The analysis contains household surveys from the endline 2 round using a representative sample of 11,500 households to quantify overall agricultural production. Non-agricultural production takes place in enterprises captured at endline 2 in two censuses of all non-agricultural enterprises operating in the study area – one census for enterprises operating in villages and homesteads, and one for enterprises operating in markets – and representative surveys with 4,721 enterprises (Section 2.1 has more detail). Importantly, these surveys matched firm owners to a concurrent household census, allowing us to richly char-

[33]Spending shares were collected *after* cash transfers and may therefore be somewhat endogenous. This data is primarily used to estimate gravity-related parameters of the model which we view as unlikely to have been substantially affected by transfers received 5-7 years prior.

acterize ownership patterns and profit flows across space. To estimate the impacts of cash transfers on output (Figure 7c below), the analysis additionally uses a census and representative enterprise survey from the endline 1 survey round, collected on average at two years after cash transfers. (Appendix D.1 has more details.)

Prices. To estimate the inflationary impacts of cash transfers in the data (Figure 7d below), we use price data from Egger et al. (2022) for up to three price quotes for each of 78 goods across 61 markets over 31 months, for a total of over 400,000 unique price observations (Appendix D.2 has more details).

Labor supply and wages. Sectoral allocation of labor and wages – which we use to conduct additional empirical tests of the impacts of cash on labor reallocation – is measured using data on hours worked and wages for all 15,702 adults living in 8,239 households surveyed at endline 1, approximately two years on average after transfers (Figure A.13 in the Appendix).

4.2 Fitting the model to the baseline economy

To estimate the structural parameters of the model, we first treat the entire economy of Siaya County as a single location. We return to the spatial representation of the economy in the counterfactual analysis below. Annual or annualized quantities of production are used throughout.

Population, land, and agricultural productivity. We normalize the total population of the economy to one, $N = 1.0$, so that all quantities coming out of the model can be interpreted in per-capita units. Since land is fixed, we also normalise total land in the economy to one ($\Lambda = 1.0$). We assume that the distribution of productivity draws follows $G \sim \text{Pareto}(q, \eta)$ and normalize average productivity in the service sector by setting $q = 1.0$.[34] To calibrate the decreasing returns to scale parameter β from the agricultural production function, we draw on Adamopoulos and Restuccia (2020) who estimate $\beta = 0.49$.[35] Measured average per capita agricultural production from the household surveys is $X/N \approx$ USD 85, and the agricultural employment share is $N_X/N = 0.56$ (measured as the share of people reporting agriculture as their primary occupation). Together with the normalization on land above, this implies that aggregate agricultural TFP is: $A = \frac{X/N}{(N_X/N)^\beta} \approx 112$.

Household consumption shares and remittances. We proceed in two steps to calibrate the share of household spending on integer-constrained local non-tradeables, α. In our value-added framework, local non-tradeable expenditure consists of value added in local non-food expenditure, plus the local (or service) component of food expenditure. We can use the dataset to speak to all of these components. First, households' reported budget share on food is 0.68. Some of this expenditure reflects spending on local services, such as the labor component of employees at a food vendor, which is arguably subject to integer constraints and not tradeable. Food stalls in the area report an intermediate cost share (i.e., purchases of raw produce) of 49%, leaving us to classify 51% of food expenditures as local non-tradeable. Second, local non-food retailers report an intermediate import share of 19%, which we subtract from total non-food expenditure. Putting it all together yields a calibration of the expenditure share of local non-traded goods:

$$\alpha = \underbrace{0.68}_{\text{food}} \times \underbrace{0.51}_{\text{non-trade}} + \underbrace{0.32}_{\text{non-food}} \times \underbrace{0.81}_{\text{local}} \approx 0.61$$

So, a bit less than two thirds of households' expenditure is (indirectly) spent on non-tradeable services.

To take into account any baseline inflows of outside transfers into this economy (before the cash transfer experiment), we make use of the household data on baseline remittance flows. On average, households report $\Delta_0 =$ USD 16 of net remittance inflows at baseline.

[34] Note that q merely shifts the price index of non-traded goods, or equivalently, the quantity Y, with no further effects on utilization, labor allocation and entry.

[35] Those authors leverage a land reform in the Philippines to estimate this parameter. In their notation, the production function is $(A\kappa_i s)^{1-\gamma}(l^\alpha n^{1-\alpha})^\gamma$. This leads us to calibrate the Cobb-Douglas parameter on labor in agriculture as $\beta = (1-\alpha)\gamma = 0.7 * 0.7 = 0.49$.

Structural parameters η, ν, θ. We jointly estimate the shape parameter of the productivity distribution η, the marginal cost of effort ν, and the elasticity of substitution θ using simulated method of moments. In particular, for a given candidate vector $\xi = [\eta, \nu, \theta]'$, we solve for the general equilibrium wage, mass of entrants, and price level, to jointly match a vector of targeted moments. We choose the following pre-specified vector of moments:

$$\begin{bmatrix} \eta \\ \nu \\ \theta \end{bmatrix} \rightarrow \begin{bmatrix} \text{Share of revenue accounted for by top 20\% of firms} \\ \text{Share of firms below full capacity} \\ \text{Variable profit-share} \end{bmatrix}$$

In the joint estimation, these pin down the vector of structural parameters. Appendix Figure A.9 presents an informal identification argument by reporting pseudo-"Jacobians" of the moment vector through local changes of ξ around the point estimates. Below, we outline a brief intuitive explanation for why these particular moments are appealing.

The share of revenue accounted for by the top quintile of firms is sensitive to the shape of the Pareto distribution η. Low values of η imply a larger right tail of very productive firms, while high values imply most firms are close to the lower bound of q. In our data, within each sector, the top 20% highest-revenue firms on average generate 51% of total revenue in that sector. In the joint estimation, we arrive at $\eta = 2.9$.

The marginal cost of effort ν is critical for the overall level of slack in the economy. High values of ν increase the incentive for small firms to not fully utilize their employees in order to save on this marginal cost. In the data, 32% of firms report being able to expand production without having to incur any additional expenses (except a higher effort payment). We match this moment by estimating $\nu = 112.9$. Given equilibrium wage levels in our model, which are endogeneously determined around $w = 122$ USD, this means a fully utilized employee receives 48% of their total compensation through effort payments and the remainder (52%) through fixed wages. Since ν can be thought of as the opportunity cost of time, we can compare our estimate to more micro-experimental elicitations: for instance, Agness et al. (2023) estimate the value of time for self-employed workers to be at around 60% of the market wage rate, close to our estimate.[36]

Lastly, the elasticity of substitution θ shifts the markup that firms charge. The markup is $\frac{\theta}{\theta-1}$ for unconstrained firms and strictly higher for constrained firms. In the study context, measuring costs is not always straightforward: most firms are single-employee firms, muddying the difference between wage payments and profits. We sidestep this issue by targeting the average *variable profit-share*, which we define as firm revenues minus all costs except wage payments, divided by revenues. Theoretically, this share is $1/\theta$ for unconstrained firms and strictly higher for constrained firms. On average, firms in the data have a variable profit-share of 0.39, which we match through an estimate of $\theta = 3.9$. Table 3 summarizes the results of the calibration exercise.

4.3 Economic geography

To calibrate the spatial version of the model, we divide the economy into the 852 villages/towns, which we define as households' home locations, and 71 market centers (defined as enterprise and shopping locations) in the study area. Households earn income through agriculture, outside transfers, and owning or working for firms at a market. They observe prices at each market and decide where to shop according to equation (8). In spatial equilibrium, market prices, wages, and the number of firms endogenously clear factor and goods markets at each market center.

The rich spatial data on employment relationships, firm ownership links, and spatial shopping patterns allow us to calibrate a detailed representation of the study area's economic geography. We outline this approach below.

[36] Since our economy is calibrated on yearly data, one natural interpretation of ν is the dollar-value of extra compensation a firm needs to pay a worker who works at full capacity for a full year, over the endogeneous base-rate wage of w. Note also that the share of firms stating they are below full capacity (37%) corresponds to the rural sample in column 1 of Table 1.

Table 3: Parameter overview

Parameter	Source	Value
Cobb Douglas share of non-ag, non-tradeable α	read from consumption data	0.606
DRS parameter for ag production β	calibrate (Adamopoulos and Restuccia, 2020)	0.49
Agricultural technology A	match agricultural production	112.33
Scale of productivity Pareto q	normalize	1.0
Total land in the economy Λ	normalize	1.0
Total population N	normalize	1.0
Shape of productivity Pareto η	estimate via SMM (revenue share of top quintile)	2.870
Marginal cost of effort ν	estimate via SMM (share of firms below full capacity)	112.9
CES elasticity within locations θ	estimate via SMM (variable profit share)	3.910
Baseline remittances Δ_0	read from income data	853×1 vector
Ownership linkage matrix Π	read from ownership data	853×71 matrix
Labor supply matrix W	assign to nearest market	853×71 matrix
Spatial gravity parameter σ	calibrate	4
Spatial sensitivity to travel times κ	infer from gravity estimate of $\sigma\kappa$	0.22
Market demand shifter γ_m	Market F.E. from gravity equation	71 estimates

Notes: Overview of model parameters. Baseline remittances and firm ownership linkages are read off the data. Market demand shifters are estimated in a gravity equation jointly with $\sigma\kappa$. The three structural parameters η, ν, θ are jointly estimated via SMM. See text for details.

Village-market linkages. For all 852 villages subscripted with v, we have data on the local labor force N_v. Similarly, for each village we have data on the cash value of the net inflow of baseline remittances $\Delta_{0,v}$. Villages and markets are linked through employment and firm ownership relationships. First, we define the 852×71 ownership matrix O, where the entry $O_{v,m}$ denotes the share of all firms in market m that are owned by households from village v. This allows us to trace out the flow of enterprise profits through the spatial economy: for instance, if market m experiences a positive demand shock, the additional profits might end up as income and eventually the spending of households living in village v. Second, we define the 852×71 employer-employee matrix W, where the entry $W_{v,m}$ denotes the share of all workers from village v that work at enterprises based in market m. In practice, we assign each worker to their geographically closest market center.[37] Not all enterprises are located within a market center, as some operate out of the homestead or another village location, and we apportion these enterprises to their geographically nearest market. Using the above linkage-matrices, total income I_v in village v can be characterized as:

$$I_v = \Delta_v + \Pi_{X,v} + w_v N_{X,v} + \sum_m O_{v,m} M_m \Pi_{y,m} + \sum_m W_{v,m} N_{Y,v}(w_m + e_m)$$

where e_m are average effort payments made to workers in market m, $\Pi_{X,v}$ is total agricultural profit, M_m is the mass of firms, and Δ_v denotes all village-level remittances plus any cash transfers.

Spatial shopping parameters κ, σ, γ_m. Detailed data on shopping patterns across space allow for the joint estimation of the gravity parameters κ (sensitivity of perceived trade costs to increases in travel time between locations), and σ (the Frechet parameter determining substitutability between locations).

Taking logs of the expenditure shares expression derived in equation (8) between village v and market location m yields the following gravity equation (following Ahlfeldt et al., 2015):

$$\log \pi_{vm} = -\sigma\kappa\tau_{vm} + \gamma_m + f_v + \epsilon_{vm} \tag{9}$$

where π_{vm} is data on observed shopping shares, and f_v and γ_m are village and market fixed-effects, respectively.[38] Travel distances τ_{vm} are calibrated using the straight-line distance between villages v and markets m. Without price variation, market prices are absorbed in the market-level fixed effect. We estimate (9) using Pseudo-Poisson

[37] There is only partial information on observed employer-employee relationships due to low match rates of employees to the census during surveys – often because owners do not know their employees' exact residence location. Since most firms have zero employees and, of the observed linkages, most workers work at their closest market center, we opt to assign every worker to their closest market.

[38] Note that γ_m recovers $\sigma\tilde{\gamma}_m$ from equation (8).

Maximum Likelihood to account for zeros in the shopping matrix.[39] Running this regression yields an estimate of $\widehat{\sigma\kappa} \approx 0.88$. To tease both parameters apart, we calibrate $\sigma = 4$ as a consensus estimate of the trade elasticity literature (see Atkin and Donaldson, 2022), which implies $\kappa \approx 0.22$. We also include the estimated market fixed-effects γ_m as demand-shifters in the household shopping decision, as outlined in equation (8).[40,41]

5 Validation and counterfactuals

The fully estimated model generates rich predictions about the topography of slack across firms and locations, as well as the macroeconomic response of rural economies to aggregate demand shocks. In this section, we leverage results from the large cash transfer experiment in Egger et al. (2022) to compare a set of untargeted moments – comparative statics of adding cash transfers into the model – to their empirical counterparts. To do so, we follow the strategy outlined in the structural pre-analysis plan accompanying this study. Crucially, all experimental moments were left untargeted in the calibration, making this an informative test of the usefulness of the model to study cash transfers and other fiscal stimuli.

5.1 Slack and Cash Transfers in General Equilibrium

We first compute the spatial equilibrium in the economy at baseline, i.e., in the absence of external cash transfers. Figure A.10 in the Appendix reports performance of the baseline model against a series of moments closely related to the calibration moments. It reveals that the model does well in capturing the size distribution of markets and firms, as well as the gravity nature of shopping flows. We then replicate the experiment within the model by allocating cash to the 329 recipient villages of the original experiment and re-computing the spatial equilibrium of this economy, and compare the model's predictions to the empirical estimates from the RCT.[42]

Aggregate Effects. How much of the transfer multiplier estimated in Egger et al. (2022) can be explained through the model of slack? Denoting counterfactual quantities with a prime, the nominal transfer multiplier is defined as the ratio of the total nominal income gain to the total experimental cash transfer across recipient villages. The real multiplier deflates the nominal income gain by price inflation:

$$M_{\text{nominal}} = \frac{\sum_v I'_v - I_v}{\sum_v \Delta'_v - \Delta_v}; \qquad M_{\text{real}} = \frac{\sum_v I'_v \frac{P_v}{P'_v} - I_v}{\sum_v \Delta'_v - \Delta_v}$$

where P_v is the price index and Δ_v is the amount of cash flowing into village v.[43]

Figure 6 presents the nominal (green) and real multipliers (black), as well as inflation (blue) from replicating the cash transfer experiment. Along the x-axis, the figure varies the size of the counterfactual cash transfer as a share of baseline GDP. To compare model estimates to the experiment, focus first on a transfer worth 15% of GDP in treated villages, corresponding to the size of the experiment. The model estimates nominal and real multipliers

[39]See Appendix E.4 for further details on the market price indices.

[40]Figure A.8 in the Appendix reveals a strong positive correlation between the estimated demand shifters and the number of firms in a given market, highlighting that $\widehat{\gamma_m}$ may in part represent love-of-variety effects.

[41]Market prices at the second endline were collected over two waves, and we initially intended to leverage this panel structure to separately identify σ from κ. When conducting this pre-specified approach, we arrive at implausibly low and noisy estimates for the price elasticity σ of between 0.1 to 0.3, far below the consensus in the literature. We opted to deviate from the pre-analysis plan by relying on the existing literature and calibrating $\sigma = 4$, close to our estimate for the within market elasticity of substitution θ. We present robustness to different values of σ, including using the pre-specified procedure, below. Results are largely robust to varying this parameter.

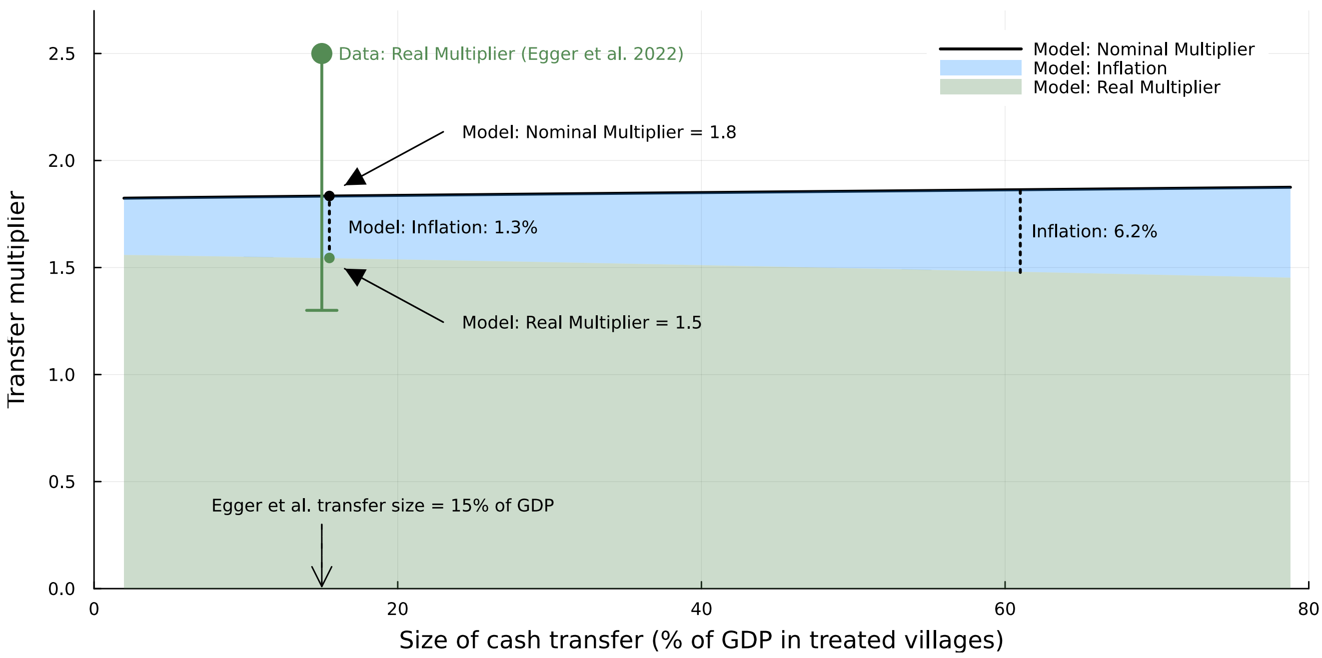
[42]We linearly re-scale the total cash transfer amount from the Egger et al. (2022) study so as to match an average size of 15% of GDP in treated villages, corresponding to the peak intensity of that experiment in terms of annual GDP. Re-scaling is necessary because our calibration does not directly target the baseline level of GDP.

[43]In practice, we compute the real multiplier as

$$M_{\text{real}} = \frac{\sum_m E'_m \frac{P_m}{P'_m} - E_m}{\sum_v \Delta'_v - \Delta_v} + \frac{1-\alpha}{\alpha} \frac{\sum_m E'_m - E_m}{\sum_v \Delta'_v - \Delta_v}$$

to avoid the computation of spatial price indices. This approach uses the fact that total market expenditure is proportional to aggregate income $\alpha \sum_v I_v = \sum_m E_m$ and spending on agriculture (not subject to inflation) is equal to $\sum_v X_v = (1-\alpha) \sum_v I_v = \frac{1-\alpha}{\alpha} \sum_m E_m$.

Figure 6: Nominal and real multipliers at different transfer sizes



Notes: Counterfactual aggregate nominal and real multipliers in the spatial economy for cash transfers of different sizes. Arrows indicate estimates for a transfer of a size comparable to 15% of GDP, which corresponds to the size of the Egger et al. (2022) experiment. The empirical estimate from that study is added for comparison, with its one-sided confidence interval (the green whisker).

of 1.8 and 1.5, respectively. This discrepancy is explained by an estimated average inflation rate of 1.3%.[44]

The figure also includes the empirical multiplier estimate of 2.5 and associated 90% confidence interval from Egger et al.. While the model prediction is substantially lower – albeit within the confidence interval of the empirical estimate – the model includes only one friction, the integer constraints that are our focus, and abstracts from other prominent ingredients in workhorse New Keynesian models such as price and wage rigidities. Adding such frictions to the model would likely generate even larger real multipliers, possibly bringing the model's estimates closer to the experimental ones. We see the value of this exercise in showcasing how the single friction at the center of this paper contributes to explaining a meaningful share of the empirically observed output responses to cash transfers in the study setting.

This approach also allows us to characterize the impacts of transfers of different magnitudes along the x-axis of Figure 6. Nominal multipliers slightly increase with transfer size, and this effect is due to the sectoral reallocation present in equation (6): an outside transfer crowds out agriculture, as the economy is less reliant on producing the importable good and instead pushes workers into the non-tradeable sector. Decreasing returns imply that this reallocation declines as transfers rise, which results in a growing nominal multiplier.[45]

Turning to inflation, we find moderate inflation on the order of 1.3% for an income weighted average of the village-level inflation rates. This estimate is larger than the central estimate from Egger et al.'s experiment (around 0.1%). This could point to the importance of price rigidities inhibiting real-world inflation, which are not part of our model. However, viewed through the lens of the spatial model, the empirical specifications in Egger et al. (2022) likely understate the amount of inflation triggered by the transfer, as we show below. Inflation picks up for larger transfer sizes and reaches around 6.2% for (counterfactual) cash transfers where treated villages receive

[44]The following calculation provides a useful approximation of the estimates for the real multiplier. In terms of endline GDP, the cash transfer averages 4.73% across all villages, which leads to a total increase in nominal GDP of $1.8 \times 4.73\% = 8.51\%$. An income weighted average of the transfer induced inflation equals 1.3%, implying a real increase of 7.21% and a real multiplier of $\frac{7.21}{4.73} = 1.5$.

[45]Recall from equation (6) that the nominal multiplier can be expressed as

$$\frac{dI}{d\Delta} = \frac{1}{1-\alpha}\left(1 + \beta N_x^{\beta-1}\frac{dN_x}{d\Delta}\right),$$

where this effect is due to the second term.

60% of their baseline GDP.

Figure 6 also shows that real multipliers decline only very modestly with the scale of the transfer, and labor reallocation is key to understanding this feature of the model. Figure A.11 illustrates the importance of labor reallocation for multiplier and inflation dynamics by replicating Figure 6 but shutting off reallocation of workers from agriculture and firm entry. The size of the agricultural sector is held fixed in this counterfactual, leading to a constant aggregate nominal multiplier of $\frac{1}{1-\alpha} \approx 2.5$. Inflation dynamics differ substantially, though, with inflation around 4.5 percentage points higher for a cash transfer of the size implemented in Egger et al. (2022) compared to the case with labor mobility. Yet a four times larger transfer (again at 60% of baseline GDP as above) without labor reallocation leads to inflation of 24% and a real multiplier of only 1.1, highlighting the convex nature of supply curves generated by integer constraints. Overall, this exercise underscores the role of reallocation from agriculture to the service sector in determining the elasticity of the aggregate supply curve (Lewis, 1954).

We have also estimated the model on 500 counterfactual treatment assignments, where we follow the same randomization procedure as Egger et al. (2022). We then estimate the model-implied multiplier for each of these counterfactual treatment assignments and compare these to the model-implied multiplier for the actual treatment assignment (Figure A.15). The distributions of the real multiplier, nominal multiplier and inflation are relatively tight, and the model estimates from the realized treatment assignment are not outliers, indicating that the patterns we document are not driven by the particular realized assignment.

We next present new evidence comparing key mechanisms in the model to their empirical counterparts.[46] We follow an estimation strategy analogous to that used in Egger et al. (2022), with slight modifications where necessary to estimate heterogeneous impacts. Appendix D provides more detail on the estimation equations.

Role of Slack. Consistent with the discussion above, Figure 7 shows that slack is the key mechanism driving the relationship between income, inflation and transfers. Panels (a) and (b) present model-implied utilization rates by market on the x-axis (with more slack markets to the left of each figure) plotted against model-implied output and pricing responses. The model predicts output quantity increases most in initially high slack markets, with the opposite pattern for inflation.

While we lack data on slack for the baseline and the first endline surveys, we can examine these predictions empirically by looking at heterogeneity in the output response across sectors and space.

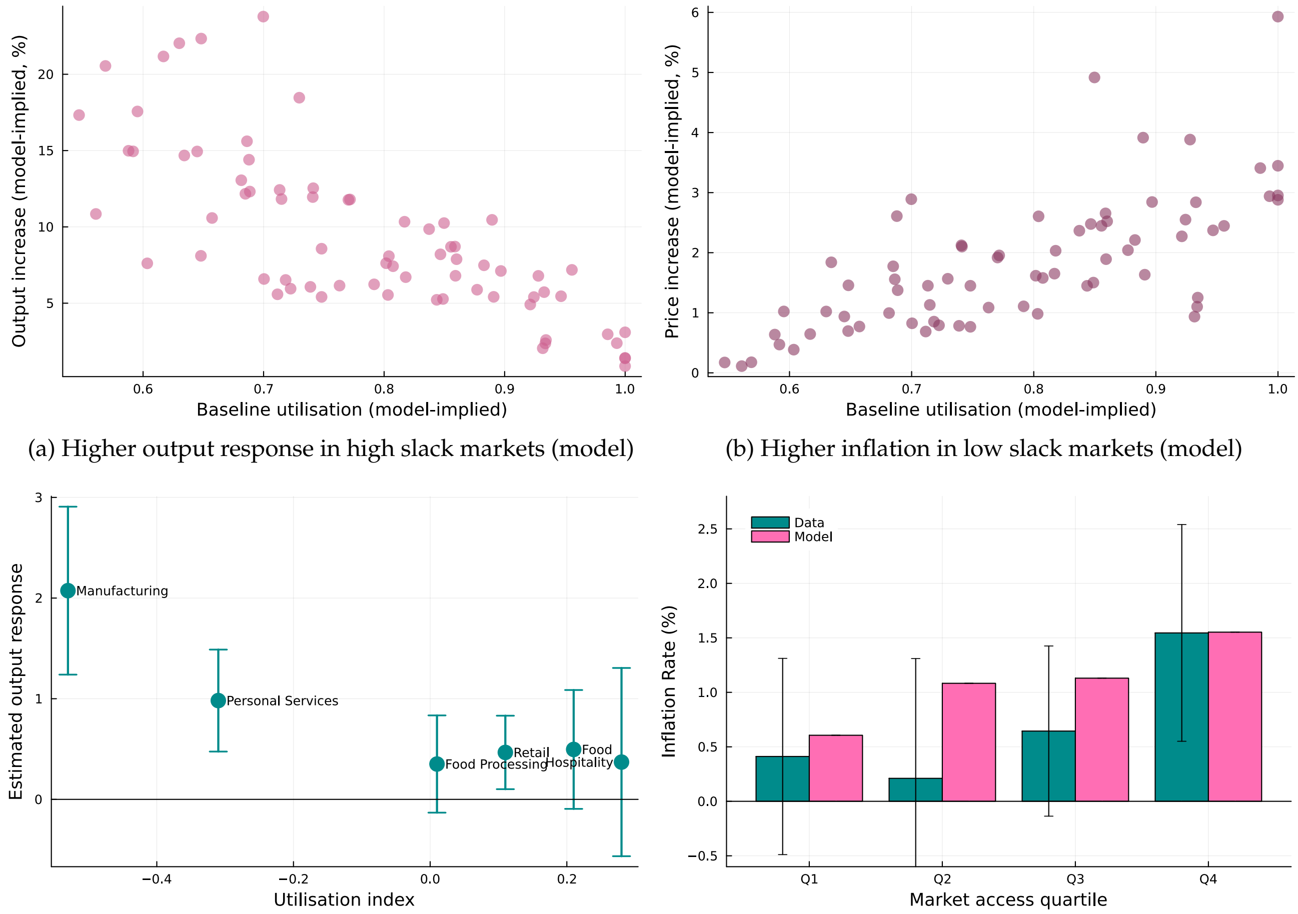
First, panel 7c confirms this pattern on a cross-sectoral level in the data: sectors with low levels of baseline utilization rates (in particular manufacturing) are empirically observed to have a much more pronounced output response than sectors with lower levels of baseline slack (such as hospitality). The Appendix additionally shows that the output response among owner-operated firms is almost twice as large compared to firms with hired labor, consistent with model predictions (Figure A.12).

To study the patterns of slack and inflation we compare counterfactual and empirical inflation rates for markets with differing degrees of market demand in panel 7d. Empirically, we test for this by computing inflation effects separately for markets in different quartiles of market access and plot experimentally estimated inflation impacts for each of these quartiles. Qualitatively, the empirical results support the model predictions. In both model and data the inflation response is concentrated in the markets with the highest market access. This indicates that firms in these busy market centers are being pushed into the steeper parts of their supply curves through the additional demand created by the external cash transfer. In terms of magnitudes, inflationary impacts are above 1.5% in both model and data for the most central markets, but model implied inflation impacts are larger in the model than in data for the remaining three quartiles.[47]

[46] In the model, we are able to look at impacts across the entire Siaya county geography. For our empirical estimates, we rely instead on data from the 653 experimental villages and 61 markets for which we have data from the original experiment.

[47] The finding of less inflation in remote markets stands somewhat in contrast to the findings of Cunha et al. (2019). Their paper provides evidence of larger pass-through of cash transfers to prices in more remote villages. They argue this larger price response results from seller market power: they report a median number of just four stores per village. In our study context, seller market power seems less likely as we study inflation at the level of markets where the median number of enterprises is 82.

Figure 7: Slack as a mediator for price and output responses to cash transfers



(a) Higher output response in high slack markets (model)

(b) Higher inflation in low slack markets (model)

(c) Higher output response in high slack sectors (data)

(d) Higher inflation in central markets (model and data)

Notes: Panels (a) and (b) decompose market-level increases in output and price levels in response to the cash transfer by model-implied baseline capacity utilization. Panel (c) prints sector-level output responses to the cash transfer, estimated at "endline 1" on average approximately 2 years after transfers, by the average sector-level utilization index (see Appendix D.1 for details). Panel (d) computes market-level inflation rates for markets in different market-access quartiles, where higher quartiles correspond to the largest and busiest markets. Price effects are estimated using data from before, during, and up to 30 months after transfers (see Appendix D.2 for details).

Labor market responses. The estimated model also successfully predicts the extent to which labor shifts from agriculture to the service sector in response to the transfer, one of the outcomes specified in the pre-analysis plan. Employment in agriculture declines because the transfer can be used to buy agricultural goods from abroad, displacing domestic agricultural employment. Figure A.13a in the Appendix compares the rates of transition from agriculture to the service sector in both model and data. Empirically, agricultural employment drops by 8.1% in response to the cash transfer. Although this moment is untargeted in the calibration, the model generates a decline of 8.8%, very close to the data. Lastly, panel A.13b compares wage responses in the model and data. The model predicts a wage increase of around 6% across the entire study area, which is substantially smaller than the empirically estimated effect of 20%. Given relatively wide confidence intervals, however, we cannot reject that the estimated effects from the model and the data are equal at traditional confidence levels.[48]

5.2 Consequences for impact evaluation and the "missing intercept"

A benefit of calibrating the model to the detailed geography in the study area is that we can use the model to measure to what extent estimates of randomized experiments intended to measure spatial spillovers suffer from SUTVA issues.

[48]Moreover, empirical estimates are likely biased due to selection. With worker heterogeneity (which is absent from the model), the least-paid workers are most likely to drop out of wage labor, thus amplifying the estimated wage impacts among those employed.

It is well-known that treatment effects estimated by regressing an outcome on treatment may be biased in the presence of spillovers. This problem is often described as the "missing intercept" problem, as places or individuals without any direct treatment exposure might still experience some treatment effect from a program, and therefore do not represent a "pure" control (Wolf, 2023). The existing literature has tried to address this concern by using econometric designs that include not only direct exposure to treatment, but also measures that capture indirect exposure to treatment within a neighborhood, typically a higher level cluster or spatial radii band (e.g., Miguel and Kremer, 2004; Muralidharan et al., 2023). Egger et al. (2022) explicitly generate variation in such indirect exposure by varying treatment intensity experimentally in a second-tier randomization across clusters of villages (sub-locations). Franklin et al. (2024) instead use model-consistent gravity-based regressors to capture indirect exposure, more closely relating their empirical strategy to a spatial general equilibrium model.

However, despite the progress that has been made in accounting for spillovers in experimental studies in economics, a remaining concern with these specifications is that they may not account for "ambient effects", i.e., general equilibrium effects that are so widespread that all units experience them – for instance, in our study setting this would be a general increase in the price level across all of Siaya County due to the cash transfer intervention. Relatedly, these analyses may suffer from functional form mis-specification.[49]

We assess the quantitative importance of this concern by carrying out the same econometric specifications employed by Egger et al. (2022) and in the literature more broadly on the model-generated data, and comparing them against model counterfactuals. Under the assumption that the model is a true reflection of reality, this comparison allows us to quantify the extent to which empirical estimates of spillovers may be biased, for instance, because they miss ambient effects. We run regressions of the form:

$$\Delta y_l = \beta_0 + x_l' \beta_l + \epsilon_l \tag{10}$$

where Δy_l is the percent change of outcome y in location l, β_0 is a constant and and x_l are a vector of treatment variables, including both direct and indirect exposure to treatment. Since Δy_l is model output, β_0 measures the strength of general equilibrium forces related to the counterfactual beyond the effects captured by the treatment variables x_l, and thus the extent of the remaining 'missing intercept' problem.

We do this for two related strategies for capturing indirect exposure to treatment. First, we follow the same "spatial buffer" strategy as Egger et al.: for village-level regressions in which income is the outcome, we include the amount of cash received by a village as well as the amount of cash received by recipients living within 2 or 4 kilometers around that village. For market-level price inflation, we include the amount of cash received by recipients living within 2 and 4 kilometers of a market. Spatial specification of this kind require a procedure for deciding how far spillovers are to be taken into account. Egger et al. use a pre-specified algorithm that typically selects a maximum buffer of either two or four kilometres (depending on the outcome), implying that the effect of cash transfers on villages located further away is zero. The data indicate that their buffer strategy may not be sufficient to capture all spillovers: while consumers shop very locally in this setting, roughly half (20%) of all consumption spending takes place outside of the 2 or 4 kilometer buffer employed in their spatial specifications. Moreover, in spatial general equilibrium, effects may further 'ripple' through the entire system even beyond locations where treated individuals shop directly.

Second, for market-level inflation estimates, we use a strategy akin to Franklin et al., which define indirect treatment exposure in a model-consistent way based on baseline shopping probabilities (in their case, commuting flows):

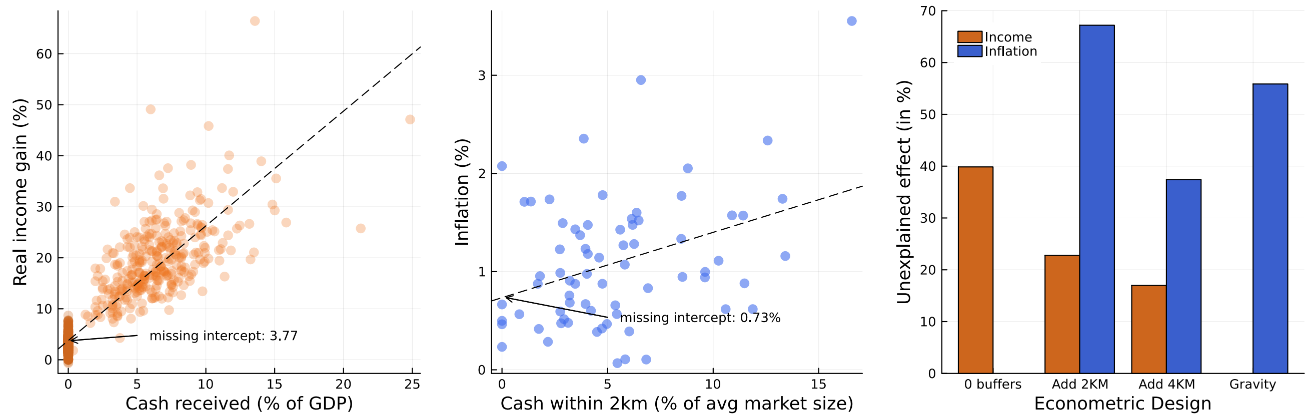
$$\text{indirect exposure}_m = \pi_{vl} Amt_l$$

where π_{vl} are the baseline shopping probabilities from village v to market m.[50] This has the advantage of pro-

[49]For instance, Egger et al. (2022) regress outcomes on own-village treatment, and the per-capita transfer amount within 2 km-wide radii bands around each observation, effectively modeling outcomes as linear in such per-capita indirect exposure. But, effects may neither be linear, nor may per-capita amounts be the right measure of exposure. Note that Egger et al. do provide some evidence that treatment effects are roughly linear in exposure.

[50]Adao et al. (2019) provide a more general treatment of shift-share approximations to economic geography models with trade and migra-

Figure 8: The "Missing Intercept" under several econometric designs



(a) Village income gain by cash received (b) Market inflation by cash received (c) Unexplained effect sizes

Notes: Illustration of the missing intercept problem and econometric techniques aimed to tackle it. Panel (a) plots the model-implied village-level income gain through the cash transfer program against how much cash a village directly received. Note that there are many control villages that did not receive any cash themselves and are here bunched at zero. Through spillover effects, these villages still experience real income gains from the program, which a naive regression would miss. The highlighted intercept quantifies the extend of these missing gains. Similarly, panel (b) repeats this exercise for inflation at the market level. Note that markets themselves did not receive any cash so the variable on the x-axis here is cash received within 2 km of a market. Panel (c) illustrates the success of various econometric designs in tackling this issue. The orange bars show how the unexplained effect size declines as more spatial buffers are added to the regression, i.e., including how much cash went to villages within 2 km and 4 km of each village. The blue bars repeat this exercise for inflation around markets. The right-most bar includes a gravity-based measure of demand-exposure for markets, where cash injunctions to villages are discounted based on how far villages are away from markets.

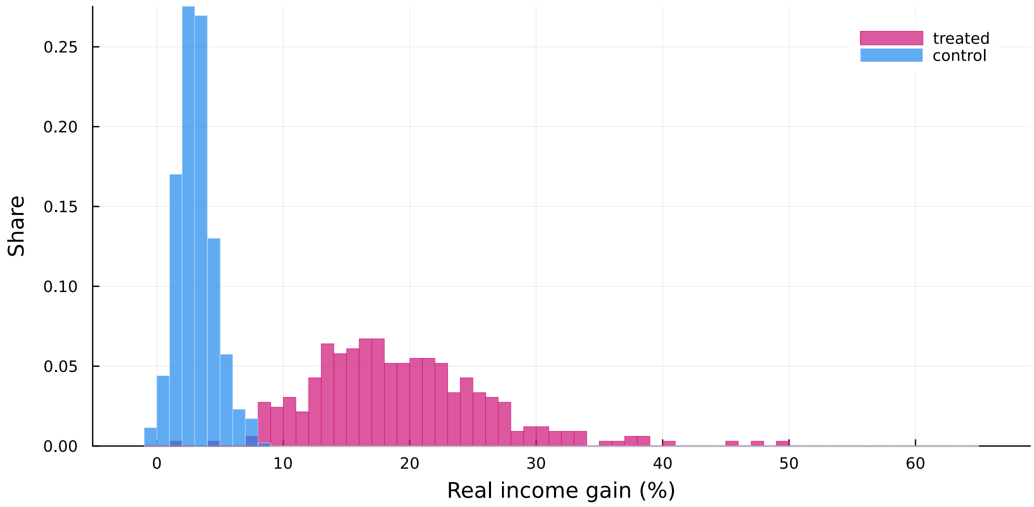
viding a model-consistent functional form and taking into account exposure beyond a fixed cutoff point. This measure of indirect exposure does not account for possible endogenous changes in the exposure shares π_{vl} that may matter for larger shocks. Since the treatment-induced changes in exposure for every location are not directly observable in the data, standard implementations assume constant exposure shares. The approach to quantifying the "missing intercept" based on equation (10) lets us compare the relative degree of misspecification in the buffer versus gravity approaches.

The Missing Intercept for Income. Figure 8a presents the cross-village relationship between income gain and cash received within the village. Unsurprisingly, the 327 villages that were direct recipients of the cash gained much more than the non-recipients, which are clustered at zero. However, the intercept is also highly significant at 3.8%, i.e., after controlling for how much cash a village itself receives, the ambient gain is 3.8% on average. The average gain across all villages is 9.5%, which leads to us to estimate that around 40% of all gains are accounted for by these ambient effects. This estimate is represented by the first orange bar in Figure 8c. These effects are missed by a standard regression of income gain on cash received at the village level. The second and third bar show the importance of ambient effects for income falls to 23% and 17% when accounting for cash received by recipients living within 2 and 4 kilometers of the village, respectively. These numbers line up well with roughly 20% of all spending occurring at markets more than 4 kilometer away from the village. Substantively, the presence of ambient income gains suggests that the multiplier estimated in Egger et al. (2022)'s preferred specification understates the true local transfer multiplier by roughly 20%.

The Missing Intercept for Inflation. We similarly study the importance of ambient inflation. Consistent with Egger et al.'s experimental evidence, Figure 8b shows that spatial exposure to the cash transfer as measured through the 2 kilometer buffer is significantly related to market level inflation. Figure 8b, however, shows that this correlation reflects only a portion of the overall inflation impacts. A simple regression of inflation on cash received within a 2 km buffer would miss ambient price changes of 0.73 percentage points on average, or 67% of total inflation. Adding a 4 km buffer (the range selected by the algorithm for price regressions in Egger et al. (2022)) reduces the unexplained effect to 37%. These results suggest the reduced form estimate of inflation impacts

tion.

Figure 9: Distribution of Real Income Gains across Villages and Towns



Notes: Histogram of real income gains from the cash transfer experiment among all 853 villages and towns. Treated villages printed in pink all benefit on the order of 10-40% of model-predicted real income gain. Control locations in blue also gain due to Keynesian multiplier effects. Six villages lose – each less than 1% – likely due to a slight uptick in price inflation.

from Egger et al. (2022) understates the true inflation impacts of the transfer in the study area as a whole. Notably, the ambient effects appear to be more meaningful in magnitude for inflation than for income.[51]

The fourth bar in Figure 8c explores whether cross-market inflation dynamics are better explained by a gravity weighted measure of spatial exposure. We use the model-implied baseline shopping probabilities to compute indirect exposure as $\sum_v \pi_{vm}(\Delta'_v - \Delta_v)$. This variable performs less well at capturing inflation impacts than the 4 kilometer buffer. Substitution forces imply that as prices move, baseline shopping probabilities are imperfect proxies for endline shopping behavior. To illustrate this point, we compute the share of ambient inflation for different values of the elasticity of substitution across markets, while recalibrating κ to match the gravity estimate of $\widehat{\sigma\kappa} = 0.88$. Figure A.14 shows that, as in Figure 8c, the unexplained effect on inflation is larger for the gravity based measure of indirect exposure above $\sigma \approx 1$. Since this range is typically considered the empirically relevant case, this finding demonstrates that the buffer approach may be more robust to econometric misspecification in this context.

5.3 Distribution of Real Income Gains across Villages

One salient concern about targeted cash transfers is that they may lead to real losses among non-recipients faced with higher price inflation. In the presence of slack and positive general equilibrium spillovers, however, it is possible that a cash transfer program has no losers if real local economic activity rises. To investigate this, Figure 9 plots the full distribution of model-implied real income gains across recipient (treated) and non-recipient (control) villages. In the notation above, village-level real income is $\frac{I_v}{P_v}$. Not surprisingly, treated villages (in pink) experience substantial real income gains, on the order of 10-40%. Control villages (in blue) gain through general equilibrium linkages, on the order of 0-10%. Indeed, the support of this distribution is nearly non-negative; only six control villages lose in terms of real income (each losing less than 1% of purchasing power), due to high local price inflation. This highlights how providing fiscal stimulus to slack economies can create nearly universal real income gains, at least over the range of transfers studied in this setting.

[51] An important component of the village-level income gain is how much cash the village itself received (cf. Figure 8a). By contrast, there is no such measure of direct exposure at the market-level since households do not live in markets.

Table 4: Counterfactual Cash Transfer Impacts in Alternative Environments

	M_{nominal}	M_{real}	**Inflation**
Main specification for study area	1.83	1.54	1.3%
A. Integer constraints + no sectoral reallocation	2.54	1.58	4.5%
B. No integer constraints	1.82	1.14	3.3%
C. No integer constraints + no reallocation	2.54	1.0	7.7%
D. Low transport cost to largest markets	2.11	1.25	3.4%
E. Targeting high-slack areas	1.81	1.56	1.0%
F. Targeting largest towns	1.89	1.42	2.2%
G. Varying elasticity of substitution σ			
$\sigma = 0.1$	1.93	1.42	2.6%
$\sigma = 2$	1.85	1.51	1.5%
$\sigma = 5$	1.83	1.55	1.2%

Notes: This table summarizes model implied transfer multipliers and inflation obtained under alternative model assumptions. In each case, we simulate the baseline economy under the alternative assumption and simulate the same cash transfer experiment considered in Figure 6. The first row replicates the main "headline" specification for the study area discussed above. "Low transport cost to largest markets" simulates an improvement in the regional transport network reducing travel costs to the 5 largest towns in the study area by a factor of 10. "No sectoral reallocation" fixes labor allocation by sector at baseline levels and shuts off labor movement between agriculture and the service sector. "No integer constraints" computes the continuous-case multiplier without indivisibilities, i.e., where firms are able to hire labor at any amount. "No integer constraints + no reallocation" additionally fixes the sectoral labor allocation at baseline levels. "Targeting high-slack areas" refers to a simulation where all cash is distributed evenly to villages that are within 1 km of markets with above-median slack. "Targeting largest markets" distributes all cash to the two largest towns in the region. In the last rows, we vary the elasticity of shopping substitution σ, which is a parameter set at $\sigma = 4$ in the baseline specification (following existing literature).

5.4 Counterfactual Cash Transfer Multipliers

The structural model also allows us to examine to what extent the effects of cash transfers depend on features of the rural economy studied here. For instance, a policymaker may wonder to what extent the high multiplier estimates obtained in rural western Kenya apply to different economic and geographic environments, such as the country's urban centers (or perhaps on the other hand, to even more remote rural areas). To examine these issues, we present a series of counterfactuals where we modify assumptions of the current model to approximate more urban environments. Of course, big cities like Kenya's capital of Nairobi differ in many respects from rural western Kenya, so these counterfactuals are not intended as tight predictions but rather as an illustration of how the impact of cash transfers may vary across settings.

The results of these counterfactual exercises are presented in Table 4. The first row again reports nominal and real multipliers obtained from the headline specification in rural western Kenya. In the remaining rows, we examine the impact of cash transfers in counterfactual environments changed to more closely resemble key characteristics of urban economies, and also examine how a targeted cash transfer could impact the aggregate multiplier; the results are discussed here below.

No Sectoral Labor Mobility. One reason why supply curves may be relatively elastic in rural areas is the ability to reallocate workers out of agricultural and into high-demand sectors (e.g., Lewis, 1954). Labor markets plausibly have more frictions to movement across sectors in urban contexts. To simulate multipliers without sectoral mobility out of agriculture, we fix the number of firms in each market and the share of workers employed in agriculture at their baseline value (panel A). Absent labor reallocation, the nominal multiplier is now equal to $^1/_{(1-\alpha)} = 2.5$ (as noted above) but there is also substantially more inflation, at 4.5% on average, although the real multiplier implied remains comparable to the baseline case.

No integer constraints. Indivisibilities are the core microfoundation for slack in small firms in the model we develop. These frictions are plausibly less relevant in highly interconnected urban areas, where workers may find it easier to multi-task or commute between multiple part-time jobs. To highlight how integer constraints are responsible for the large multipliers the model generates, we re-compute the model for the benchmark case in which labor is available at continuous levels (panel B). We set $\nu = 0$ and re-calibrate θ and η to match the average profit share and top quintile sales share (Appendix C.2 provides more detail on the model and calibration). We discuss the robustness of our results with respect to how we include ν in the continuous model in Appendix section C.3.[52] Indeed, the continuous environment produces much smaller real multipliers (approximately 1.14) and higher average inflation rates (3.3%) than the headline specification with indivisibilities. This multiplier is larger than one because of sectoral reallocation in the presence of markups, which positively contributes to the real multiplier because markups imply a higher marginal product of labor in the service sector (see Appendix section C.3 for a more detailed discussion). When additionally shutting off this channel by fixing the sectoral labor allocation at baseline levels (panel C), we find $M_{\text{nom}} = {}^{1}/_{1-\alpha} = 2.5$ and $M_{\text{real}} = 1.0$, with substantial inflation responsible for the difference.

Low transportation cost to central markets. In the rural study setting, high transportation costs exacerbate slack as remote markets face very low levels of effective demand. Urban markets, by contrast, are able to coordinate demand because they are often relatively easy to reach by a large share of the population. We simulate the effects of cash transfers in a more integrated environment by lowering the effective transport cost to reach the five largest markets in the study area by a factor of ten.[53] With demand now highly concentrated in these town markets, aggregate slack falls and the impacts of the cash transfers are muted: the real multiplier falls to 1.25, with significantly more inflation, at 3.4% on average (panel D).

Targeting Higher Slack Areas. Policymakers with limited fiscal resources might seek to maximize the economic impact of a cash transfer program by targeting certain areas (Fajgelbaum and Gaubert, 2020; Haushofer et al., 2022). To increase the overall real multiplier from a transfer program, one intuitive approach might be to distribute cash to higher-slack locations. We thus consider a counterfactual exercise in which the same total amount of cash is distributed in the study area, yet all transfers go to households living in villages within 1 kilometer of a market with above-median slack (measured in the firms operating in and near that market, panel E). This approach targets around 15% of villages, which consequently receive about 2.5× higher transfer amounts than households in treated villages in the original experiment. Such a program would achieve a slightly higher real multiplier (1.56) with lower aggregate inflation of only around 1.0%. It is noteworthy that these effects are only slightly different than the headline estimates that distributed cash more broadly and without regard to baseline slack. This is likely because the rural villages targeted by the experiment are already relatively dispersed and remote.

Targeting the largest towns. Conversely, a targeting policy could send cash to locations close to the major centers of commerce in the study area. Intuitively, this could mute the real effects of the program as demand stimuli are offset by locally higher price inflation. In panel F of Table 4, the simulation concentrates the total cash disbursed to the two largest towns in the study area (Siaya and Ugunja), which leads to more inflation (2.2%) and a lower real multiplier (1.42) than in the actual experimental design, which sent cash to villages.[54]

Taken together, several of these counterfactual cases thus suggest that the multiplier effects of cash transfer programs might be smaller, and inflation impacts higher, in more integrated urban areas, which are characterized by lower levels of equilibrium firm slack. However, multipliers remain above one across cases because households are able to freely import goods from abroad using the externally financed transfer.

[52] Effort costs ν acts as a wedge between the two sectors which by itself can give rise to demand multipliers. To investigate to what extend this wedge is responsible for our main multiplier estimate, we re-estimate a version of the integer-constrained model where work in agriculture also requires an effort payment. As we report in more detail in Appendix section C.3, estimating this model yields slightly lower estimates of ν, with overall very similar real multipliers ($M_{\text{real}} = 1.6$), leading us to conclude that distortions induced by effort costs are not responsible for the large multipliers we find.

[53] These markets are already located in small towns in the study area. In qualitative terms, such a reduction in transport costs could result from upgrading (paving) dirt roads connecting villages to the main road through Siaya County.

[54] To quantify the difference of concentrated cash sent to two high market access locations as in the text versus two average market access locations, we select 1000 pairs of villages at random and disperse the total amount of cash between them. We find a median real multiplier of 1.48 across these draws.

Varying σ. Panel G of Table 4 examines robustness to plausible alternative values of σ, the elasticity of substitution across markets (by consumers). We assumed a value of $\sigma = 4$ in the main specification. Setting this elasticity to a lower value of $\sigma = 2$ yields a slightly lower real multiplier and higher inflation rates than in the headline case. Lower substitutability between markets implies consumers are less willing to respond to price increases in one market by switching their shopping to a neighboring market, and so are more vulnerable to local price inflation. For the same reason, assuming a higher value of $\sigma = 5$ yields less inflation on average and a slightly higher real multiplier than the base case. Note that even an implausibly low value of $\sigma = 0.1$ yields a real multiplier of 1.4, quantitatively not too far off the headline estimate of 1.5.

5.5 Quantitative extensions

The model prioritizes parsimony to highlight how indivisibilities can lead to slack and large real multipliers. Below, we outline two quantitative extensions that could plausibly interact with our results.

Calibrating the indivisibility constraint. The baseline specification imposes the assumption that firms hire labor inputs at full integer levels, $n \in \mathbb{N}$. Since the model is calibrated to annual production and income data, this implies that hiring in effect happens on a *yearly* basis. While setting up a business or training a new employee likely represents a substantial fixed costs, anecdotally many labor arrangements in the region are for shorter periods of time. Figure A.6a in the appendix reports enterprise owners' qualitative answers about the typical unit of time an employee is hired for, and indeed, the most common arrangement is a monthly time frame, followed by daily labor.

To quantify the importance of allowing for different indivisibility steps, we follow a pre-specified extension and re-estimate a version of the model in which labor input n is not constrained to come from the integers, but rather $n \in \{s, 2s, 3s, ...\}$, where s is the size of the indivisibility in labor hiring. We then jointly estimate s together with the other structural parameters (θ, ν, η). We use the share of total labor compensation taking the form of variable effort payments, relative to fixed payments as an additional targeted moment in a joint SMM estimation of the four parameters. We adapt this moment from Foster and Rosenzweig (2022), who study Indian agriculture and report a ratio of variable to fixed payments of 1.347. As described in more detail in appendix C.4, we estimate a step size of $s = 0.52$ years or about 6 months. Even though this is a bit larger than the monthly labor arrangements reported in our context, step sizes of this magnitude appear plausible as in our model, they additionally embody the fixed ("first integer") cost to setting up a business in the first place – which may be a more discrete choice and require a longer-term commitment than hiring a worker for a fixed amount of time.

Using this step size when simulating the cash transfer yields multipliers that are larger compared to the base case of annual hiring (i.e., $s = 1$), at $M_{\text{real}} = 1.61$ with 1.1% average price inflation, and also implies slightly more baseline slack (at $e/n = 81\%$ compared to 86%). This is a somewhat counter-intuitive result, but it appears that the explanation for greater slack in this case, despite there being a smaller unit of indivisibility, is that the moment we draw from Foster and Rosenzweig (2022) implies larger effort costs than in our baseline model. Since the calibration only targets the share of firms that are unconstrained at baseline, these larger effort costs imply greater under-utilization of labor among the baseline unconstrained firms. In light of this, we opt to focus throughout on the simpler base model with integer-constraints. Yet we note that understanding how indivisibility constraints are shaped by incentives and policy remains a promising area for future research.

Entrants knowing their type. Integer constraints bite most significantly for owner-operators. A natural question is the extent to which prospective entrants accurately forecast the amount of slack they will face as firm owners. In line with recent evidence from other studies, between 18% and 30% of firm owners in our sample would be willing to accept a wage job if offered to them (cf. Figure A.6b).[55] Figure A.7 empirically documents

[55] Breza et al. (2021) find a similar share (24%) of such "involuntary" self-employment among the self-employed in rural India. Furthermore, given that owners likely answer this question with some form of regret aversion, the real number in either study might be even higher.

significantly more slack among these marginal entrepreneurs. The baseline model assumes agents cannot anticipate their productivity, which in the headline calibration leads 72% of all firm owners to prefer wage work to the profits they make after learning their type. Without knowing their type, potential entrants also accept that entrepreneurship may be associated with significant under-utilization if productivity turns out to be low.

In a quantitative extension, we use the model to investigate how much involuntary self-employment of this kind contributes to the slack and multiplier dynamics in the model, assuming that all households in the population know their type prior to entry. The modified entry condition requires indifference between wage work and entrepreneurship for the marginal entrant φ^*:

$$\pi(\varphi^*) = w.$$

The share of the labor force active as entrepreneurs is equal to $\mathbb{P}(\varphi > \varphi^*) = \left(\frac{q}{\varphi^*}\right)^\eta$. We re-calibrate this model, using the same target moments as in section 4.[56] As previously stated, the calibration strategy does not directly target overall utilization in the data. Thus, the modified model generates slightly less slack at baseline than the model with ex-ante unknown productivity (on average $e/n = 87\%$ versus 86% in the baseline model). Intuitively, knowledge of entrepreneurial ability makes the (ability-independent) outside option of wage employment relatively more attractive for most individuals.

Interestingly, in this case the model implies somewhat larger nominal (2.08) and real (1.68) multipliers. Lower baseline slack and higher multipliers can be reconciled by focusing on the reallocation of labor from agriculture: with known individual entrepreneurial productivity, the entry margin becomes less elastic, which leads to less reallocation and a larger increase in utilization. Similar to the discussion of multiplier estimates without sectoral mobility (cf. Figure A.11), frictions to entry can lead to larger multipliers for moderate transfer sizes. Thus, the results are robust to several distinct assumptions about agents' information sets about their own ability prior to entry.

6 Conclusion

The fact that slack – the under-utilization of factors of production – decreases with the level of economic development is an important but underappreciated fact in contemporary development economics. We use new large-scale survey data and novel measures on capacity utilization across rural western Kenya and Nairobi to understand the causes and consequences of underutilization in a low-income setting. We argue that indivisible input choices may lead to underutilization as firms cannot incrementally adjust capacity as their productivity or demand increases. Consistent with this, the data show that utilization rates are lower in smaller firms, and particularly in single-person and owner-operated firms. This is also consistent with individuals turning to micro-entrepreneurship out of necessity in an environment with few attractive wage employment opportunities (Breza et al., 2021; Donovan et al., 2023). In the data, slack is also more prevalent in regions with low market-access and during agricultural lean seasons. These features – small firms, low market-access and seasonality in economic activity – characterize many low and middle-income economies. Input indivisibilities may thus have meaningful aggregate implications in these settings.

A general equilibrium model motivated by these facts, and incorporating indivisibilities in inputs as a key friction, is able to quantitatively match the pre-specified and untargeted reduced-form impacts of cash transfers from a large-scale RCT, which found a substantial transfer multiplier of 2.5 and minimal local price inflation (Egger et al., 2022). The model is also in line with new evidence on the underlying mechanisms, including higher inflation and lower output responses in lower-slack parts of the economy, the sectoral reallocation of labor out of agriculture, and wage increases.

This has important implications for economic policy in developing economies: over some range, demand-side interventions may be highly effective in stimulating economic output (Goldberg and Reed, 2023). The analysis

[56] We obtain $\eta = 3.5$, $\nu = 247.2$ and $\theta = 3.4$. This larger value of ν implies that 78% of compensation comes through variable effort payments, which is still in the range of the evidence reported in Foster and Rosenzweig (2022).

also makes clear, however, that this is unlikely to be unbounded, and that inflationary pressures eventually kick in once the size of external transfers or other demand-side interventions become sufficiently large. The real multiplier is also likely to be substantially smaller in lower-slack settings, such as more urban areas.

Using the model, we show that state-of-the art empirical strategies that leverage variation in the indirect exposure of individuals to treatment to estimate spillover effects (e.g. Miguel and Kremer (2004); Adao et al. (2018); Egger et al. (2022); Franklin et al. (2024); Borusyak et al. (2024) may miss a substantial share of the ambient or 'missing intercept' effects changing outcomes for all individuals within a study. Combining structural modeling with experimentation at-scale may thus be a promising avenue for quantifying such effects, and for shedding light on the full distribution of impacts from large-scale interventions.

More speculatively, our findings have implications for longer-term growth and development. The relevance of the indivisibility constraints at the core of the model diminishes in firm size and market integration. An intriguing question for future work is thus whether a large coordinated increase in demand across sectors within the economy, amplified by reductions in utilization, may allow economies to permanently exit a high-slack steady-state equilibrium (Murphy et al., 1989). Moreover, we model input indivisibilities as a fixed feature of technology. Innovations in information technology giving rise to the gig-economy and more flexible work arrangements might plausibly weaken this constraint. Workers who would have been tied to a single firm can now in some settings provide labor services for multiple firms at the same time. Online marketplaces and increasing mobile phone coverage partially remove the need for firm owners to mind the shop, reduce transportation frictions and increase market access. Improved rental markets for equipment (Bassi et al., 2022), the promotion of thicker markets through product standardization, the coordination of economic activities through weekly market places, export access, industrial policy, and rising population densities – especially in Sub-Saharan Africa – may all be levers to lessen the aggregate impacts of such indivisibilities over time.

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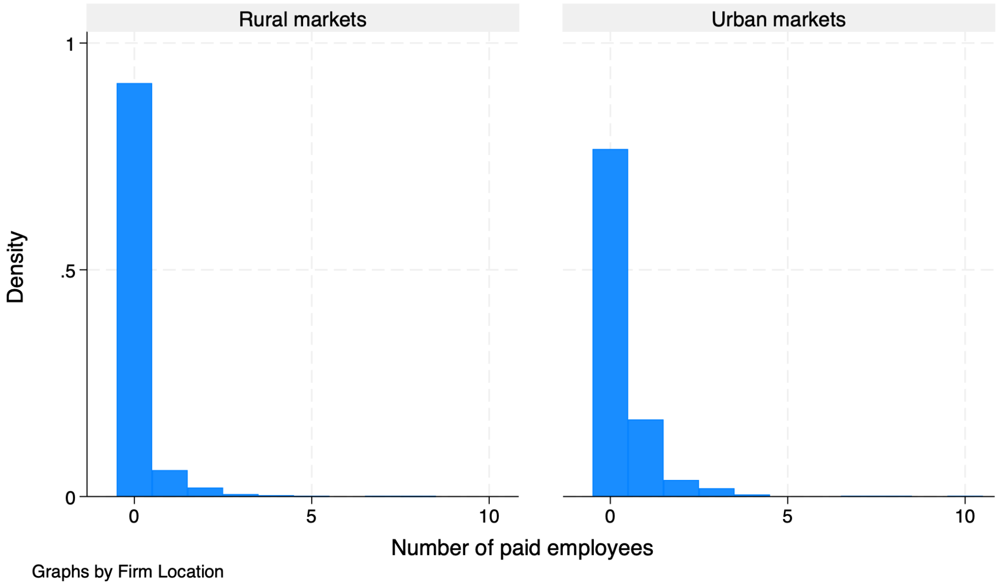
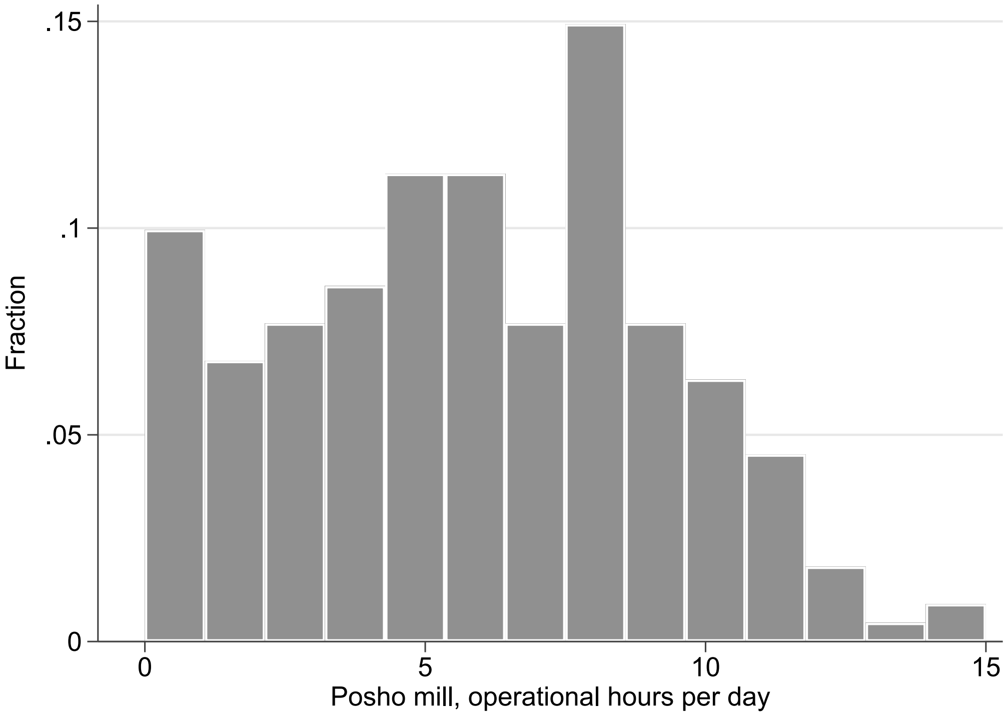
A Appendix Figures

Figure A.1: Firm size distribution by rural vs urban market status



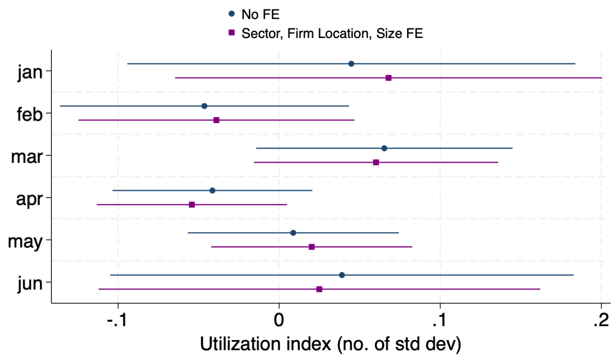
Notes: This figure presents the firm size distribution (based on the number of paid employees per firm) separately for rural and urban markets. 90% of enterprises in rural markets have no paid employees and 76% of markets in urban areas have no paid employees.

Figure A.2: Utilization of grain (posho) mills

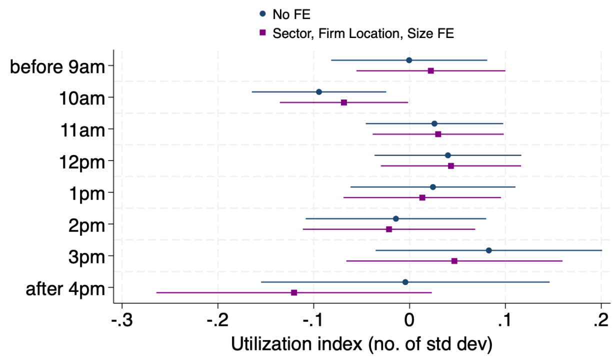


Notes: This figure presents the utilization of grain (posho) mills by firms, measured by the hours these are operational during the last work day. The average utilisation was **6.27** hours per day

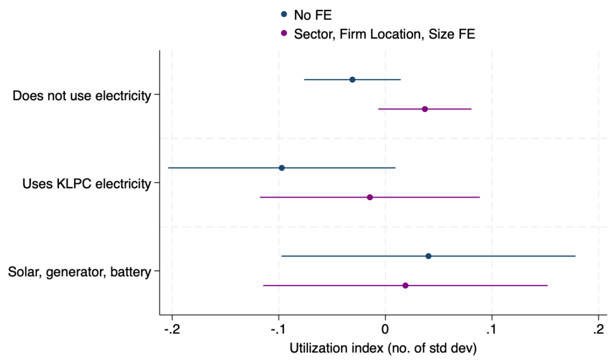
Figure A.3: Slack patterns by season, time of day, and electricity use



(a) Utilization index by month for rural enterprises



(b) Utilization index by time of day

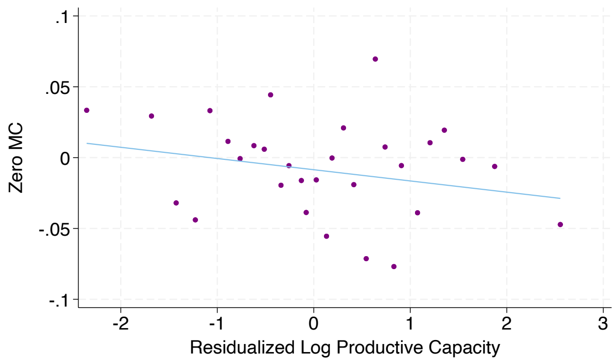


(c) Utilization index by use of electricity

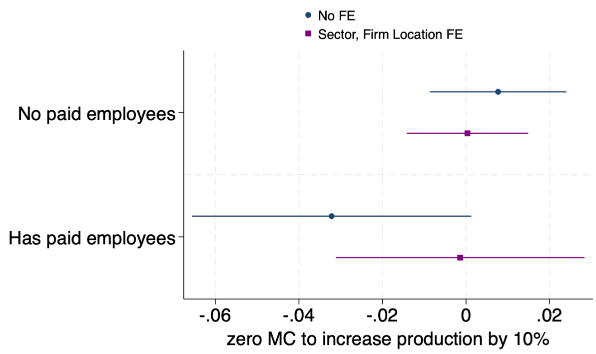
Notes: Descriptive patterns of the utilization index in rural Western Kenya across survey month (a) and time of day (b), as well as by source of electricity for surveyed firm (c). For Panel (a), we rely on data only from the 'endline 2' surveys in the rural study area (including enterprises operating from the homestead, in villages, and rural markets). We exclude data from Nairobi markets, and the additional 2024 market surveys, since these were only conducted over a small number of weeks and thus cannot be used to estimate seasonality. In panel (b), we also exclude the additional 2024 market surveys. Harvest seasons in Western Kenya are July-August and November-December. We did not conduct surveys during most of these months.

Figure A.4: Stylized facts about slack: Zero Marginal Costs

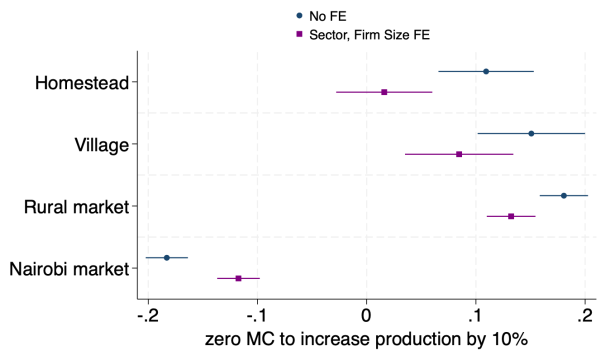
(a) Zero marginal costs by productive capacity (residualised by sector and firm location)



(b) Zero marginal cost by firm size (number of employees)

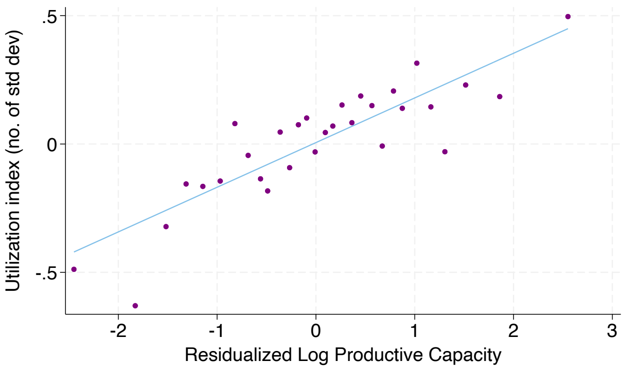


(c) Zero marginal cost by firm location

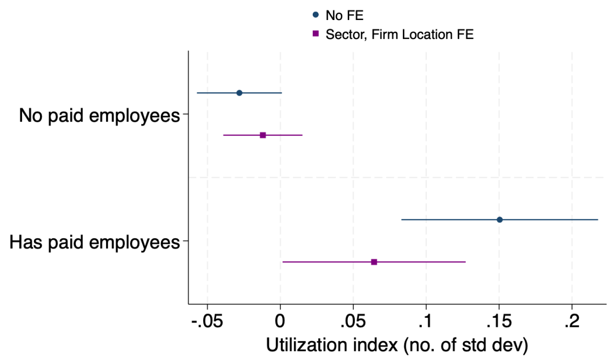


Notes: This figure displays stylized facts around slack using a measure based on whether the firm reports that zero marginal costs would be required to generate 10% higher firm revenue. More detail on sample and outcome construction in the notes to Figure 2. N=3017. Note that a higher value of this measure implies more slack in a firm, which is the opposite from the utilisation index in Figure 2.

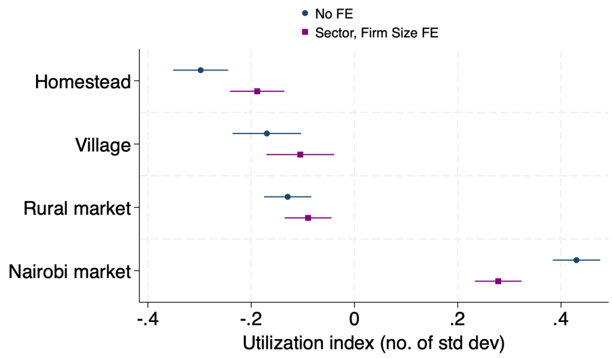
Figure A.5: Stylized facts about slack, index including labor utilization



(a) Utilization index by log firm revenue in best week



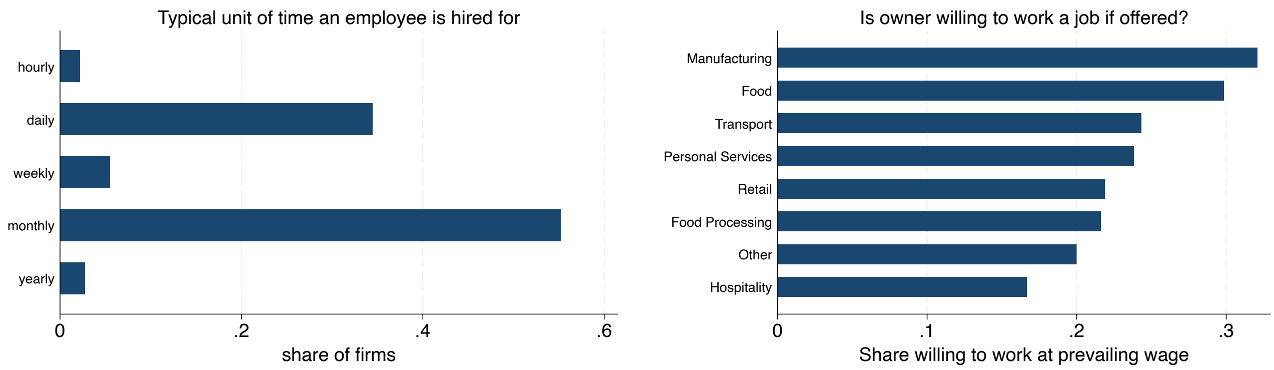
(b) Utilization index by firm size



(c) Utilization index by firm location

Notes: Similar to Figure 2, this figure depicts stylized facts about slack using a"utilization index" of all the utilization-related measures. However, the index in this figure now includes the self-reported labor utilization measure. We exclude this measure from our primary index because it was uncorrelated with the (more objective) labor utilization directly observed by enumerators for a random subset of enterprises. These measures are standardized following Anderson (2008) so that magnitudes are interpretable as standard deviations. N=5380.

Figure A.6: Further qualitiative characteristics of the labor market

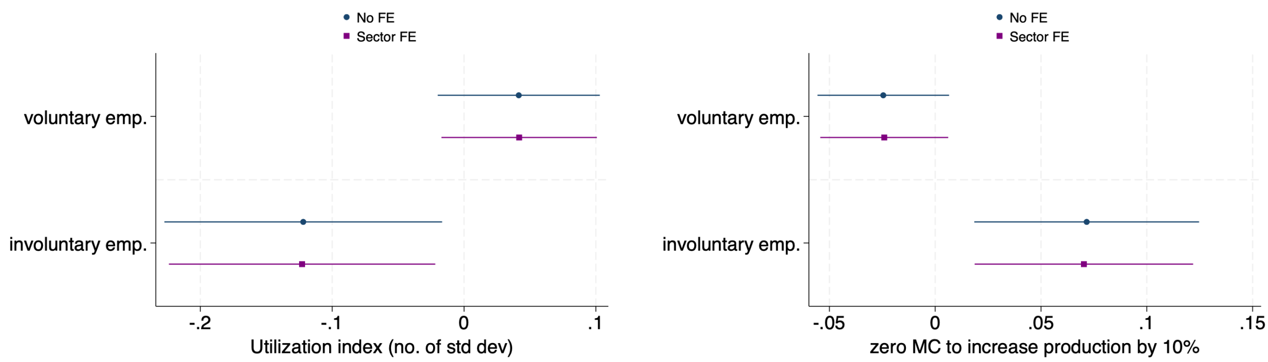


(a) Typical unit of time for hiring

(b) Willingness to take outside option

Notes: This data is from a representative survey of rural market enterprises in Siaya county conducted from April-May 2024. The specific question asked to firms to produce panel (a) was: 'In the last 12 months, what is the most typical unit of time you have hired an employee for?' To produce panel (b), firms were asked 'Suppose someone offered you work at the prevailing wage in your village/town today. Would you have accepted the work?' N = 1303.

Figure A.7: Slack patterns by availability of an outside option

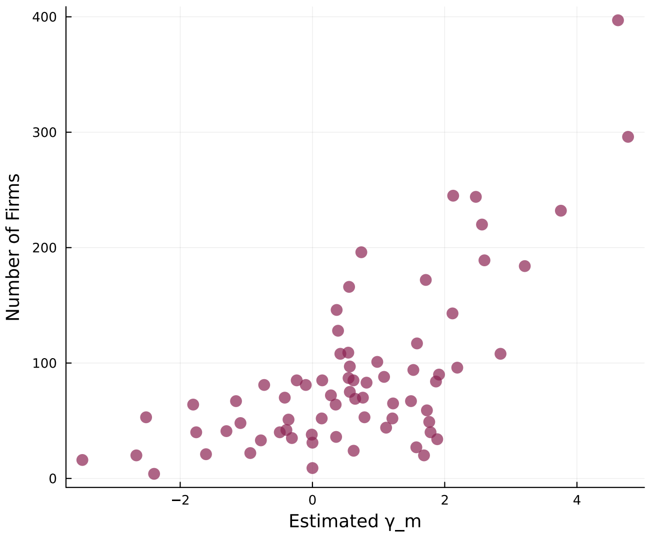


(a) Utilization index by outside option availability

(b) Zero marginal cost by outside option availability

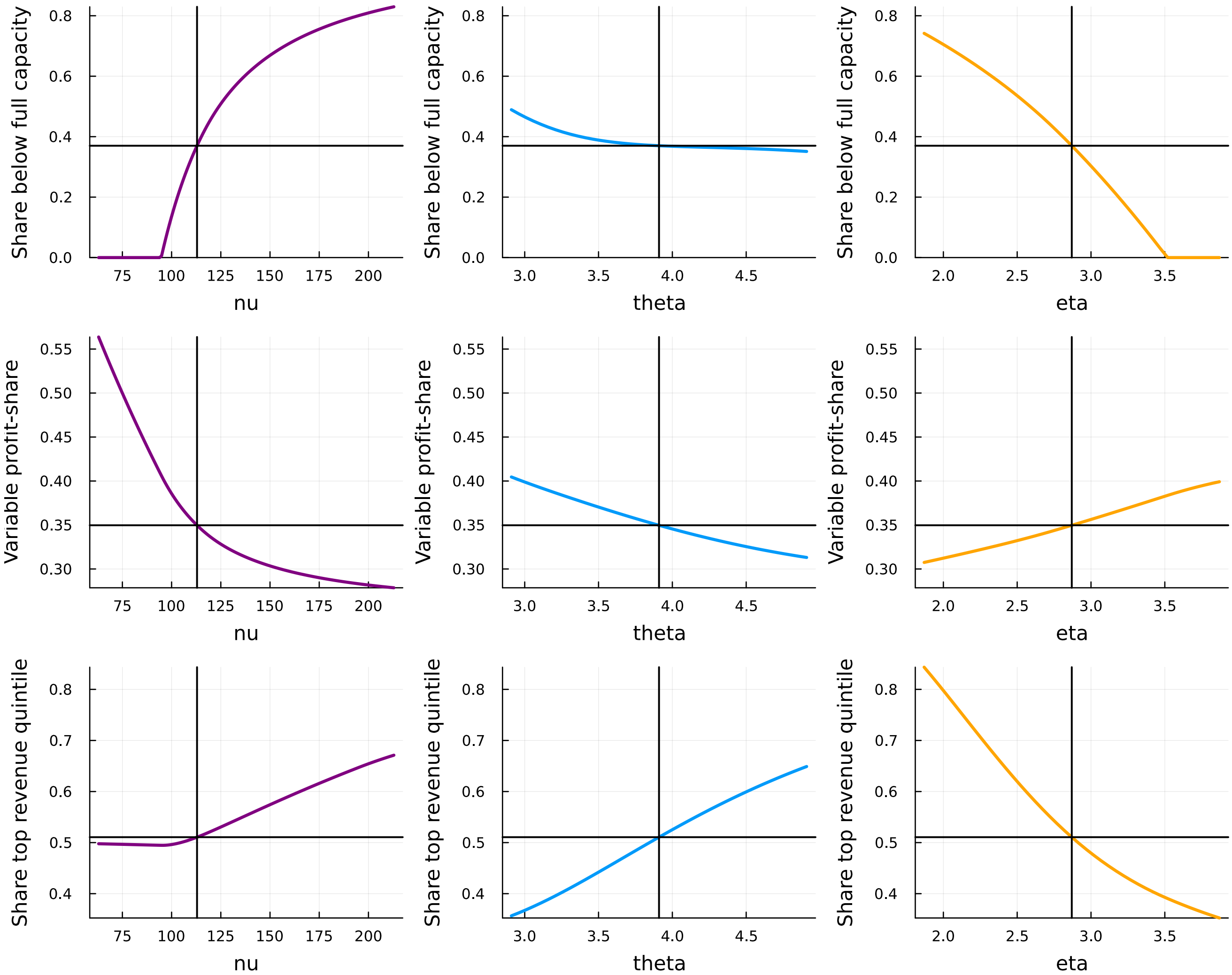
Notes: This figure shows the differences in the utilization index for firms where the owner is voluntarily vs involuntarily employed. This data is from a representative survey of rural market enterprises in Siaya county conducted from April-May 2024. We classify an owner as being involuntarily (voluntarily) employed if they answer Yes (No) to the question: 'Suppose someone offered you work at the prevailing wage in your village/town today. Would you have accepted the work?' N = 1303.

Figure A.8: Correlation of estimated demand shifters γ_m with Number of Firms per market



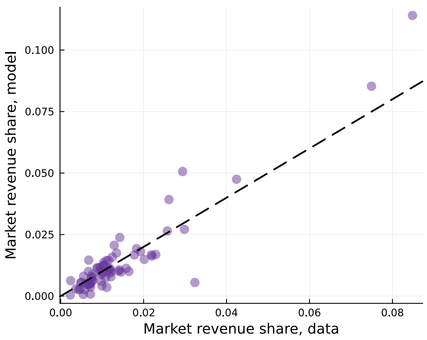
Notes: Market-level demand shifters γ_m estimated from the gravity equation (9) plotted against data of the total number of firms at a given market, according to our enterprise census. The strong positive correlation is consistent with love of variety effects.

Figure A.9: Structural estimation: local pseudo-Jacobians

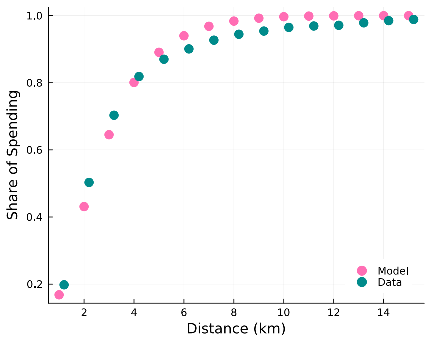


Notes: Local "pseudo-Jacobians" plotted by locally perturbing parameter values and recomputing moments. The marginal cost parameter ν moves around the share of firms reporting to be below full capacity, the elasticity of substitution θ shifts the variable profit share, and the firm size distribution parameter η moves the share of revenue incurred by the top quintile of firms. Off-diagonal elements are sensitive and hence necessitate joint identification.

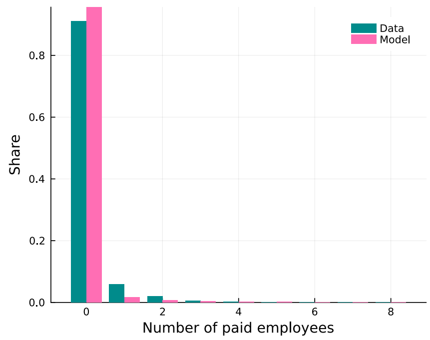
Figure A.10: Baseline fit of the spatial model



(a) Market size



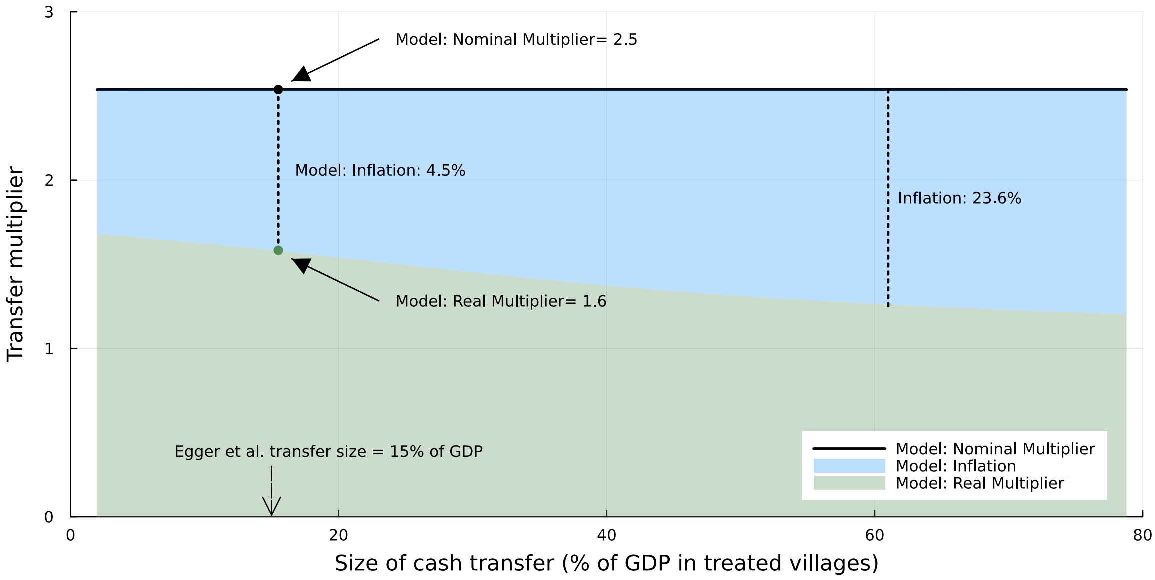
(b) Spending shares by distance



(c) Firm size distribution

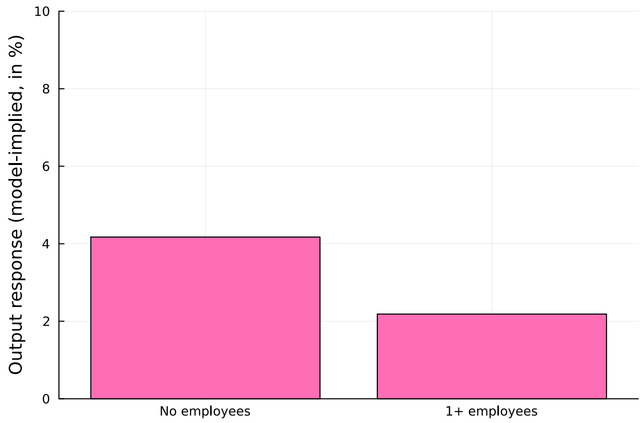
Notes: Baseline fit of the calibrated spatial model along three untargeted dimensions. As we see performance against untargeted *experimental* moments from the Egger et al. (2022) RCT as the main measure for success of the model, we did not pre-specify the baseline moments outlined here. Panel (a) reports the correlation of market sizes in model compared to data. Market sizes reported in the share of total revenue made by firms in this market (these shares sum to one over the full geography). Our calibration routine pins down the relative size of each market by its labor supply, the amount of land allocated to it and the amount of baseline remittances available to households that shop at these markets. Panel (b) compares model and data in terms of spatial spending shares. We pin down the spatial distribution of spending by calibrating the elasticity of substitution across markets, $\sigma = 4$, and picking the elasticity of transport cost with respect to distance $\kappa = 0.22$ to match the gravity regression. Figure A.10b shows this provides a good fit to how much consumers spend within buffers of varying distance away from their home. The model slightly understates just how local spending is – empirical spending shares are higher at shorter distances – and overstates consumers aversion to travel further than 5km away from their home. Panel (c) reports the firm size distribution in model and data. Our calibration partially pins down the firm size distribution through targeting the share of revenue accounted for by the largest firms in our sample. The share of owner operated firms remains endogenous to our modelling of firm entry: Since entrants pay no further fixed cost of operation, all potential entrepreneurs taking a draw from the productivity distribution also become active. The model predicts 94% of firms to be owner-operated (thus having zero employees), compared to 90% in the data.

Figure A.11: Real and Nominal Multipliers without Sectoral Reallocation of Labor

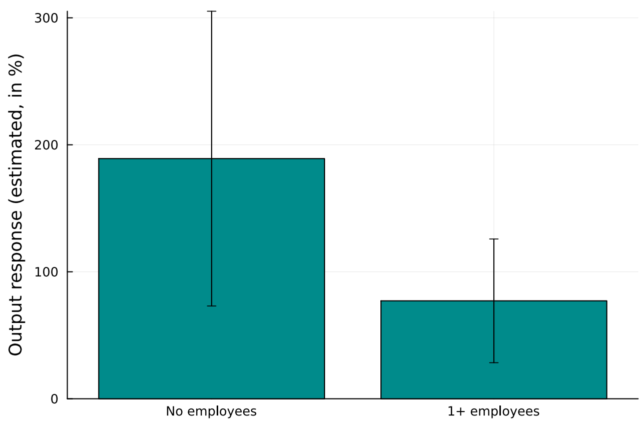


Notes: Replication of Figure 6 presenting model-implied nominal and real multipliers, yet shutting off labor reallocation from agriculture into the service sector. Nominal multipliers in this case are mechanically fixed at $1/1-\alpha \approx 2.53$, yet inflation is much higher than with reallocation, leading real multipliers to more rapidly decrease with the economy-wide transfer size, eventually approaching a real multiplier of 1.

Figure A.12: Output Response by Firms Size: Model versus Data (note the different y-axes)



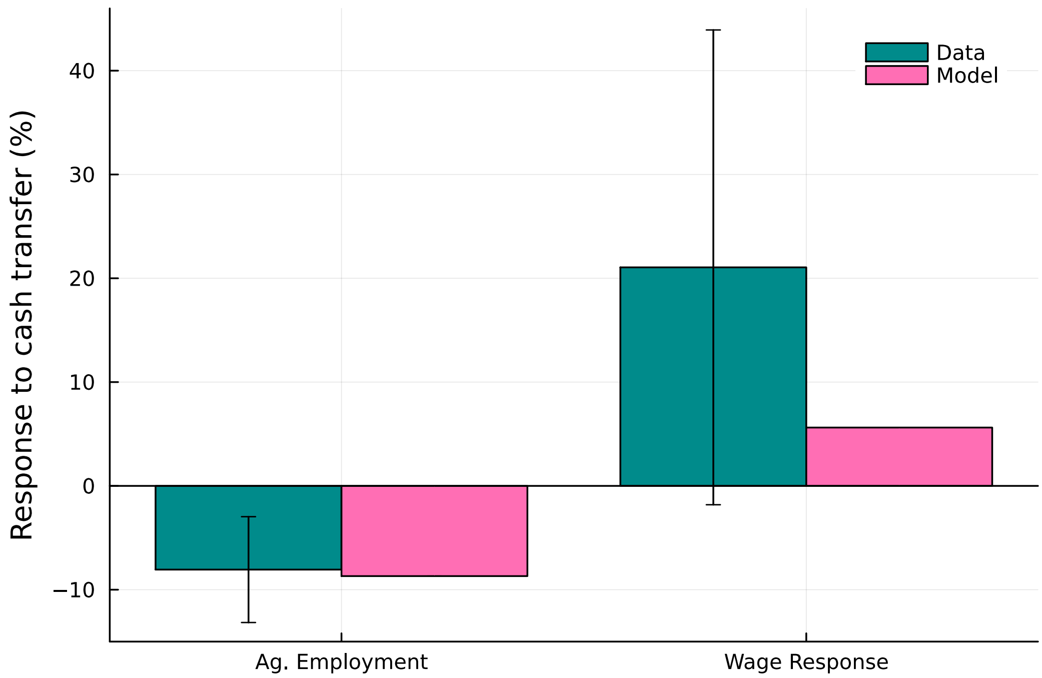
(a) Model



(b) Data (note the different y-axis scale)

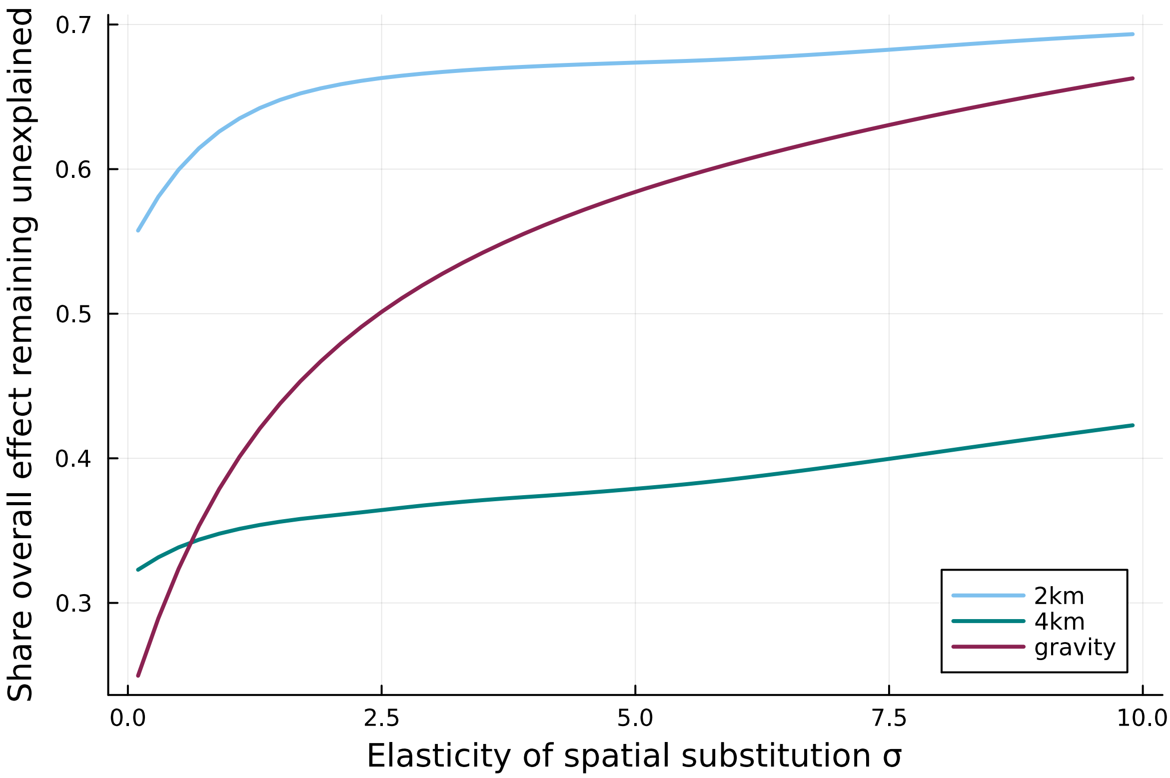
Notes: Revenue responses to the cash transfer program for firms with no employees and one or more employees at baseline. Empirical effects are estimated at ’endline 1’, approximately 1-2 years after transfers. Effect sizes reported in % of baseline revenues. Both in the model and in the data, smaller firms experience a larger proportional revenue increase in response to the cash transfer. This is consistent with smaller firms having more slack at baseline. Treatment effects are much larger in the data than in the model, likely reflecting the fact that firms which survived from baseline to ”endline 1” in the data in a setting where there is substantial churn in entry, are positively selected, and best placed to capitalize on a large demand increase. Moreover, since enterprise surveys were repeated cross-sections, not panel, baseline data on employees is only available for 349 enterprises, leading us to interpret these results with caution. (Empirical specifications and additional detail are in Appendix D.1.)

Figure A.13: Structural Transformation and Wage Response



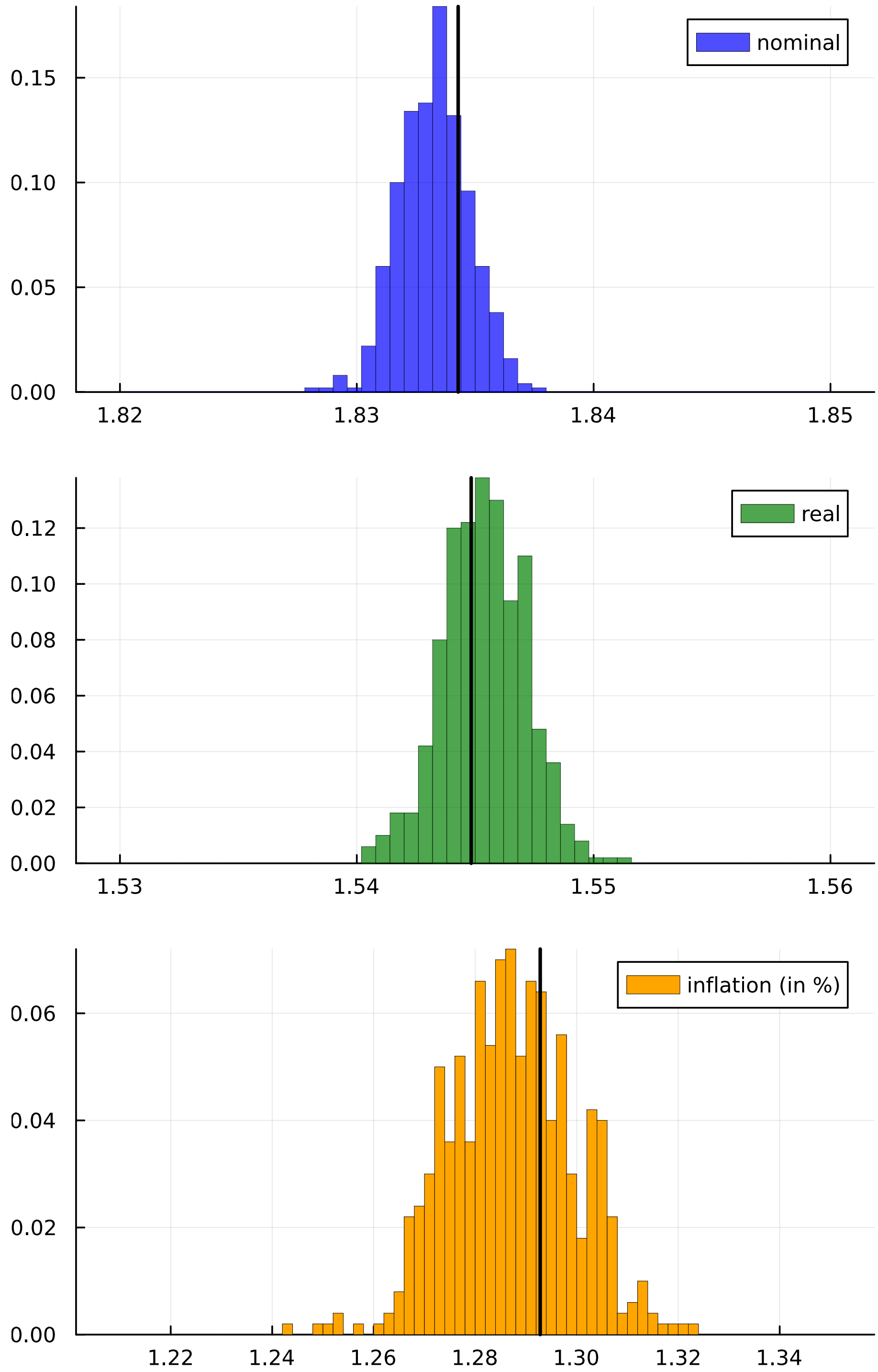
Notes: The figure compares reductions in the share of agricultural labor supply and average wage effects from the model to analogous reduced-form estimates from the experiment in Egger et al. (2022) at 'endline 1', approximately 1 - 2 years after transfers. Details on the empirical strategy are in Appendix D.3).

Figure A.14: Cross-Market Substitution and Ambient Effects on Inflation



Notes: As in Figure 8c, the y-axis gives the share of counterfactual inflation that remains unexplained by different measures of spatial exposure. The x-axis varies the cross-market elasticity of substitution σ, while recalibrating the distance cost parameter κ to match our estimate of $\widehat{\kappa\sigma} = 0.88$. For larger values of σ, the gravity-based treatment variable performs worse than the buffer approach, because baseline expenditure shares become increasingly misspecified as consumers switch spending across markets in response to transfers.

Figure A.15: Multipliers across counterfactual treatment assignments



Notes: This Figure plots the distribution of model-predicted nominal and real multipliers, as well as inflation rates across 500 counterfactual treatment assignments. These assignments were created by hypothetically re-conducting the two-staged clustered cash transfer randomisation from Egger et al. (2022) 500 times, and simulating the effects every time. In vertical black lines, we report the model-implied multiplier for the actual treatment assignment. Distributions are very tight, with nominal multipliers always around 1.83, real multipliers always around 1.54, and inflation rates around 1.3%, suggesting the realized assignment is no outlier.

B Appendix Tables

Table A.1: Correlation between different measures of slack

	Capacity utilization	Worst/best week sales	Capital utilization	Zero MC	Labor utilization
Capacity utilization	1.00	0.20	0.04	-0.01	0.02
Worst/best week sales	0.20	1.00	0.06	-0.09	-0.03
Capital utilization	0.04	0.06	1.00	-0.04	0.12
Zero MC	-0.01	-0.09	-0.04	1.00	-0.11
Labor utilization	0.02	-0.03	0.12	-0.11	1.00

Notes: The table displays the (unweighted) pairwise correlations between all the different measures of slack in our data. The data for this table is a combination of the endline 2 rural enterprise surveys, the 2023 Nairobi market surveys, and the 2024 rural market surveys.

Table A.2: List and counts of all firm types within sectors

Sector	Firm type	Number of firms
Food	prepared food vendor	1709
Food	food stall	3768
Food	fish sale / mongering	1010
Food	butcher	131
Food Processing	grain mill	267
Food Processing	livestock/animal products vendor	183
Food Processing	agrovet	41
Food Processing	ploughing	4
Food Processing	fishing	13
Food Processing	jaggery	12
Food Processing	tea buying centre	10
Hospitality	restaurant	236
Hospitality	bar	48
Hospitality	guesthouse/ hotel	25
Hospitality	cyber café	61
Hospitality	video room/football hall	24
Manufacturing	non-food producer	258
Manufacturing	bicycle repair / mechanic shop	90
Manufacturing	carpenter	156
Manufacturing	welding / metalwork	62
Manufacturing	motorcycle repair / shop	34
Manufacturing	motor vehicles mechanic	5
Personal Services	tailor	512
Personal Services	barber shop	250
Personal Services	m-pesa	363
Personal Services	beauty shop / salon	324
Personal Services	non-food producer	66
Personal Services	mobile charging	25
Personal Services	photo studio	13
Retail	small grocery stall/store	8170
Retail	small retail	1893
Retail	sale or brewing of homemade alcohol / liquor	229
Retail	cereals	871
Retail	chemist	117
Retail	large retail	84
Retail	hardware store	75
Retail	non-food producer	2
Retail	bookshop	97
Transport	boda driver	327
Transport	piki driver	223
Transport	petrol station	25

Notes: This table displays the firm types within each sector, and the number of firms of each type. Data comes from combining the enterprise census conducted at Endline 2, the market census conducted in 2024, and the census of four Nairobi markets conducted in late 2023.

C Additional results

C.1 Integer constrained equilibrium

As outlined in section 3, we arrive at the following schedule for prices, quantities, and profits for unconstrained and constrained firms, given a chosen integer-sized labor input n:

$$p_u(\varphi, n) = \frac{\theta}{\theta - 1}\frac{\nu}{\varphi}, \quad y_u(\varphi, n, \zeta) = \zeta \left(\frac{\theta}{\theta - 1}\frac{\nu}{\varphi}\right)^{-\theta}, \quad \pi_u(\varphi, n, \zeta) = \frac{\zeta}{\theta}\left(\frac{\theta}{\theta - 1}\frac{\nu}{\varphi}\right)^{1-\theta} - w(n-1)$$
$$p_c(\varphi, n) = \zeta^{1/\theta}(\varphi n)^{-1/\theta}, \quad y_c(\varphi, n, \zeta) = \varphi n, \quad \pi_c(\varphi, n, \zeta) = \zeta^{1/\theta}(\varphi n)^{\frac{\theta-1}{\theta}} - \nu n - w(n-1)$$

Firms choose n according to cutoff rules explained in the main text: they choose $n = 1.0$ as long as their productivity $\varphi \leqslant \varphi^+(2, \zeta, w)$, they then choose $n = 2.0$ as long as $\varphi^+(2, \zeta, w) < \varphi \leqslant \varphi^+(3, \zeta, w)$, etc. Computing these cutoffs is fast for fully constrained firms:

$$\begin{aligned}
\varphi^+(n, \zeta, w): \quad & \pi_c(\varphi^+(n, \zeta, w), n-1, \zeta) = \pi_c(\varphi^+(n, \zeta, w), n, \zeta) \\
&= \left(\frac{\zeta^{1/\theta}\left[n^{\frac{\theta-1}{\theta}} - (n-1)^{\frac{\theta-1}{\theta}}\right]}{\nu + w}\right)^{\frac{\theta}{1-\theta}}
\end{aligned}$$

There is not analytical solution, however, if firms go from being fully constrained at $n-1$ to being unconstrained at n. We solve these cases numerically.

Taken together, this yields a formulation for **aggregate labor demand** given w and ζ:

$$\begin{aligned}
N^d &= M\sum_n n\int_{\varphi^+(n,\zeta,w)}^{\varphi^+(n+1,\zeta,w)} g(\varphi)d\varphi \\
&= Mq^\eta \sum_n n\left[\varphi^+(n, \zeta, w)^{-\eta} - \varphi^+(n+1, \zeta, w)^{-\eta}\right]
\end{aligned}$$

where $g(\varphi)$ is the PDF of the productivity distribution, which in the second line we have used our assumption that it follows a Pareto distribution $g(\varphi) = \eta q^\eta \varphi^{-\eta-1}$.

For the **aggregate price level** we need to, furthermore, distinguish between the constrained and the unconstrained case. For this, we compute the full-capacity cutoff $\varphi^f(n, \zeta)$:

$$\begin{aligned}
\varphi^f(n, \zeta): \quad & y_u(\varphi^f(n, \zeta), n, \zeta) = y_c(\varphi^f(n, \zeta), n, \zeta) \\
&= \left[\frac{\zeta}{n}\left(\frac{\theta}{\theta - 1}\nu\right)^{-\theta}\right]^{\frac{1}{1-\theta}}
\end{aligned}$$

Then, the aggregate price level is defined piece-wise by integrating over firms at every integer level, and within each integer, unconstrained and constrained firms:

$$\begin{aligned}
P^{1-\theta} &= M\sum_n \left[\int_{\varphi^+(n,\zeta,w)}^{\varphi^f(n,\zeta)} (p_u(\varphi, n))^{1-\theta} g(\varphi) + \int_{\varphi^f(n,\zeta)}^{\varphi^+(n+1,\zeta,w)} (p_c(\varphi, n))^{1-\theta} g(\varphi)\right] \\
&= M\sum_n \left(\frac{\theta\nu}{\theta - 1}\right)^{1-\theta} \frac{\eta q^\eta}{\eta + 1 - \theta}\left[\varphi^+(n, \zeta, w)^{\theta-\eta-1} - \varphi^f(n, \zeta)^{\theta-\eta-1}\right] \\
&\quad + \left(\frac{\zeta}{n}\right)^{\frac{1-\theta}{\theta}} \frac{\eta q^\eta}{\eta - \frac{\theta-1}{\theta}}\left[\varphi^f(n, \zeta)^{\frac{\theta-1}{\theta}-\eta} - \varphi^+(n+1, \zeta, w)^{\frac{\theta-1}{\theta}-\eta}\right]
\end{aligned}$$

Following a similar logic, we can derive **expected profits** as

$$\begin{aligned}
\mathbb{E}\,\Pi &= \sum_n \left[\int_{\varphi^+(n,\zeta,w)}^{\varphi^f(n,\zeta)} \pi_u(\varphi,n) + \int_{\varphi^f(n,\zeta)}^{\varphi^+(n+1,\zeta,w)} \pi_c(\varphi,n) g(\varphi) \right] \\
&= \sum_n \zeta \left(\frac{\nu}{\theta-1} \right)^{1-\theta} \theta^{-\theta} \frac{\eta q^\eta}{\eta-\theta+1} \left[\varphi^+(n,\zeta,w)^{\theta-\eta-1} - \varphi^f(n,\zeta)^{\theta-\eta-1} \right] - w n q^\eta \left[\varphi^+(n,\zeta,w)^{-\eta} - \varphi^f(n,\zeta)^{-\eta} \right] \\
&\quad + \zeta^{1/\theta} n^{\frac{\theta-1}{\theta}} \frac{\eta q^\eta}{\eta - \frac{\theta-1}{\theta}} \left[\varphi^f(n,\zeta)^{\frac{\theta-1}{\theta}-\eta} - \varphi^+(n+1,\zeta,w)^{\frac{\theta-1}{\theta}-\eta} \right] - (\nu+w) n q^\eta \left[\varphi^f(n,\zeta)^{-\eta} - \varphi^+(n+1,\zeta,w)^{-\eta} \right]
\end{aligned}$$

as well as **aggregate revenues**:

$$\text{Rev} = \zeta M \sum_n \left[\int_{\varphi^+(n,\zeta,w)}^{\varphi^f(n,\zeta)} (p_u(\varphi,n))^{1-\theta} g(\varphi) + \int_{\varphi^f(n,\zeta)}^{\varphi^+(n+1,\zeta,w)} (p_c(\varphi,n))^{1-\theta} g(\varphi) \right] = \zeta P^{1-\theta}$$

Equilibrium in the single-location economy is defined as a vector (w, M, ζ), such that

- labor markets clear: $N = N^d + N_X$, where $N_X = (A\beta/w)^{1/(1-\beta)}$ is agricultural demand at wage w
- there is free entry: $\mathbb{E}\,\Pi = w$
- goods markets clear: $\zeta = \alpha E \frac{P^{\theta-1}}{M}$, where $E = \frac{\Delta + A N_X^\beta}{1-\alpha}$ is total expenditure on the integer-constrained service sector.

Equilibrium in the spatial economy is as above, yet with the added conditions that

- shopping happens according to the gravity equation: $\pi_{od} = \frac{(P_d D_{od})^{-\sigma}}{\sum_{d'} (P_{d'} D_{od'})^{-\sigma}}$ and total expenditure in location m is $E_m = \sum_o \pi_{om} I_o$
- profits, wage and effort payments get redistributed according to the data on ownership and labor relations, such that $I_o = \Delta_o + \Pi_{X,o} + w_o N_{X,o} + \sum_m O_{o,m} M_m \Pi_{y,m} + \sum_m W_{o,m} N_{Y,o}(w_m + e_m)$

We compute spatial equilibrium by guessing a $4 \times N_m$ matrix $\xi = (P, w, M, E)'$ where N_m is the number of markets (71 in our data) and iterating until convergence.

C.2 Continuous benchmark

The case with no indivisibility constraints can be implemented by changing the production function (2) to a linear analogue:

$$y_i = \varphi_i n$$

Note that we do not need to distinguish between effort and labor input, as firms will always set $e = n$ (with n being any number) and just pay their employees the wage w. All other model elements stay the same.

We can then solve the partial equilibrium response of firms in a single location to arrive at

$$\begin{aligned}
N^d &= M \eta q^{\theta-1} \zeta \frac{(\theta w)^{-\theta} (\theta-1)^\theta}{\eta+1-\theta} \\
P^{1-\theta} &= \eta q^{\theta-1} \frac{(\theta w)^{1-\theta} (\theta-1)^{\theta-1}}{(\eta+1-\theta)} \\
\text{Rev} &= \zeta P^{1-\theta} \\
\Pi &= \text{Rev}/\theta
\end{aligned}$$

The same equilibrium conditions hold as before.

Calibration. The parameter vector (θ, η) of the continuous model can be calibrated by hand:

- in the continuous model, the variable profits share is always $1/\theta$, as firms set a constant markup of $\frac{\theta}{\theta-1}$ throughout. We can calibrate by hand: $1/\theta = 0.35 \implies \theta = 2.86$.
- revenue in the continuous model follows a Pareto distribution: $rev(\varphi) = \zeta\eta q^{\theta-1}\left(\frac{\theta w}{\theta-1}\right)^{1-\theta}\varphi^{\theta-1-\eta}$. To calibrate, we make use of the generalised formula for the Pareto principle, implying that if share q of the population generate share p of the total revenue, this is generated by a Pareto coefficient of $\alpha = \frac{\log(1/q)}{\log(p/q)} = 1.717$, which implies $\theta - 1 + \eta = \alpha$ or $\eta = 3.58$.

Since there is no slack in this continuous economy, we set $\nu = 0$ and let the wage w comprise the entire input cost for (fully utilized) firms.

C.3 The effect of reallocation and effort costs on the real multiplier

In our baseline model, compensation differs between agriculture and services with effort cost ν ultimately leading to a wedge in the marginal product of labor across sectors, which by itself can lead to real multipliers larger than one. In this section, we first illustrate this point formally. We then present results from a quantitative extension of the model where no wedge due to effort cost is present because agricultural labor is also assumed to incur an effort cost. We document that simulating the cash transfer experiment in this set-up yields a multiplier of similar size to our headline estimate, leading us to conclude that sectoral wedges are not quantitatively important for the multiplier, and that integer constraints are the main source of high multipliers in our setting.

Consider the single-region version of the model without integer constraints, where utility is equal to

$$U = \left(M^{\frac{1}{1-\theta}}\left(\int_i y(i)^{\frac{\theta-1}{\theta}}di\right)^{\frac{\theta}{\theta-1}}\right)^{\alpha} X^{1-\alpha}$$

with price index equal to average price $P_y = \frac{\mu\tilde{w}}{\tilde{\varphi}}$ where $\tilde{\varphi} = \left(\int_q \varphi^{\theta-1}dG(\varphi)\right)^{\frac{1}{\theta-1}}$ is the relevant notion of average productivity among entrants. $\tilde{w} = w + \nu$ is the composite wage that workers receive in the integer constrained sector, reflecting the wage plus a compensation for effort. The demand shifter for the Y sector is $\zeta = \alpha\frac{I}{M}P^{\theta-1}$ and labor demand is equal to $n(\varphi) = \zeta(\tilde{w}\mu)^{-\theta}\varphi^{\theta-1}$. Total labor demand is equal to

$$Mn(\tilde{\varphi}) = M\frac{\alpha I}{M}P^{\theta-1}\left(\frac{w\mu}{\tilde{\varphi}}\right)^{-\theta}\tilde{\varphi}^{-1} = \frac{\alpha I}{P\tilde{\varphi}} = \frac{Y}{\tilde{\varphi}}.$$

The labor market clearing condition becomes

$$\frac{Y}{\tilde{\varphi}} + N_x = N \implies \frac{dY}{d\Delta}\frac{1}{\tilde{\varphi}} = -\frac{dN_x}{d\Delta}.$$

This labor market clearing implies that any increase in service sector output can only occur if labor reallocates from agriculture.

The real multiplier (as derived in section 3.3) is equal to the increase in expenditure not driven by changes in market prices:

$$P\frac{dY}{d\Delta} + \frac{dX}{d\Delta} = P\frac{dY}{d\Delta} + 1 + \beta N_x^{\beta-1}\frac{dN_x}{d\Delta}.$$

Using $P = \frac{\tilde{w}\mu}{\tilde{\varphi}}$ and $\beta N_x^{\beta-1} = w$, we can re-express this as

$$1 + P\frac{dY}{d\Delta} + \tilde{w}\frac{dN_x}{d\Delta} = 1 + \left[(\mu-1)\frac{w}{\tilde{\varphi}} + \frac{\nu\mu}{\tilde{\varphi}}\right]\frac{dY}{d\Delta}.$$

The formula shows that the reallocation from services to agriculture leads to a multiplier above one in the presence of the wedge $(\mu-1)\frac{w}{\bar{\varphi}}+\frac{\nu\mu}{\bar{\varphi}}$.

The results in Table 4 show that the mark-up wedge for the continuous model increases the multiplier from 1 to a multiplier of 1.16, even without effort costs. Although the difference is quantitatively small compared to the contribution from integer constraints, positive effort costs contribute to this wedge, complicating the comparison between the integer-constrained model (with positive effort costs) and the continuous model (without).

To investigate this, we conduct an extension of the *integer-constrained model*, where work in agriculture also requires the same effort cost ν as the service sector, in effect eliminating the wedge caused by ν. We implement this by assuming agricultural employment (which is not subject to integer constraints), also needs to reimburse workers for their effort provided, yielding an agricultural wage equal to $w+\nu$, with all equilibrium conditions remaining the same. Repeating estimation as before, we calibrate $(\theta,\nu,\eta)=(3.89, 78.8, 2.90)$, implying slightly lower effort costs with other parameters largely unchanged. Simulating multipliers in this set-up, we find a real multiplier of $M_{\text{real}}=1.57$, nominal $M_{\text{nom}}=2.04$, with 2.1% inflation. This real multiplier is very close to the headline estimate.

Overall, this section shows analytically that wedges, whether due to differences in effort cost or mark-ups, create differences in the marginal product of labor. Reallocation across sectors can then lead to multipliers above one. Based on an additional simulation that eliminates the effort cost wedge, we conclude that integer constraints, and not wedges, provide amplification in terms of increasing real multipliers in our setting.

C.4 Estimating the stepsize s

In this pre-specified extension, we relax the integer-constraint in the microeconomic production function (2) and replace it with the following, more general, indivisibility constraint:

$$y_i=\varphi_i \min\{e,n\} \quad n\in\{s,2s,3s,...\}$$

In this function, s represents the size of the indivsibility constraint. Note that this set-up nests the baseline case with $s=1.0$.

We jointly estimate s together with the remaining structural parameters by adding a new targeted moment:

$$\begin{bmatrix}\eta\\ \nu\\ \theta\\ s\end{bmatrix}\rightarrow\begin{bmatrix}\text{Share of revenue accounted by top 20\% of firms}\\ \text{Variable payments ratio}\\ \text{Variable profit-share}\\ \text{Share of firms below full capacity}\end{bmatrix}$$

Variable payments share corresponds to the share of total labor renumeration that is paid out in variable payments (ie. through the piece rate ν times endogeneous utilisation), relative to the fixed component (ie. the endogeneous wage w). Intuitively, this helps indentify ν, where the share of firms below capacity (which previously helped pin down ν) now pins down s.

Since we lack data on the variable payments share in our setting, we rely on work by Foster and Rosenzweig (2022), who study agricultural employment contracts in rural India.[57] They find that variable payments make up 34.7% more than fixed component payments (in their notation: $\bar{w}^p=1.347\bar{w}^f$, see Foster and Rosenzweig (2022), p. 650), implying a variable payments ratio of 1.347.

[57] Although we do not observe the share of compensation that is paid out in fixed vs. variable components in our data, anecdotal evidence and qualitative work suggest that a contract structure that features a fixed wage and a piece-rate component is prevalent in our setting, and in may other developing country settings.

We jointly estimate this four-parameter problem and arrive at

$$\begin{bmatrix} \eta = 3.08 \\ \nu = 129.1 \\ \theta = 3.77 \\ s = 0.52 \end{bmatrix}$$

implying a step size of around $s = 0.52$ years or 6 months.

C.5 Deviations from the Pre-Analysis Plan

Most of our structural estimation and empirical validation exercises were pre-specified in AEA Trial Registry 13210 (https://www.socialscienceregistry.org/trials/13210). In a few instances, we deviated from the procedure outlined there. Below, we explain each decision to deviate from the PAP.

Gravity estimation and market fixed-effects. As outlined in section 4.2, we originally pre-specified to estimate σ and κ jointly using an approach which exploits a short panel-structure in the market data:

$$\log \pi_{odt} = -\sigma \log P_{dt} - \sigma\kappa\tau_{od} + f_o + f_d + f_t$$

Since market prices at 'endline 2' were collected over two waves (indexed by t), we initially intended to leverage this market-level variation to separately identify σ from κ. When conducting this pre-specified approach, we arrive at implausibly low and noisy estimates for the price elasticity σ between 0.1 and 0.3, far below the scientific consensus of around $\sigma = 4$ (Atkin and Donaldson, 2022). We believe that this is due, firstly to insufficient variation of market expenditure across the 4-6 months in between the two survey waves. Second, price data was collected as the average price across a fixed set of goods and hence does not include information on the number of varieties available, thereby likely underestimating shopping flows to larger markets. Third, regressing demand on prices introduces endogeneity and we lack an instrument to convincingly tease supply and demand effects apart, rendering the pre-specified estimation equation to rest on tenuous grounds. In light of this, we deem it justified to deviate from the pre-analysis plan by relying on previous literature and calibrating $\sigma = 4$, which implies $\kappa = 0.22$. We also include the estimated fixed-effects γ_m as demand-shifters in the shopping decision, as outlined in equation (8). We present robustness of our main multiplier estimates to various values of σ, including the implausibly low value obtained using the pre-specified procedure in Table 4. Our main estimate of the real multiplier (which we estimate at 1.5 in our headline specification) drops to around 1.3 when using $\sigma = 0.1$.

Larger geographical scope. We initially pre-specified the spatial model for the experimental geography used in the Egger et al. (2022) experiment, consisting of 653 villages and 61 markets. In reality, however, this region is embedded in a wider spatial geography which also includes 5 peri-urban towns as well as 194 other villages and 10 markets not considered in the original experiment. These locations, however, might have an impact on spatial equilibrium, as they house a relatively large population. We hence calibrated our model to 852 villages and 71 markets instead of 653 villages and 61 markets. This necessitated additional data collection on the 10 additional markets (full enterprise censuses and surveys) and 194 villages (population estimates), and increased (in our view) the credibility of the resulting quantification, and characterization of general equilibrium.

No off-diagonal labor links. We assign each worker to their closest market and disregard the (incomplete) data we have on off-diagonal wage employment links. Most firms do not have any employees and of those that do hire, the match rates to households where employees lived were low, since many employers did not have this information for their employees (or were not willing to share it during surveys). Of those that do match, most workers are employed at their nearest market. We had initially planned to just extrapolate from these partial matches, but to keep the model simple and not be overly leveraged on a few off-diagonal observations, we now assign each worker to their closest market, noting that it likely will not make a quantitatively big difference. We never conducted the originally planned procedure.

Frictional labor market. As a possible extension, we had pre-speficied the existence of frictions in the labor market. These were going to take the shape of potential entrants drawing an iid preference shock co-determining their utility from starting a business (beyond the current equilibrium condition of potential entrants merely deciding between earning the wage w or the expected entrepreneurship profit $\mathbb{E}\,\Pi$). This was only specified as a possible extension beyond our baseline model, which turned out to describe the labor market dynamics reasonably well. We hence did not explore this further.

D Empirical Strategy for additional reduced form estimates

Reduced form impacts of cash transfers are, unless otherwise noted, directly from Egger et al. (2022). In particular, the headline multiplier and inflation results are directly taken from the paper. Additional results presented in this paper typically follow an analogous empirical strategy, with variations to accommodate differences in units of observations, samples, and additional interactions. We specify those here.

D.1 Heterogeneous impacts on output by firm size and sector

To quantify the effects of cash transfers on firm output, we estimate the following equations for enterprises:

$$y_{iv(s)} = \sum_{r=2}^{R} \beta_r \mathrm{Amt}_{v,r} + X_{iv(s)}\gamma + \delta_1 \bar{y}_{iv,t=0} + \delta_2 M_{iv} + \varepsilon_{iv}. \tag{11}$$

where y_{ivs} is log revenue for enterprise i in village v, $X_{iv(s)}$ is a vector of indicators for enterprise type and sampling strata (operating outside the homestead, operating from the homestead), $Amt_{v,r}$ is the per-capita amount of cash transfers distributed to people living between r and $r-2$ kilometers from village v. $\bar{y}_{iv,t=0}$ is and M_{iv} are ANCOVA controls for the average village-level outcome at baseline (set to the mean where this is missing), and an indicator for when this is missing. We use the village average because enterprise surveys are repeated cross-sections, not a panel. As in Egger et al. (2022), we select the maximum radius R by minimizing the Schwartz BIC across a set of nested models that add buffers up to 20km, and the share of eligible households within the $r-2$ to r km buffer that are assigned to treatment as an instrument for $Amt_{v,r}$. Regressions are weighted by inverse sampling probabilities, and we account for spatial correlation in calculating standard errors (Conley (1999)).

We use data from ”endline 1” enterprise survey collected from a representative set of 3,133 non-agricultural enterprises approximately 2 years after transfers (as in Egger et al. (2022)), and run this specification separately for enterprises in each of 9 sectors (Figure 7c), and for firms with or without paid employees at baeline (Figure A.12).[58] To obtain average effects, we compute $\sum_{r=2}^{R} \hat{\beta}_r \cdot \overline{\mathrm{Amt}}_{v,r}$ where $\overline{\mathrm{Amt}}_{v,r}$ is the average amount transferred across all enterprises for each sector or firm size bin.

The main difference between these specifications and those in Egger et al. (2022) is that a) we do not separately estimate effects of transfers within vs. outside the village within which an enterprise operates, and b) we pool effects for firms operating within the homestead and those operating outside the homestead instead of separately estimating treatment effects (though we do apply sampling weights). These aggregations were required to reduce the number of estimated parameters, as there are some sectors with few firms in our sample, and few enterprises with any employees.

[58] Enterprise surveys at baseline and ”endline 1” were repeated cross-sections, not panel data. Thus, data on baseline employee numbers are only available for 359 non-agricultural enterprises.

D.2 Impacts on inflation

We estimate the impacts on inflation by market access (Figure 7d) analogously to Egger et al. (2022)) using

$$p_{mt} = \sum_q \beta_q \mathbf{1}(\text{MA = q})\text{Amt}_{m(6\text{m}),4\text{km}} + \alpha_m + \lambda_t + \varepsilon_{mt}, \tag{12}$$

where p_{mt} is the logarithmic price index for market m in month t (defined as in Egger et al. (2022)). $\text{Amt}_{m(6\text{m}),4\text{km}}$ is the per-capita amount transferred within 4 kilometers around market m over the previous 6 months, expressed as a fraction of GDP. MA denotes market access, which we measure (consistent with market access in our model) by the total revenue of all firms operating in this market, and we split the 61 markets for which we have price data into 4 quartiles of this measure.[59]. We exploit our panel setup by conditioning on fixed effects for both markets (α_m) and months (λ_t). The latter account for seasonal differences and other time trends common to all markets. It also controls for the share of households that are eligible within a market catchment area, so we do not need to instrument for the transfer amounts as above. We again account for spatial correlation in calculating standard errors (Conley (1999)).

To obtain average effects of markets in each quartile of market access q, we compute $\hat{\beta}_q \cdot \overline{\text{Amt}}_{m(6\text{m}),4\text{km}}$ where $\overline{Amt}_{v,r}$ is the average amount transferred across all markets within each market access quartile.

This specification is again a simplified version of that used in Egger et al. (2022) to reduce the number of parameters to be estimated. First, instead of separately including the 0 to 2 km and 2 to 4 km buffer amounts, we aggregate them to a 0 to $4km$ buffer. Second, instead of including separate monthly transfer amounts up to l months as regressors, we include only the cumulative transfers over the last 6 months.[60]

D.3 Impacts on labor supply and wages

We estimate impacts on labor supply (hour worked) and wages, which underlie the results presented in Figure A.13, analogously to Egger et al. (2022). Using data from on 15,698 adults living in 8239 household surveyed at "endline 1", on average 1.5 years after cash transfers.

For adults in recipient households, we estimate:

$$y_{iv} = \alpha + \beta\text{Amt}_v + \beta_2\text{Amt}^{\neg v}_{v,2\text{km}} + \delta_1 y_{iv,t=0} + \delta_2 M_{iv} + \varepsilon_{iv}. \tag{13}$$

where Amt_v is the per-capita amount transferred to village v and $\text{Amt}^{\neg v}_{v,2\text{km}}$ is the amount transferred to other villages within 2 km. These are again instrumented using a treatment indicator for treated village v, and the share of eligible households in other villages within 2km that are assigned to treatment. $y_{iv,t=0}$ and M_{iv} are ANCOVA controls for the baseline outcome (set to the mean if missing), and an indicator for missingness. The maximum radius was selected using the pre-specified algorithm in Egger et al. (2022). Observations are weighted by their inverse sampling probability, and standard errors account for spatial correlation (Conley (1999)).

For adults in non-recipient households, we estimate:

$$y_{iv} = \alpha + \beta_2^1\text{Amt}_{v,2\text{km}} + \beta_2^2(\text{Amt}_{v,2\text{km}} \cdot \text{Elig}_{iv}) + \gamma\text{Elig}_{iv} + y_{iv,t=0} \cdot \delta + \varepsilon_{iv}. \tag{14}$$

The only difference here is that we do not separate between within village and across-village effects of treatment, as in Egger et al. (2022).

To calculate overall impacts for all households in the study area, we stack regressions for treated and untreated households, and compute average effects as the weighted average of effects for recipients and non-recipients:

[59] Results look similar when we use the raw enterprise count, or the population-based market access measure from Egger et al. (2022)

[60] The pre-specified procedure from Egger et al. (2022) selects only the contemporaneous treatment amounts. But sensitivity checks in the appendix suggests that inflationary impacts (though not significant) may increase up to 3-6 months before stabilizing. To be conservative, we therefore select 6 months as our maximum range. Results are similar when restricting to contemporaneous transfers only.

$s_r\big(\hat{\beta}\cdot\overline{\text{Amt}_v}+\hat{\beta}_2\cdot\overline{\text{Amt}}^{\neg v}_{v,2\text{km}}\big)+s_{nr}\big(s_{nr,\text{elig}}\big(\hat{\beta}^1_2\cdot\overline{\text{Amt}}_{v,2\text{km}}+\beta^2_2\cdot\overline{\text{Amt}}_{v,2\text{km}}\big)+s_{nr,\text{inelig}}\big(\hat{\beta}^1_2\cdot\overline{\text{Amt}}_{v,2\text{km}}\big)\big)$ where s_r is the share of recipients among households in the study area, s_{nr} is the share of non-recipients, and $s_{nr,\text{elig}}$ and $s_{nr,\text{inelig}}$ are the shares of eligibles and ineligibles among non-recipients respectively.

E Data appendix

Here, we provide more details on the newly collected data employed in this study. We also rely heavily on data collected as part of Egger et al. (2022). Rather than describing those data again here, we refer to the original paper, Appendix, and pre-analysis plans (AEA Trial Registry 505).

E.1 Rural enterprise sampling details

Endline 2. The primary data sources for the characterization of slack, and distribution of economic activity inrural enterprises are enterprise surveys conducted as part of the "second endline", or Endline 2, a longer-term follow-up of the cash transfer program studied in Egger et al. (2022) (which used data from baseline and Endline 1).

In this section, we describe the additional data collection conducted since 2019 (Endline 2). Endline 2 data collection comprised the following activities: (i) an enterprise census (conducted September 2019 - December 2019); (ii) an enterprise survey (conducted March 2021 - June 2022).

During Baseline and Endline 1, we conducted full enterprise censuses in all 653 villages in the study area. To accurately capture firm death, firm survival, and firm creation since Endline 1, we conducted another full enterprise census at the beginning of Endline 2. During the Endline 2 census, for enterprises that remained operating since Endline 1, we verified basic enterprise characteristics. For enterprises that closed since Endline 1, we collected information on when and why the enterprise stopped operating. For enterprises that were new since Endline 1, we collected the date the enterprise began operating along with basic enterprise characteristics such as location, sector, type, ownership structure, and contact information.

We matched pre-existing enterprises from Endline 1 to those captured during the Endline 2 census where possible. Taking both censuses, this yields a full list of the following categories of enterprises:

- Old Enterprises (enterprises that already existed at Endline 1 that continue operating): 48%
- "Ghost" Enterprises (enterprises that report operating within the study area at Endline 1, but that were not listed in our Endline 1 enterprise census): 27%
- New Enterprises (enterprises that report being newly established in the study area since Endline 1): 25%

We then conducted enterprise surveys with a random subset of enterprises collected during the Endline 2 census. Sampling was stratified within the categories described above, and by enterprise location, and the type of location enterprises were operating from. We classified all enterprises according to their primary location as either operating in a village or in a market center, and as either operating from a homestead or from outside of a homestead. The Endline 2 target sample was determined in the following way.

For old enterprises, all enterprises that were targeted for enterprise surveys at Endline 1 and are still operating as of the Endline 2 enterprise census remained in the sample. Then, we augmented with a random sample of additional enterprises so that the total number of enterprises sampled in each village met the following:

- Operating from homestead: min(2, 20%) per village
- Operating outside homestead: min(3, 20%) per village

For "ghost" enterprises, for those reporting to operate from villages, we drew a sample in the following manner:

- Operating from homestead: min(1, 20%) per village Operating outside homestead: min(.5 the number of villages, 20%) per sublocation

For "ghost" enterprises operating from market centers, we drew:

- Operating from homestead: min(.5 the number of markets, 20%) per sublocation
- Operating outside homestead: min(1, 20%) per market center

The last set of enterprises are new enterprises to the study area since Endline 1. For these, we take a similar approach to the "ghost" enterprises, drawing a set of enterprises to target for surveys based on whether they were operating from villages or market centers, and inside versus outside the homestead. For firms in villages, we drew:

- Operating from homestead: min(1, 20%) per village
- Operating outside homestead: min(.5 the number of villages, 20%) per sublocation

For firms in market centers, we drew:

- Operating from homestead: min(.5 the number of markets, 20%) per sublocation
- Operating outside homestead: min(1, 20%) per market center

Taken all together, this sampling approach yielded a total target sample of 5,015 enterprises. We then split the full sample into two waves. For enterprises operating in villages, we selected 50% of villages at random, and targeted the first set of villages for Wave 1, and the second set of villages in Wave 2. For enterprises operating in market centers, we selected a random 50% of each enterprise category in each market center for Wave 1, and the remainder for Wave 2.

2024 Market census. In addition to the enterprise census and survey conducted at Endline 2, we conducted a full enterprise census of 54 rural markets in Siaya county from April-May 2024. Of these 54 markets, 10 markets were not part of the 61 markets recorded in the study area at baseline (or Endline 2), and the remaining 44 were recorded at baseline (and Endline 2) but we were not confident of having full coverage, as Endline 2 surveys were not necessarily conducted during a market day, and because the enumeration protocol for markets that were not located within any of the 653 experimental villages in the Egger et al. (2022) study was somewhat ambiguous. The remaining 17 markets were located completely within the 653 villages, and we were confident we had covered the full extent of enterprises operating there.

The census captured basic enterprise characteristics such as location, sector, type, owner and employee information, revenue and profits for all market enterprises. For a random subset of enterprises (drawn with a fixed probability on the spot by the electronic survey tool), we conducted a longer enterprise survey that collected additional details on enterprise characteristics including: capacity utilization, customers, employment/wage structure, asset ownership, intermediate goods, and marginal costs. In total, we surveyed 1801 enterprises across all 54 markets.

To get a full representation of market-based enterprises and activity, we combine data (both census and surveys) from the 2024 enterprise census for the 54 markets together with data from the remaining 17 rural markets covered fully at Endline 2 census. Overall, the censuses captured 6,753 enterprises operating in rural markets, of which 2,497 were successfully surveyed.

E.2 Urban enterprise sampling details

We conducted a full enterprise census of four large urban markets in Nairobi (Muthurwa, Gikomba, Toi and Kawangware) from November-December 2023. These markets were chosen as they are anecdotally considered common shopping locations that represent a meaningful share of urban consumer expenditure. However, these markets *do not* constitute the full universe of enterprises operating in Nairobi.

Upon arriving at a market, enumerators first walked through the market, dividing up the market into sections for each enumerator and generating an estimate of the number of enterprises an enumerator was expected to cover. Enumerators would then go through their section of the market, recording the business type for each enterprise on their tablet. Each enumerator's tablet was programmed to randomly select a number of enterprises that they were expected to be able to complete within one visit to the market (20 surveys per day). When the tablet indicated that an enterprise was selected for surveying, the enumerator would seek to conduct a survey and collect the measures of slack capacity. In total, the census captured 12,108 enterprises across four urban markets, of which we surveyed a representative 659 enterprises.

E.3 Economic geography data details

Household shopping patterns. We conducted a census and representative survey of households at Endline 2 of the Egger et al. (2022) study. The census served as a sampling frame for the surveys, and sampling was stratified by village and household categories. In particular, we surveyed all households from earlier survey rounds (Baseline and Endline 1) still present in the study area, and an additional random sample of households that had newly moved to the study area, yielding a representative sample of households in the 653 experimental villages.

In these household surveys, we asked households about their shopping patterns for key food and non-food items.

For food items, we asked about: cereals, grinding of cereals, pulses, vegetables, meat, roots, fish, dairy/eggs, oils/fats, fruits, sugar products, non-alcoholic drinks, and alchohol/tobacco. For non-food items, we asked about: airtime, internet, petrol, lottery tickets, clothing, prepared meals (restaurants), entertainment, household items, firewood/charcoal, electricity, and water. In addition, our consumption module included longer-term/larger expenses such as: rent/mortgage, home maintenance/repair, religious expenses, charity, weddings/funerals, medical expenses, and durables.

For food items, we asked households how much they spent on these items over the past 7 days, and which specific village/market they usually purchased from. For non-food items, we ask the same question but increase the time horizon to 30 days. For the larger expenses, we further increase the horizon to 12 months.

Based on this information, we collapse the data to construct village-by-market level data on expenditure flows and shares. In cases where households buy an item from another village (i.e. a village-to-village transaction), we assign the destination village to it's nearest market.

Firm ownership patterns In the Endline 2 enterprise census, and in the 2024 rural market enterprise census, we ask the respondent for the origin location (i.e. village of residence) of the firm owner. We collapse this data to the village-by-market level, which allows us to determine how localized firm ownership is, as well as to map out profit flows between markets and villages.

E.4 Market price data collection details

We have price data for 61 markets – identified at baseline as all markets operating at least weekly within Siaya county. Details on data collection on the first endline – from before until approximately 30 months after cash transfers can be found in Egger et al. (2022).

In this paper, we use additional data collected as part of the second endline, approximately 5-7 years after tranfers. We collect data for the same 70 products as Egger et al. (2022), but augment this list with an additional 18 commonly sold service goods. The 61 markets are split into two groups, stratified by subcounty and market size. We visit each group bi-monthly and collect both current prices as well as prices for the same items last month to yield a monthly panel, where a representative 50% of prices are collected contemporaneously, the other 50% with recall a month later. We assign enumerators randomly to different markets and different products, and collect 3 price quotes from randomly selected sellers for each product at each market on a weekly market day. We record enumerator and seller gender, and follow a consistent protocol for eliciting price offers.

Products included at both Endline 1 and Endline 2:
Food: Cassava, Irish potato, Maize, Millet, Plantains, Rice, Sorghum, Sweet potato, Beans, Cabbage, Cowpea leaves, Green grams, Groundnuts, Kales, Onions, Saka (Local Vegetable), Tomatoes, Avocado, Banana-sweet, Mango, Orange, Papaya, Pineapple, Water Melon, Jackfruit, Passion Fruit, Beef, Fish (Tilapia), Pork, Eggs, Milk (Fresh), Biscuits, Bread, Cake, Maize flour, Wheat flour, Milk (Fermented), Soda, Sugar, Tea
Livestock: Bull (local), Calf (local), Chicken (hen), Goat, Sheep
Non-food non-durables: Bar soap, Toothpaste, Vaseline/lotion, Washing powder, Bleach, Panadol/aspirin, Cooking fat, Batteries (3-volt), Firewood, Kerosene, Charcoal, Leso, Small sufuria, Slippers
Durables: Bicycle, 1 Iron sheet (32 gauge), Cement, Large Padlock, Nails (3 inch), Roofing Nails, Timber (2x2), Water Paint, 20L Jerry can, Thermos flask, 3 1/2 X 6 Mattress, Mosquito net
Temptation Goods: Cigarettes, Alcohol
Services: Puncture repair (bicycle), Puncture repair (motorcycle), Puncture repair (car), Car cleaning (full), Air refill, Motorcycle wash, Head shave (men), Blow dry (women), internet access (1h), Mobile charging (once), Shoe polish, Patch hole in trousers, Hem trousers, Movie watch (one), photocopy

E.5 Capacity utilization measures: Details

Using our enterprise surveys at Endline 2, we construct several measures of capacity utilization in firms.

Operating capacity. We elicit firms' operating capacity using a combination of two questions.

1. 'Assume this business was operating at full production capability 30 days. Assume the following conditions: a) existing machinery and equipment in place and ready to operate normal downtime, b) labor, materials, utilities, etc. are fully available, c) the number of shifts, hours of operation and overtime pay that can be sustained under normal conditions and a realistic work schedule in the long run, and d) the same product mix as the actual production. What would be the total earnings of this business at full production capability over 30 days?'

2. 'Earlier, you stated your best guess of this business' total earnings over the last 30 days as [TOTAL REVENUE] KSh. If this business could earn [ESTIMATED EARNINGS OVER 30 DAYS AT FULL PRODUCTION CAPABILITY] KSh over 30 days if operating at full production capability, that means this enterprise was operating at [TOTAL REVENUE / FULL CAPACITY * 100] % of full capacity over the past 30 days. Does that sound right?'

Essentially, we ask each firm what their monthly revenue would be if operating at full capacity (question 1 above), and compare this to the actual revenue they report in order to generate a percentage value of utilization. We then ask firms if this value seems appropriate (question 2), and allow them to select yes or no. If they select no, they are prompted to provide a more accurate percentage value.

Capital utilization. In order to determine capital utilization, we first ask each firms to think about the (up to three) main machines, equipment, or tools in their enterprise, and how many hours per day each machine is used for. Using this, we compute the average number of hours a machine, equipment, or tool is used for per day in each enterprise. We then divide this average per day usage by the average hours the enterprise is open for each day to compute capital utilization.

Hence, capital utilization is a fraction between 0 and 1, with 0 meaning that the enterprise's machines were used for none of the day on average, and 1 meaning that, on average, the enterprise's machines were used for the entire time that the enterprise was open during the day.

Labor utilization (self-reported). We elicit self-reported labor utilization through the following exercise. First, we ask respondents which hours they worked during their last working day.

Next, we select a random hour within that time interval, and ask: 'On your last day at work, you worked between [START HOUR] and [END HOUR]. I want you to think specifically about what you were doing at [ONE HOUR SLOT RANDOMLY SELECTED WITHIN SURVEYCTO] and over the following hour.'

'Think of that hour as a continuous series of scenes or episodes in a film, where the episode changes when you switch activities. Give each episode a brief name, for example, "interacting with customers", or "taking lunch", or "buying supplies". Think about the approximate minutes at which each episode began and ended / how long each episode was. Try to be as specific and detailed as you can. (FO Note: Give the respondent enough time to think it through. They may also write it down on a piece of paper)'

We then collect their responses, in 5-min intervals, from the following categories:

1. Away from business premises doing an activity not related to this business (e.g.going to the doctor, picking up kids, shopping etc.)
2. Book-keeping / business records
3. Eating or resting
4. Interact with customers
5. Look for new input suppliers
6. Look for / apply for new loans
7. Look for / buy new machines
8. Look for / interview potential workers
9. Maintenance of machines or equipment
10. Manage existing loans
11. Organizing the stock, cleaning, tidying up
12. Procure inputs for the production of products from suppliers
13. Supervise other workers
14. Train other workers
15. Waiting for customers at the business premises
16. Work on production of any product
17. Other productive activity

We classify items 1, 3, and 15 as 'idle' or 'non-productive', and express labor utilization as the share of 5-min slots during which respondents report doing something productive, i.e. not being idle.

Note, we only collect self-reported labor utilization at Endline 2.

Labor utilization (observation). Because we were worried about experimenter demand, social desirability, and recall bias in self-reported labor utilization measures, we additionally collected more objective observations of labor utilization. Enumerators would spend one hour at a randomly selected business, at a random time of day, discreetly observing a randomly chosen employee at work. They would classify employees' activities using the same categories as above. (For Nairobi market surveys, we instead observed each surveyed enterprise for a random 5 minute interval only, yielding more, but shorter, random interval observations). Idleness and utilization are defined analogously as for self-reported labor utilization. Unfortunately, self-reported utilization is uncorrelated with directly observed (for a random subset of firms) labor utilization. Because of this, we consider self-reports unreliable, and omit labor utilization from our primary index (though results remain robust to including it).

Worst week utilization. We use a combination of two survey questions to calculate this measure.

1. Think of the BEST WEEK for this business in the last 30 days. This is the week where the business sold the MOST. What were the total earnings of this enterprise in THAT BEST WEEK? Note: in this instance,

"earnings" refers only to revenue, not profit. Only count money in, do not subtract any expenses. Therefore, even if a business is not profitable / loses money, their revenue must be a positive number.

2. Think of the WORST WEEK for this business in the last 30 days. This is the week where you sold the LEAST. What were the total earnings of this enterprise in THAT WORST WEEK? Note: in this instance, "earnings" refers only to revenue, not profit. Only count money in, do not subtract any expenses. Therefore, even if a business is not profitable / loses money, their revenue must be a positive number.

We take the ratio of worst week revenue over best week revenue to calculate 'worst week utilization'. This is a fraction between 0 and 1.

Zero marginal cost indicator. To determine whether a firm has zero marginal cost, we use the following sequence of questions:

- We first ask a firm about their three most common products. For each product, we ask for the most common unit and quantity sold. For example, if the product is sugar the most common unit might be kilograms and the most common quantity might be 0.5.
- For each product, we then ask how many 'most common quantities' of this product the firm sold over the past week. E.g. 'How many 0.5 kg bags of sugar did this business sell in the last 7 days?'
- We then ask the firm to consider only their *most common product*. For this product we ask the following question:

  You said that this business sold [UNITS SOLD] units of [COMMON QUANTITY] of [COMMON PRODUCT] in the last 7 days. Suppose that next week, you wanted the business to sell more, specifically 10% more of [COMMON PRODUCT]. That would mean selling [0.1 $\times$ UNITS SOLD] more units of [COMMON QUANTITY] of [COMMON PRODUCT]. Think carefully about what that would entail, what you would need to procure, and where/who you might be able to sell those additional [0.1 $\times$ UNITS SOLD] more units to.

  What would be the additional cost involved in producing / procuring [FACTOR * UNITS SOLD] additional units of [COMMON QUANTITY UNIT] of [COMMON PRODUCT] ? Please do not consider costs this business already incurs. For example, if you could produce those additional units on your existing premises, with existing workers, DO NOT include rent / wages you are already paying. If, on the other hand, you would need to rent a new building or machine, hire more workers, or hire existing workers for more hours, make more trips to the market, etc. then DO include such costs.

In short, we ask the firm to estimate how much it would cost to produce 10% more of their most common product. We then construct the zero marginal cost indicator to be 1 if the estimated cost is 0 Kenyan shillings, and 0 otherwise.