

Who Creates New Firms When Local Opportunities Arise?

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ABSTRACT

We examine the characteristics of the individuals who become entrepreneurs when local opportunities arise. We identify local demand shocks by linking fluctuations in global commodity prices to municipality-level agricultural endowments in Brazil. We find that the firm creation response is mostly driven by young and skilled individuals. The characteristics of these responsive entrepreneurs are significantly different from those of average entrepreneurs in the economy. By structurally estimating a novel two-sector model of a local economy, we highlight how the demographic composition of the local population can significantly affect the entrepreneurial responsiveness of the economy.

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1. Introduction

How does new firm creation affect the economy? While it is well understood that new businesses create the majority of new jobs ([Haltiwanger et al., 2013](#)), a growing literature in macroeconomics emphasizes the importance of new firm creation in propagating economic shocks through the economy by strengthening these shocks' impact and persistence.¹ These studies are consistent with micro-level evidence that new firms generate the majority of jobs created in response to fluctuations in local demand ([Decker et al., 2017](#); [Bermejo et al., 2018](#); [Adelino et al., 2017](#)). Since new firm creation is a function of individual entrepreneurial decisions, to fully understand firm dynamics in response to economic shocks, one must go beyond the firm-level analysis and investigate who the *individuals* who create new businesses in response to such shocks are. This is the focus of our paper.

Who are the responsive entrepreneurs? A long-standing literature explores the nature and characteristics of the average entrepreneur.² However, responsive entrepreneurs, those who start a business in response to economic shocks, might differ from average entrepreneurs in substantive ways. For example, responsive entrepreneurs may have a unique ability to identify and quickly respond to a fast-changing environment. To illustrate these differences, consider the case of entrepreneurs' age. [Azoulay et al. \(2020\)](#) find that successful entrepreneurs are on average experienced and middle-aged, rather than young. Possibly, such older individuals are likely to be able to respond quickly to changes in economic conditions because they have already accumulated the necessary skills and financial resources. However, older individuals may have families and other responsibilities that cause them to prioritize job security. Therefore, they may not necessarily be well positioned to start a firm when opportunities arise. In contrast, younger individuals may be more flexible, more tolerant to risks, and may have less attractive alternative career opportunities, putting them in a better position to respond to a fast-changing environment. Hence, the average entrepreneur might be older than the responsive entrepreneur.

Characterizing responsive entrepreneurs has important implications. If these individuals are concentrated in particular socio-demographic groups, for example, then the composition of the local population would matter for the entrepreneurial responsiveness and dynamism of the local economy. Identifying such characteristics may also be important to policymakers, as the incidence and welfare impacts of local demand shocks will depend on the firm creation response.

Understanding the characteristics of responsive entrepreneurs requires a unique empirical setting

¹For example, [Bilbiie et al. \(2012\)](#) show that firm entry can increase product diversity, which in turn leads to the propagation of the effects of the initial shock. [Clementi and Palazzo \(2016\)](#) argue that firm entry strengthens the impact of economic shocks and makes their effects more persistent. [Chatterjee and Cooper \(2014\)](#) and [Devereux et al. \(1996\)](#) share similar features. [Jaimovich and Floetotto \(2008\)](#) show how procyclical firm entry can lead to countercyclical variations in markups, leading to procyclical movements in TFP. [Sedlacek et al. \(2017\)](#) show that the presence of high-growth startups are key for TFP shocks to translate into aggregate and persistent gains.

²See, among others, [Kihlstrom and Laffont \(1979\)](#); [Blanchflower and Oswald \(1998\)](#); [Hamilton \(2000\)](#); [Moskowitz and Vissing-Jorgensen \(2002\)](#); [Humphries \(2016\)](#); [Hvide and Oyer \(2018\)](#); [Kerr, Kerr, Xu et al. \(2018\)](#). [Parker \(2018\)](#) provides an extensive review of the literature.

where it is possible to identify specific economic shocks, and to simultaneously trace individual career trajectories and entrepreneurial choices. In this paper, we combine local demand shocks driven by commodity price fluctuations with granular employer-employee data on millions of firms and individuals. Then, we supplement our empirical design with a structural framework that allows us to illustrate how different socio-demographic characteristics of the local economy impact the firm creation response to local demand shocks.

Specifically, we focus on Brazil, a resource-rich, upper-middle income country, and rely on administrative employer-employee matched data from the Ministry of Labor, which capture all the employees in the formal sector, and include information on their work history, wages, education, and occupation. These data allow us not only to identify the founders of new firms, but also to observe a rich set of information regarding their personal characteristics *before* the creation of the new firm.³ Moreover, the large agribusiness sector in the Brazilian economy allows us to identify exogenous local demand shocks arising from global commodity price fluctuations, and therefore to study who the individuals driving the firm creation response are.⁴ To do so, we interact municipality level historical production endowments of agricultural crops with contemporaneous changes in global commodity prices, a strategy similar to [Allcott and Keniston \(2017\)](#) in the context of U.S. oil and gas booms. By focusing on individual entrepreneurial responsiveness to commodity-price-driven changes in the value of local agricultural endowments, our identification strategy simply requires that unobserved shocks to demographic-specific entrepreneurial opportunities at the local level cannot themselves drive fluctuations in global commodity prices. Since there are thousands of local municipalities in Brazil, such a scenario seems quite unlikely.⁵

We start by formulating our hypotheses through a novel two-sector model of a local economy which combines the [Lucas \(1978\)](#) insights of individual entrepreneurial choice with models of heterogeneous firms and firm entry, such as [Krugman \(1979\)](#), [Melitz \(2003\)](#), and [Chaney \(2008\)](#). This framework is especially helpful for a number of reasons. First, it formally demonstrates how our specific commodity price shock translates into a demand shock for local non-tradable goods and services, which in turn spurs firm entry. In particular, the model shows that commodity price shocks lead to increased local employment and income, which increases the profitability of firms catering to the local economy. This leads employees to transition from paid wage employment to entrepreneurship, thus fostering new firm creation. The model also highlights that the magnitude

³We follow standard practice in the entrepreneurship literature (e.g. [Kerr et al. 2015](#); [Babina 2015](#); [Kerr and Kerr 2016](#); [Azoulay et al. 2020](#)) and define a founder as the top paid manager or employee of a new firm in the year the firm was founded.

⁴Brazil is among the largest producers in the world of coffee, sugarcane, orange juice, soybean, corn, and ethanol, among other crops. These crops provide the basis for the large agribusiness industry in Brazil, which represents 22% of Brazil’s GDP, a third of its employment, and almost 40% of its export ([PwC, 2013](#)).

⁵In any case, we show that our results are robust to dropping municipalities whose agricultural output accounts for a significant share of the global total in any given year. The results are also robust to municipality-by-year fixed effects in our individual level regressions, which control for shocks correlated with entrepreneurial opportunities across all demographics.

of the firm entry response depends on the willingness and ability of individuals in the local population to transition to entrepreneurship and take advantage of new economic opportunities when they arise.

In addition, the model emphasizes that the local composition of the population can meaningfully impact aggregate firm entry, local economic dynamics, and ultimately consumer welfare. Moreover, it illustrates that responsive entrepreneurs, those on the margin of adjustment when the economy expands, can differ in substantive ways from other inframarginal entrepreneurs. Finally, and importantly, we use the model as the basis for a structural framework that allows us to estimate how firm entry in response to local economic shocks may vary with different counterfactuals of local demographics.

Empirically, we begin by confirming the model’s aggregate-level prediction that increases in commodity prices in affected municipalities do lead to a significant increase in local employment and aggregate income. Our estimated effects are economically meaningful. A 10% change in the value of local commodities significantly increases employment in the municipality by 2.1%. As shown explicitly in our model, this increase in local income may create new investment opportunities in sectors that depend on local demand (Basker and Miranda, 2016; Mian and Sufi, 2012b; Stroebel and Vavra, 2014), which in turn may lead some paid employees to switch into entrepreneurship. Consistent with the predictions of the model, we find that the local demand shock does trigger significant firm entry, driven almost entirely by increases in the non-tradable sector.

We then turn to our main empirical analysis and explore the characteristics of those entrepreneurs who respond to local demand shocks by forming new firms. We start by focusing on the role of age in driving entrepreneurial responsiveness. According to standard models such as Lucas (1978), ability is the relevant dimension along which individuals sort into entrepreneurship. In this type of model, to the extent that ability is an innate characteristic; the age profile of the population does not matter per se. Alternatively, we might expect older individuals to be more responsive, as they may have had the time to accumulate the experience, skill, and wealth needed to exploit new opportunities. Perhaps surprisingly, however, we find that the responsive entrepreneurs are significantly, disproportionately driven by young individuals (less than 30 years old).

Our findings are consistent with the idea that lifecycle considerations strongly influence an individual’s decision and ability to respond quickly to exogenous new local economic opportunities by forming a new venture. Indeed, younger individuals have been shown to have higher degrees of risk tolerance than older individuals, and thus may be better able to tolerate risks associated with a fast transition to entrepreneurial activity (Kihlstrom and Laffont, 1979; Miller, 1984b; Levesque and Minniti, 2006). Likewise, young individuals may have less constraints in the form of family or looming retirement needs, and may therefore have sufficient flexibility to respond quickly to changes in economic opportunities.⁶

⁶One may be concerned that our findings are driven by the particular nature of the shock. For example, if the

Interestingly, we also find that responsive entrepreneurs are significantly younger than the average new entrepreneurs in the economy. While roughly 40% of the new entrepreneurs in Brazil are at the bottom quartile of the age distribution, we find this to be the case for more than 60% of the entrepreneurs responding to the demand shock. This is again consistent with the notion that being a responsive entrepreneur requires the ability, typical of the young, to react rapidly to exogenous changes in market conditions.

We next show that individual skills also appear to be key drivers of the firm creation response. We find that, among the young, more educated individuals are more responsive to local economic shocks by forming new firms. This is also the case for individuals who previously worked in positions requiring managerial and general business skill sets.⁷ We finally provide evidence that it is both innate and acquired skills that matter, in that it is those individuals with greater occupational experience who are more responsive. On the other hand, we find that skilled but older individuals are not responsive to the local shock.

While skills appear to matter for the entrepreneurs driving the firm creation response during an economic expansion, a natural further question is whether these entrepreneurs are of similar quality to the average entrepreneur. On the one hand, when the economy is expanding, and thus drawing more individuals into entrepreneurship, the individuals on the margin may be of lower quality. On the other hand, we know that entrepreneurship and self-employment are a multifaceted phenomena. For example, in developing countries, subsistence entrepreneurship is prevalent (Schoar, 2010). Other individuals may become entrepreneurs simply due to large private benefits of self-employment (Hurst and Pugsley, 2011). Responsive entrepreneurs – those acting specifically through changing market conditions – could therefore be more skilled than the total pool of (inframarginal) entrepreneurs operating in the economy. Our evidence shows this is the case. While the average new young entrepreneur is slightly more skilled when compared to the average young person in the population, as measured by experience, education, and engagement in occupations that require cognitive skills, these traits are considerably more pronounced among the *responsive* young entrepreneurs who form businesses when local opportunities arise. This again reinforces the idea that the responsive entrepreneurs of our study are meaningfully different than the average entrepreneur at startup, both in age and skill set.

In sum, both age and skills matter for the decision of whether to become an entrepreneur

shock increases demand for local bars or nightclubs, it may not be surprising that younger individuals are better able to identify this shift in demand and take advantage of it. However, we find that the increase in local income following the shock is not concentrated specifically among the young, as one would expect if this were a “youth-specific” demand shock. In a similar vein, another potential concern is that the shock is actually relaxing financing constraints, with the young being more financially constrained than the old. This would imply, however, that controlling for income, educational status, white-collar status, and other covariates would likely reduce the estimated impact of age itself. However, the inclusion of such controls has almost no impact on the estimated effect.

⁷Following Autor et al. (2003) and Levine and Rubinstein (2017), we use detailed occupational data to identify occupations that involve significant cognitive skills, such as creativity and problem solving, as well as complex interpersonal skills such as negotiation and management.

in response to new opportunities, and responsive entrepreneurs are different from the average new entrepreneurs in the economy. These findings also suggest that the composition of the local economy may have important implications for aggregate entrepreneurial responsiveness. To explore such aggregate implications, we turn to the model and estimate it structurally following the methodology of [Suárez Serrato and Zidar \(2016\)](#).

We start by constructing counterfactuals based on the age distribution of the local population. Such counterfactuals are consistent with one of the most profound demographic transitions of the past fifty years towards aging populations, stemming from both declines in fertility rates and increased longevity. We find that a 10% increase in the fraction of the young population increases the firm creation response by 1.5-2.5%. Put differently, this suggests that aging populations may face a significant decline in their entrepreneurial responsiveness to economic shocks. The model further suggests that this lower responsiveness could have meaningful ramifications for local welfare. Using these structural estimates, we additionally find that if the increase in the young population share occurs among the non-educated, the effect of the demographic change is significantly muted by about 30%, highlighting the importance of education in promoting an entrepreneurial and responsive economy.

Our work relates to several strands of literature. First, as discussed above, a variety of macroeconomic studies have emphasized the crucial role that new firm creation plays in the amplification and propagation of aggregate economic shocks ([Bilbiie et al., 2012](#); [Clementi and Palazzo, 2016](#); [Chatterjee and Cooper, 2014](#); [Devereux et al., 1996](#); [Jaimovich and Floetotto, 2008](#); [Sedlacek et al., 2017](#); [Hoffmann, 2019](#)). To the best of our knowledge, our study is the first to shed light on the characteristics of responsive entrepreneurs, and the first to structurally estimate the implications of aggregate demographic changes for the firm entry responsiveness to economic shocks. Our paper also relates to a large literature that explores the characteristics of entrepreneurs ([Azoulay et al., 2020](#); [Blanchflower and Oswald, 1998](#); [Hamilton, 2000](#); [Humphries, 2016](#); [Hvide and Oyer, 2018](#); [Kerr et al., 2018](#); [Kihlstrom and Laffont, 1979](#); [Moskowitz and Vissing-Jorgensen, 2002](#); [Parker, 2018](#)). Our paper illustrates that there are stark differences between the average entrepreneurs in the economy and those who start a company in response to changes in aggregate economic conditions. The finding that responsive entrepreneurs are young and skilled highlights the importance of flexibility and risk tolerance in explaining entrepreneurial dynamics in response to macroeconomic fluctuations.⁸

Our paper also makes a contribution to a literature in urban economics studying the effects and incidence of local demand shocks and place-based policies. [Notowidigdo \(2020\)](#) studies the asymmetric incidence of positive and negative local demand shocks on skilled and unskilled workers.

⁸Our paper also relates to a large literature studying the role of entrepreneurship in developing countries. A few notable contributions to this literature include [Bruhn et al. \(2010\)](#); [Naudé \(2010\)](#); [Desai \(2011\)](#); [Bianchi and Bobba \(2012\)](#); [Schoar \(2010\)](#) and [McKenzie and Woodruff \(2013\)](#).

Bartik (2015) examines how the effects of local demand shocks varies with the initial unemployment rate. Cadena and Kovak (2016) show that the incidence of local demand shocks on US unskilled workers is highly influenced by Mexican immigrants. Suárez Serrato and Zidar (2016) show that the incidence of local tax changes on local workers is influenced by firm relocation choices. Our paper shows that the incidence of local demand shocks is influenced by the local entrepreneurial response, and that the magnitude of this response is a function of local demographic conditions.

The remainder of the paper proceeds as follows. Section 2 provides a theoretical framework. Section 3 describes the various data sources used in the analysis, while Section 4 describes the empirical strategy. Section 5 presents our municipality-level aggregate results. Section 6 describes the individual-level analysis and reports the key results of the paper. Section 7 reports the results of the structural estimation. Section 8 concludes.

2. Model

We construct a two-period structural model of a local economy which combines the Lucas (1978) insights of entrepreneurial choice with models of heterogeneous firms and firm entry (Krugman, 1979; Melitz, 2003; Chaney, 2008). This model motivates our reduced-form empirical analyses. Moreover, in Section 7, we structurally estimate key parameters of the model and evaluate the counterfactuals of how changes in population demographics impact the entrepreneurial responsiveness of the local economy.

Each local economy comprises two sectors, producing tradable, commodity goods and local non-tradable goods, indexed respectively by C, N . The commodity sector provides a single homogenous good, while the local non-tradable sector is comprised of a continuum of differentiated goods, indexed by varieties ω .⁹ The model features exogenous revenue productivity shocks to the local resource sector, consistent with our empirical identification strategy.

Locations are indexed by r . Each individual i in location r inelastically supplies one unit of labor. Paid employment in any of the sectors earns a wage w_{rt} . We denote the size of the initial local population in location r at the beginning of the model's timeline as L_{r0} . We assume that each individual i belongs to some demographic category, $j(i) \in \mathcal{J}$, where \mathcal{J} is the set of all demographic categories. Let L_{rj0} denote the population of demographic j in location r . Individuals living in location r can either provide a single unit of labor, earning the prevailing wage, or choose to become an entrepreneur in the non-tradable sector, producing a single differentiated variety ω and earning profits $\pi_{rt,N}$. Each entrepreneur produces a single differentiated variety, so the total number of entrepreneurs is equal to the number of varieties produced M_{rt} . We assume labor is perfectly mobile.

⁹Since our empirical identification strategy focuses on entrepreneurial activity in the non-tradable sector, we model the Lucas (1978) choice only for this sector. Moreover, there is greater product diversity and less firm concentration in the non-tradable sector than other sectors.

In what follows, since our focus will be on a single local economy, we suppress the dependence of the variables on location r .

2.1. *Individuals*

We assume that all individuals in the local economy have Cobb-Douglas preferences over commodity and non-tradable goods, given by the specification in period t :

$$U_t = (1 - \alpha) \log C_{t,C} + \alpha \log C_{t,N},$$

where $C_{t,N}$ is a composite good given by the [Dixit and Stiglitz \(1977\)](#) Constant Elasticity of Substitution (CES) aggregator:

$$C_{t,N} = \left(\int_0^{M_t} c_{t,N}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}},$$

with $\sigma > 1$ and M_t equal to the equilibrium number of varieties produced in the non-tradable sector. Tradable goods are produced elsewhere and have a normalized price of one. This implies that all individuals spend a constant fraction, $1 - \alpha$, of their total income on tradable, commodity goods, and a constant fraction, α , on the locally produced non-tradable composite. Due to the homotheticity of CES preferences, standard results imply that the total demand for variety ω in the non-tradable sector is equal to:

$$C_{t,N}(\omega) = Y_t p_{t,N}(\omega)^{-\sigma} P_{t,N}^{\sigma-1}, \quad (1)$$

where Y_t is local income, $p_{t,N}(\omega)$ is the price of variety ω , and $P_{t,N}$ is the aggregate price index parallel to the CES aggregator:

$$P_{t,N} = \left(\int_0^{M_t} p_{t,N}(\omega)^{-(\sigma-1)} d\omega \right)^{\frac{-1}{\sigma-1}}.$$

In particular, consumption of a variety ω is increasing in income, decreasing in its own price, and increasing in the (aggregated) price of other varieties. The higher σ , the greater the substitutability is between varieties, and the more sensitive consumption is to the price of other varieties. Recall that the total number of local varieties equals the total number of entrepreneurs. Consumer welfare thus depends on the number of entrepreneurs operating in the non-tradable sector since, with CES preferences and $\sigma > 1$, consumers benefit from greater product diversity (see [Dixit and Stiglitz, 1977](#)).

We assume individuals have either non-pecuniary preferences or fixed costs associated with becoming an entrepreneur or a paid employee. These will drive an individual's decision of whether to

become an entrepreneur. One can view these heterogeneous costs as arising from skill, as those who bring greater entrepreneurial and managerial skills will likely find the burden of running the business lower.¹⁰ Specifically, given Cobb Douglas preferences, the indirect utility from entrepreneurship and paid employment for individual i are, respectively:

$$V_{E,it} = v_{E,j(i)t} - F_{E,it} = \log \pi_{t,N} - \alpha \log P_{t,N} - \bar{F}_{E,j(i)t} - F_{E,it} \quad (2)$$

$$V_{W,it} = v_{W,t} - F_{W,it} = \log w_t - \alpha \log P_{t,N} - F_{W,it}, \quad (3)$$

where $\bar{F}_{E,jt}$ denotes mean fixed costs across all demographic categories. Both $F_{E,it}$ and $F_{W,it}$ denote idiosyncratic shocks to the fixed costs, which we assume are i.i.d Type 1 extreme value. That is, the difference $F_{E,it} - F_{W,it}$ follows a logistic distribution. We assume that $\bar{F}_{E,lj(i)t}$ is infinite except for a fraction φ_j of individuals living in location r at time $t = 0$. Intuitively, we are assuming that only the local population has sufficient local knowledge to be able to take advantage of new local economic opportunities when they arise. We allow the dispersion $\kappa_{j(i)}$ of the logistic distribution governing differences in idiosyncratic fixed costs between entrepreneurship and wage employment to differ across demographic categories.

Note that these dispersion parameters will inform the magnitude of the firm-creation response to local demand shocks, such that some demographic categories may be more able to respond to the shocks when they arise. For example, if κ_j is small, that is, the dispersion in fixed costs is low, then we may expect to see a larger entrepreneurial response in the local economy when entrepreneurship becomes more profitable, since there is a larger mass of potential entrepreneurs on the margin. On the other hand if κ_j is large, then the distribution of fixed costs would be wide, so that only a small number of individuals would find it optimal to switch from wage employment to entrepreneurship in response to an increase in potential profits.

Importantly, the model also illustrates the distinction between studying average entrepreneurs and responsive entrepreneurs. Suppose, for instance, that \bar{F}_E was smaller for older individuals but κ was smaller for younger individuals. Then it could be the case that the typical entrepreneur in the economy is older, consistent with [Azoulay et al. \(2017\)](#), while the dynamics in entrepreneurship are mediated through the younger population. That is, responsive entrepreneurs would typically be younger. This is why a specific, targeted empirical design is needed to understand the characteristics of responsive entrepreneurs and thus the demographic determinants of firm creation dynamics.

Finally, recall from above that we assume labor, unlike entrepreneurship, is perfectly mobile in the overall economy. This implies that the utility from paid employment, $v_{W,t}$, equals \bar{v}_W for some constant, exogenous \bar{v}_W . Intuitively, with highly mobile labor, the response to a local demand shock should be largely accommodated by changes in the magnitude of local employment, rather than by

¹⁰An alternative would be to model differences in skill through heterogeneous productivity levels. However, doing so would significantly increase the complexity of the analysis, while adding little in the way of intuition or to the empirical implications of the model.

changes in local wages. This is consistent with our findings discussed later in the text. We discuss the implications of relaxing the assumption of perfect mobility at the end of Section 7.

2.2. Production

The commodity sector is perfectly competitive with a composite firm producing a homogeneous good. The price of the commodity good $P_{t,C}$ is set by global demand and thus taken to be exogenous. The commodity sector hires $l_{t,C}$ workers at wage w_t and earns revenue $R_{t,C} = A_{t,C} l_{t,C}^{1-\gamma}$, where $0 < \gamma < 1$ and $A_{t,C} = \Omega_C P_{t,C}$ is the revenue productivity, equal to the physical productivity Ω_C times the price of the commodity good in period t . In what follows, we assume that $\gamma(1 - \alpha) > \alpha/(\sigma - 1)$, which will hold under our structural estimation and calibration. Profit maximization requires that the marginal revenue product of inputs be equal to the marginal cost of hiring:

$$(1 - \gamma) A_{t,C} l_{t,C}^{-\gamma} = w_t. \quad (4)$$

The non-tradable sector comprises a continuum of differentiated goods denoted by ω , produced by monopolistically competitive firms run by individual entrepreneurs. Following standard modeling devices in the heterogeneous firms literature (Krugman, 1979; Melitz, 2003; Chaney, 2008), we assume that an individual entrepreneur operates the following CRS production technology:

$$q_{t,N}(\omega) = l_{t,N}(\omega).$$

That is, one unit of labor produces one unit of differentiated product. Market clearing requires production, $q_{t,N}(\omega)$, equal demand, $C_{t,N}(\omega)$, for each variety, ω . Taking the aggregate price index as given, entrepreneurs set the price, $p_{t,N}(\omega)$, to maximize profits:

$$\pi_{t,N}(\omega) = C_{t,N}(\omega) (p_{t,N}(\omega) - w_t),$$

where $C_{t,N}(\omega)$ is consumer demand for variety ω , whose expression is provided above in equation (1). Taking the first order condition with respect to price yields the standard result in monopolistic competition that the price is equal to a constant markup over marginal cost;

$$p_{t,N}(\omega) = \frac{\sigma}{\sigma - 1} w_t. \quad (5)$$

For each variety ω , the labor employed and entrepreneurial profits are:

$$\begin{aligned} l_{t,N}(\omega) &= \alpha Y_t p_{t,N}(\omega)^{-\sigma} P_{t,N}^{\sigma-1} \\ \pi_{t,N}(\omega) &= \sigma^{-1} \alpha Y_t \left(\frac{p_{t,N}(\omega)}{P_{t,N}} \right)^{1-\sigma}, \end{aligned}$$

where recall that Y_t is the local income. By equation (5), since marginal costs, i.e. the wage, are the same for each entrepreneur, each differentiated variety carries the same price. This implies that the total amount of differentiated product that consumers demand, denoted by M_t , and the total employment in the non-tradable sector satisfy that:

$$M_t q_{t,N} = M_t l_{t,N} = \frac{\sigma - 1}{\sigma} \frac{\alpha Y_t}{w_t}. \quad (6)$$

It further implies that each entrepreneur earns the same profits:

$$\pi_{t,N} = \alpha Y_t / \sigma M_t. \quad (7)$$

We can now solve for the model's equilibrium.

2.3. Equilibrium

In equilibrium, firms and individuals optimize and labor supply equals labor demand. Note that the size of the local population in period $t = 1, 2$ is given by $L_t = l_{t,C} + l_{t,N} + M_t$. That is, the size of the local population is equal to the number of entrepreneurs in the local economy plus the number of salaried workers in the two sectors.¹¹ Local income equals:¹²

$$\begin{aligned} Y_t &= l_{t,C} w_t + l_{t,N} w_t + M_t \pi_{t,N} \\ &= l_{t,C} w_t + \alpha Y_t. \end{aligned}$$

Note that the second equality arises because $l_{t,N} w_t + M_t \pi_{t,N} = \alpha Y_t$. Total revenue in the non-tradable sector αY_t is distributed as total wages paid to salaried workers, $l_{t,N} w_t$, and total entrepreneurial profits, $M_t \pi_{t,N}$. Solving the equation above for Y_t yields:

$$Y_t = \frac{l_{t,C} w_t}{1 - \alpha}. \quad (8)$$

Using standard results from discrete choice theory, the total number of entrepreneurs is:

$$M_t = \sum_j M_{tj} = \sum_j \frac{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right)}{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right) + 1} \varphi_j L_{0j}. \quad (9)$$

Finally, perfect mobility requires that $\log w_t - \alpha \log P_{t,N} = \bar{v}_W$. Equilibrium thus involves solving, in each period t , for the labor employed in the local commodity sector, local income (Y_t), the local wage (w_t) and the equilibrium number of entrepreneurs (M_t).

¹¹Recall that salaried workers can come from outside the local economy but all entrepreneurs come from the initial local population at the beginning of the model's timeline.

¹²We assume that the local population does not share in the profits of the local commodity sector.

2.4. Commodity Price Shocks

Our empirical strategy relies on local demand shocks driven by changes in global commodity prices. In this subsection, we explore the equilibrium implications of an exogenous increase in the price of the locally produced commodity good bundle in period 2. We begin by stating a basic result.

Proposition 1. *An increase in the price of the local commodity good bundle between periods 1 and 2, $P_{2,C} > P_{1,C}$, leads to increased employment and new firm creation in the local non-tradable sector.*

The formal proof is in Appendix Section A.1. To understand this result, first suppose that the number of entrepreneurs remains fixed at its initial level. The higher price raises the marginal revenue productivity, $A_{2,C}$, of the commodity sector, relative to period 1. Since workers are perfectly mobile, the increased revenue productivity leads to in-migration of workers until the marginal revenue productivity of the commodity sector is equal to the wage, w_1 , in period 1. By equation (8), this inflow of workers raises local income Y_2 relative to period 1, which shifts the demand $C_{2,N}(\omega)$ for non-tradable goods by the local population upwards. Since demand is homothetic and marginal costs are unchanged, the price, $p_{t,N}(\omega)$, of the non-tradable goods does not change between periods 1 and 2. Therefore, by equation (6), relative to period 1, there is an increase in non-tradable output and higher employment in the non-tradable sector in period 2.

However, this would then imply that entrepreneurial profits, $\pi_{2,N}$, are now higher than $\pi_{1,N}$. Since the value of the outside option, wage employment, remains unchanged, allowing now for the number of entrepreneurs to adjust, there will be firm entry. That is, $M_2 > M_1$. Local workers who are willing/capable of entrepreneurship, i.e. those in the fraction φ of the initial local population L_0 , and those with sufficiently low idiosyncratic non-pecuniary costs will become entrepreneurs, increasing the number of differentiated varieties and reducing entrepreneurial profits through greater competition. This will continue until the marginal entrepreneur is again indifferent between entrepreneurship and wage labor.

Equation (9) also shows that the proportional increase in entrepreneurs within any demographic category in response to the shock depends on κ_j , the scale parameter of the Type I extreme value distribution. In particular, a smaller κ_j implies a larger entrepreneurial response, since there will be a larger mass of potential entrepreneurs at the margin. This implies that, in contrast to models such as Hopenhayn (1992) and Melitz (2003), there is not free entry in our framework. When there is free entry, all increases in non-tradable output and employment occur at the extensive margin, and individual firm profits do not increase in response to the demand shock. In our model, some of the increase in non-tradable output occurs on the intensive margin and individual firm profits do increase. When firm entry in response to local demand shocks is limited, there is greater incidence of the shock on firm profits. When there is more entry, there is greater incidence on local product diversity and the non-tradable aggregate price index. We return to these issues at the end of Section 7.

In what follows, we will first explore in reduced-form how entrepreneurial responsiveness depends on demographics. In Section 7, we structurally recover the κ_j parameters and use these estimates to quantitatively evaluate the impact of counterfactual demographic changes on the firm-creation response.

3. Data

In this section, we discuss the main datasets used in our analysis. We start by describing the RAIS dataset, which provides matched employer-employee information on all employees in the formal sector in Brazil. We supplement these data with data on municipal agricultural crop endowments, as well as data on global commodity prices and accessory datasets discussed in the text.

3.1. Employer-Employee Data

The RAIS (*Relacao Anual de Informacoes Sociais*) is an administrative database from the Brazilian Ministry of Labor (MTE), which provides individual level data on the universe of formal sector employees. RAIS is widely considered a high-quality census of the Brazilian labor market (Dix-Carneiro, 2014). The database, created in 1976, is used by several government agencies (such as the Brazilian Central Bank) to generate statistics of the Brazilian economy. The RAIS database also forms the basis for national unemployment insurance payments and other worker benefits programs. As a result, ensuring the accuracy of the information is in the interest of both firms (who would otherwise be subject to monetary fines) and individuals (who want to be eligible to receive government benefits), as well as the central government.

RAIS contains information on the firm and the establishment of each employee, including tax identifiers, location, industry, and legal status. At the individual level, RAIS includes employee-specific identifiers, which allow individuals to be tracked over time and across firms (as well as across establishments of the same firm).¹³ Similar to other employer-employee matched data, for each employee we observe payroll, tenure in the firm, and hiring and firing dates. RAIS additionally has rich personal data on gender, nationality, age, and education, as well as a few less commonly available variables such as hours worked, reasons for hiring and firing, and contract details. Finally, each employee is assigned to an occupational category specific to her current job. There are 2,511 such categories, which follow the detailed Brazilian classification of jobs (*Classificacao Brasileira de Ocupacoes* - CBO).

Using data on occupations, we are able to identify individuals that are managers of a firm, as

¹³Individuals with multiple jobs in a given year therefore appear multiple times. Following standard practice in the literature (Menezes-Filho, Muendler, and Ramey, 2008; Colonnelli, Pinho Neto, and Teso, 2020a), we keep only the highest paying job of the individual in a given year. If there are two or more such “highest paying” jobs, we break ties by keeping the earlier job.

well as lower-ranked workers, both blue collar and white collar.¹⁴ We follow standard practice in the entrepreneurship literature (e.g. [Kerr et al. 2015](#); [Babina 2015](#); [Kerr and Kerr 2016](#); [Azoulay et al. 2020](#)) and we define an entrepreneur or founder as the top paid manager or employee of a new firm in the year of birth. If more individuals have the same exact wage at the top of the distribution, we pick one randomly. As discussed by [Kerr and Kerr \(2016\)](#), the top employees in the firm at the year of birth are usually the founders, as confirmed in 90% of the cases by [Azoulay et al. \(2020\)](#) in the U.S.. While there is certainly some degree of inaccuracy, as some founders may opt to receive only a very small salary or no wage at all, these cases are likely to be a small share of the total. In fact, our context is mostly comprised of small firms in the retail sector, which are likely to be well modeled by this approach, relative to, say, the case of high-tech startups.

Furthermore, following [Autor et al. \(2003\)](#), [Gathmann and Schönberg \(2010\)](#), and [Levine and Rubinstein \(2017\)](#), we distinguish between workers who perform different types of tasks. *Non-routine cognitive* tasks require creativity and problem-solving ability, as well as negotiation, management, and coordination skills. *Non-routine manual* tasks require physical work together with the ability to adapt to different situations. Finally, *routine* tasks are all other tasks based on well-specified processes and activities.

The analysis samples are constructed as follows. We focus on individuals that are within the ages of 18 to 65, and who have wage data in RAIS for at least 3 years during the period 1993-2014. Under these restrictions, the sample includes roughly 80-million individuals. In the municipality-level analysis, we aggregate these data across the 5,570 municipalities in Brazil, and we restrict the sample further to municipalities with a population less than 500,000 and that produce crops at any point in time, and derive a final sample of 5,443 municipalities.¹⁵ In the individual-level analysis, we additionally restrict the sample to individuals who we can clearly link to a specific municipality at the time of the shock; that is, at any given year, we keep individuals who were working in the same municipality as the previous year. We finally extract a random 10% sample of the data to overcome computational barriers. The entire analysis focuses on the period 1998-2014, since we rely on the prior 5 years (1993-1997) to construct the historical agricultural endowments, as discussed in Section 4. All statistics in the paper refer to these samples.

In Panel A of Table 1, we provide summary statistics on the relative importance of different industries. The two largest industries in the economy are the non-tradable and services sectors, which capture 48.9% and 26.3% of the annual number of firms, and 24.8% and 37.2% of annual em-

¹⁴We match the (profession-based) CBO classification to the (skill-oriented) International Standard Classification of Occupations (ISCO-88) using the procedure outlined in [Muendler et al. \(2004\)](#). ISCO classifies workers into ten major groups of occupations. The top group consists of managers, which include managing directors and chief executives, administrative and commercial managers, production managers, and hospitality, retail and other services managers. In previous work in the organizational economics literature, the ISCO correspondence has been used to categorize workers into broad organizational layers consisting primarily of managers, white-collar workers, and blue-collar workers (see, for example, [Caliendo and Rossi-Hansberg \(2012\)](#)). See [Colonnelli and Prem \(2020\)](#); [Colonnelli et al. \(2020b\)](#) for more details on the data construction.

¹⁵The population restriction simply helps to overcome computational constraints in the individual-level analysis.

ployment, respectively. Panel A also documents the annual creation of new firms across industries, with most new firms being created in the non-tradable and services sectors.

In the empirical analysis, we focus on municipalities as the local economic unit and explore how municipalities respond to plausibly exogenous economic shocks triggered by fluctuations in global commodity prices. Panel B of Table 1 provides municipality level summary statistics. The average municipality in the sample has a population of 23,680 and an income per capita of \$3,093 (USD 2000). There is an average (median) of 274 (64) firms and an average (median) total number of formal private-sector employees of 4,214 (850) per municipality, with significant dispersion in size across regions. The average (median) number of new businesses created in a given municipality in a given year is 33 (7). Once again, there is a significant heterogeneity across municipalities.

Panel C of Table 1 provides summary statistics at the individual level. On average, we find that in any given year there are 2.9 founders per each 1,000 employees. Moreover, 61% percent of all workers are male (57% among founders). Based on the occupational status of the workers, we find that most workers can be characterized as either blue collar (48%) or white collar (42%), while only a small fraction consists of managers (4%). Founders have similar occupational characteristics, as computed in the year before founding a firm. Additionally, we find that 32% of the workers have less than high school education, 47% of the workers graduated from high school, and the remaining 21% have higher education. The set of entrepreneurs appears to be more educated, as seen in the significant differences among the set of individuals having less than high school education. Finally, the average worker is 35.6 years old, while the average new entrepreneur is significantly younger at 31.9 years old.

3.2. Agricultural Crops in Brazil

The Brazilian economy relies heavily on agriculture. For example, Brazil is among the largest producers in the world of coffee, sugarcane, soybean, and corn. These crops, and products derived from them like orange juice and ethanol, provide the basis for the large agribusiness industry in Brazil, which represents 22% of Brazil's GDP, a third of its employment, and almost 40% of its exports (PwC, 2013). The agribusiness industry captures not only farming production, but also the supply of farming inputs such as machinery and seeds, as well as the selling and marketing of farm products, such as warehouses, wholesalers, processors, and retailers.

The empirical strategy in this paper relies on local demand shocks caused by fluctuations in the profitability of the local agricultural sector driven by global commodity prices. We obtain information on agricultural crops from the Brazilian Institute of Geography and Statistics (IBGE), which is responsible for the census as well as most of the statistical analyses of the Brazilian economy. The data provide the annual production at the municipality level of all different agricultural crops, for the period 1993-2014. We standardize the different crops to the same unit of measure (i.e., tons)

to construct a panel dataset of the universe of agricultural crops production.

Panel B of Table 1 illustrates that the average aggregate dollar value of local crops in a municipality across all years in our sample is equal to approximately 120% of local income, with the median equal to 15.6% of local income. Similarly, the value of local crops per capita is on average \$3,038 (USD 2000). Figure 1 illustrates the wide spatial distribution of agricultural resources across municipalities. Municipalities are divided into quintiles based on the production value of natural resources relative to the local income in the year of 2000. The bottom quintile has production values of roughly 1% to 5% of municipality income. In contrast, in the top quintile, municipalities have production values worth more than 45% of local income. The figure illustrates significant heterogeneity across municipalities. In fact, the heterogeneity across municipalities is even wider than what the figure suggests, given that different municipalities specialize in different portfolios of agricultural products.

International commodity prices are obtained from the Global Economic Monitor (GEM) Commodities database of the World Bank, which covers our full sample period. For each crop, we create a yearly measure of commodity prices by taking the average price within the year. In some cases, there may be a single price that matches to multiple crops. For example, the price of tea is assigned to both “indian tea” and “yerba mate.” Hence, we consolidate several agricultural crops to match prices, and drop the cases where we cannot establish a match between crops and commodities. We standardize all units of measure to US dollars per ton. In the final dataset, we have 17 different commodities present in Brazil which are traded on the international commodity markets. We list the distribution of these agricultural commodities across municipalities in Table A.1.

4. Empirical Strategy

We aim to study the entrepreneurial response to new local opportunities generated by fluctuations in local income. Simply running regressions of new firm creation on local income, however, is confounded by reverse causality concerns. In particular, the main identification threat to our primary individual-level analysis is that unobserved shocks to the investment opportunities of specific sets of individuals could mechanically affect local income. For example, the introduction of local government programs providing start-up incentives to the young would likely increase both the firm creation rate of the young as well as local income. To the extent that such programs are unobserved by the econometrician, regressions of firm creation on local income would reflect this reverse causality.

To address this issue, we create a measure that isolates exogenous changes in municipality-level local income over time. To do so, we identify fluctuations in the value of locally produced agricultural commodity crops, and thus also in the profitability of the local agricultural sector, by interacting the local agricultural endowment with movements in global commodity prices. Such commodity

price fluctuations are an important source of economic variability for emerging economies, as well as for developed economies rich with natural resources (Fernández et al., 2018; Allcott and Keniston, 2017). Moreover, as shown by Allcott and Keniston (2017) in the context of U.S. oil and gas booms and by Benguria et al. (2018) in the context of Brazil, such shocks do appear to increase local demand, leading to increased employment in the local non-tradable sector.

The agribusiness sector in Brazil is large, highly developed, and highly diversified. Different municipalities are endowed with different types of agricultural crops that they can grow locally. We calculate the local value of a crop in a given year as the product of the local crop quantity (Q) with its unit price (P) in international commodity markets. While international prices are likely exogenous to current municipality-specific economic conditions, quantities are less likely to be so. We therefore hold endowments fixed, prior to the start of our sample period, so as to remove the endogenous component in the fluctuations of commodity values.¹⁶ We construct a proxy for the local endowment by averaging production quantities in the five years preceding the beginning of our analysis sample, i.e. between 1993-1997.¹⁷ Specifically, let $Q_{kj,98}$ be our proxy for the regional endowment of crop k in municipality j , measured by the average production in the years 1993-1997. Let P_{kt} be the international price of crop k in year t . The annual Crops Index (CI) for municipality j in year t is the sum over all crops of time-invariant local agricultural endowments, multiplied by the respective time-varying international prices:

$$CI_{jt} = \sum_k Q_{kj,98} * P_{kt}. \quad (10)$$

The Crops Index can be viewed as an endowment-weighted average of total commodity values in affected municipalities. The endowment part of the formula, $Q_{kj,98}$, generates cross-sectional variation in the pre-existing exposure of different municipalities to different agricultural resources. International commodity price fluctuations generate time-series variation that is plausibly independent of shocks to local investment opportunities. Together, they provide a municipality-year varying series of exogenous demand shocks generated by the differential exposure of different municipalities to the changing global value of agricultural commodities. Our empirical strategy is inspired by the shift-share approach of Bartik (1991) and Blanchard and Katz (1992), which interacts local manufacturing shares with national trends in manufacturing employment to identify local income and demand shocks.¹⁸ A body of recent studies has used the framework of instrumental variables to formalize the identification assumptions underpinning the validity of shift-share research designs

¹⁶This approach is standard in the literature. See, for example, the discussions in Dube and Vargas (2013); Goldsmith-Pinkham et al. (2018); Jaeger et al. (2018).

¹⁷These historical endowments of agricultural crops are persistent due to the accumulation of local expertise and economic activity over long periods of time, and because of the physical characteristics of the regions such as climate and soil.

¹⁸This strategy has been widely adopted in the economics literature. See, for instance, Gallin (2004); Saks and Wozniak (2011); Diamond (2016), and Adelino et al. (2017).

(Goldsmith-Pinkham et al., 2018; Borusyak et al., 2018; Jaeger et al., 2018; Adão et al., 2018). Our approach fits well into the framework developed by Borusyak et al. (2018), who argue that shift-share designs provide causal estimates as long as the shocks themselves are exogenous to local economic conditions.¹⁹ Borusyak et al. (2018) further emphasize that panel-data settings, with several periods and a large number of shocks in which it is possible to flexibly control for both location and time fixed effects, are especially well suited for such empirical designs. This is precisely the case in our context, as we are able to exploit commodity shocks across thousands of municipalities and over a long time series.

The primary identification risk with this approach is that unobserved municipality level shocks in Brazil could impact global commodity prices, biasing the results. More specifically, since we can control for municipality by year fixed effects in our main analysis at the individual level, our identification would be threatened by *within*-municipality shocks that both increase entrepreneurial opportunities for a particular demographic, and also influence global commodity prices. As noted above, this concern is significantly mitigated by the fact that our analysis exploits shocks across thousands of local municipalities. We nonetheless directly address this general concern in Section 5.5.2, by dropping those municipalities which, in any year, ever constituted a significant share of the total global output in a specific commodity.

In our main municipality-level specifications, we examine the impact of changes in local endowment once municipality and year fixed effects are controlled for. To better understand such variation, we estimate the model:

$$\ln(CI_{jt}) = \alpha_j + \delta_t + u_{jt}, \quad (11)$$

including year and municipality fixed effects. For each municipality-year we define the shock as \hat{u}_{jt} , capturing deviations from municipality averages and aggregate variations over time. Figure A.1 in the Appendix illustrates the variation we observe in the value of municipal endowments of crops, as captured by this index. The thin grey lines provide the time series for a 10% random sample of municipalities in our sample. The other lines are median (solid line), 10th and 90th percentiles (dashed lines) of the distribution of residuals in each year. As the figure illustrates, there is both significant cross-sectional variation within a given year, and considerable time variation within a given municipality in the value of agriculture commodities.

For robustness purposes, we also build the variable Z_{jt}^X that equals one if \hat{u}_{jt} is in the top X^{th} percentile of its distribution, and equal to zero otherwise. We consider municipality j to be “treated” in year t if $Z_{jt}^X = 1$. Both at the municipality and individual level, the results are robust to the use of alternative binary versions of the shock that rely on different thresholds (e.g. top 10th percentile,

¹⁹While sufficient for identification, the exogeneity of the cross-sectional distribution of commodity shares across locations (Goldsmith-Pinkham et al., 2018) is not a necessary condition for the validity of the research design.

top 25th percentile, and so on). We further discuss these and other robustness tests in Section 5.5.2. Moreover, as we discuss in Section 6, we use the binary shock Z_{jt}^{10} to estimate the characteristics of the individuals who create new businesses in response to local demand shocks, and to compare these characteristics both to the average worker and the average new entrepreneur in the economy.

5. Municipality-Level Analysis

Motivated by the theoretical predictions of the model described in Section 2, we start by estimating the impact of global commodity price fluctuations on municipality level economic activity:

$$Y_{jt} = \alpha_j + \delta_t + \beta \ln(CI_{jt}) + \gamma X_{jt} + u_{jt}, \quad (12)$$

where Y_{jt} is the municipality-level outcome variable of interest, α_j are municipality fixed effects, δ_t are year fixed effects, $\ln(CI_{jt})$ is the (log) Crops Index we built as described earlier, and X_{jt} the control for log-population.

5.1. Local Employment and Firm Creation

The main results are presented in Table 2. We find that positive changes to the value of local crops generate higher employment, estimating an elasticity of employment to such changes of 0.21 (column 1). A 10% change in the value of local crops significantly increases the level of formal employment in the municipality by 2.1%. Once time invariant heterogeneity, aggregate fluctuations, and size differences across municipalities are accounted for by the controls in our specification, the residual standard deviation in log-employment is 0.38, and the residual standard deviation in the Crops Index is 0.13. Hence, a one standard deviation in the Crops Index increases log-employment by 3%.²⁰ In Table A.2 in the Appendix, consistent with the model of Section 2, we find that part of the increase in employment is driven by both migration to the municipality from other regions, as well as entry of new individuals into the labor force.

In column 2 of Table 2, we find that the increase in local employment translates into a highly significant increase in total local income, as measured by aggregate payroll across all local firms. In this case the elasticity is 0.22, suggesting an almost one-for-one relationship between the increase in employment and the increase in local income. Thus the shock is consistent with being a local demand shock.²¹

²⁰This 3% increase is equivalent to 7% of the log-employment residual standard deviation. Specifically we first regress each variable (log-employment and log-Crop Index) on time and municipality fixed effects and log-population. Then we compute the standard deviation of the residuals. Such residual standard deviation equals 0.126 for the Crop index and 0.382 for the log-population. Thus we get $0.126 * 0.206 / 0.382 \approx 0.068 \approx 7\%$.

²¹Figure A.2 shows the relationship between the crops index and the local income once population, year and municipality fixed effects are controlled for. The figure illustrates that residual fluctuations in commodity prices are excellent predictors of fluctuations in local income.

As in the model in Section 2, higher levels of local income suggest that new profit opportunities become available to be exploited by potential entrepreneurs, particularly in those sectors which are highly dependent on local demand conditions. We see that the commodity price shock does indeed lead to an increase in the total number of local firms. As reported in column 3 of Table 2, there is a statistically significant increase in the number of local firms following the shock. This increase is primarily driven by the creation of new firms, rather than a higher likelihood of survival of existing firms, which instead seems unaffected given the small and statistically insignificant effect on firm closures (column 4). Note here and in Section 6, we are running reduced form regression equations of new firm creation directly on the crop index. In Section 5.5.2.1 and Section 7 we discuss, and provide evidence for, the exclusion restrictions justifying a structural interpretation of firm creation in response to a local demand shock. In Section 7, we further use our reduced-form results to recover structural parameters governing the firm creation response to local demand shocks by demographic category.

Table 3 illustrates the impact of the shock by economic sector, which we categorize using the Brazilian CNAE industry codes into Agriculture and Mining (column 1), Manufacturing (column 2), and Non-tradable and Services (column 3).²² Panel A focuses on employment, and shows a statistically significant increase in employment levels in all sectors. As illustrated in column 1, this finding is consistent with rising commodity prices having a positive direct effect (elasticity of 0.35) on the sector responsible for the production of these commodities (Agriculture and Mining). Moreover, the evidence points to the presence of positive spillover effects to other sectors, as illustrated for example by the 0.18 elasticity estimated for employment in Non-tradable and Services, and a smaller elasticity estimated for manufacturing (0.09). When studying the aggregate sectoral impact on number of firms, in Panel B, we find that the the non-tradable/services sector (column 3) shows the largest responsiveness.²³

Our aggregate results emphasize the importance of entrepreneurship and firm entry for the dynamics of local economic activity. While these results are consistent with the technology in the non-tradable sector having a lower efficient scale than in other sectors, these findings are also consistent with the model presented in Section 2, in which shocks to the commodity sector increase local employment and local income, subsequently leading to a strong entrepreneurial response in the local non-tradable/services sector. Our findings are also consistent with [Adelino et al. \(2017\)](#), who study the U.S. and similarly find that local income shocks lead to a significant response by new firms in the non-tradable sector. Altogether, these findings provide a preliminary step towards our

²²In particular, we start from the classification used by [Dix-Carneiro \(2014\)](#), but combine High and Low Tech Manufacturing into Manufacturing, and Construction and Trade into Non-tradable. We drop Transportation/Utilities/Communications from the analysis.

²³The result that the vast majority of new firm creation is in the non-tradable sector in response to a shock could also be a function of the technology in the non-tradable sector having a lower efficient scale than the technology in the tradable sector, making firm entry in the former sector more responsive to shocks than firm entry in the latter.

main analysis, in which we study the individual entrepreneurs who account for the firm creation response.

Finally, we also explore the characteristics of the newly created firms following the shock. This test aims to understand whether these new firms may be short-lived, therefore contributing little to long-run employment creation, relative to the average new firms in the economy. We explore these concerns in Table 4. We construct a dataset at the firm-level covering all firms in the economy at their year of entry. We then estimate a specification where the dependent variable is an indicator (scaled by 1,000) for whether the firm survives for at least 1, 2, 3, and 5 years.²⁴

We find that, if anything, firms created in response to the local demand shock are (slightly) more likely to survive after 2, 3 and 5 years. While survivorship just proxies for firm success, these results provide suggestive evidence that new firms created in response to local demand shocks play an important role in driving the persistence and propagation of aggregate economic fluctuations. These results are consistent with Sedláček and Sterk (2017), who find that firm success is influenced by aggregate conditions at the time of entry.

5.2. Robustness

In this subsection, we describe additional tests to provide empirical support for the exclusion restrictions, probe the robustness of the results to alternative definitions of the shock, and provide further characterization of the main aggregate effects. All tests are reported in the Appendix.

5.2.1. Influencing Global Commodity Prices

The key endogeneity concern with structurally interpreting the empirical results as a response to a local demand shock is that the local agricultural sector could be sufficiently large relative to global production so as to potentially influence international prices. In that case, unobserved municipality-level shocks impacting local firm creation, such as government incentive schemes, might also impact global commodity prices and thus bias the results. Indeed, Brazil is a leading global player in the production of crops, accounting for more than 10% of world’s exports for some of them (e.g., sugar cane, coffee, soybeans, yerba mate, tobacco). Nevertheless, it is useful to note that our analysis is at the municipality level, rather than at the national level. Therefore, the concern is that *municipality*-level shocks could affect *global* commodity prices. To add an even further layer of complexity, our analysis in Section 6 also relies on individual-level variation *within* municipalities, making the identification threat even more nuanced. There, the concern arises from potential shocks in one of more than five thousand municipalities, increasing firm creation opportunities for specific

²⁴The precise specification is:

$$S_{fjt} = \alpha_j + \delta_t + \beta \ln(CI_{jt}) + u_{fjt},$$

where α_j are municipality fixed effects, δ_t are year of entry fixed effects, and $\ln(CI_{jt})$ is the (log) Crops Index. Standard errors are clustered at the municipality level.

segments of the local population, while also impacting the prices of commodities traded on world markets.

To test the robustness of our results and evaluate the plausibility of this channel, we re-estimate the main specifications, dropping municipalities with high levels of production of specific crops, which may be able to affect global commodity prices. In particular, we complement our municipality-level data with data from the United Nations Food and Agriculture Organization (FAO) to compute the share of world production of municipalities across different crops. Panel A of Table A.3 in the Appendix reports the results after dropping 64 municipalities that have ever produced, in any given year, 1% or more of the world production of any commodity in the period 1996-2015. In Panel B we report even more conservative results, obtained after dropping 167 municipalities with at least a 0.5% share of world production at some point in our sample. The results remain largely unaffected.

5.2.2. *Alternative Definitions of the Shock*

Table A.4 in the Appendix reports the main estimation results when we vary our definition of the shock using the dummies defined in Section 4. The first four rows estimate the effects of variation in the Crop Index of different intensity. We find that all of the main findings continue to hold when we focus on these measures, and that the effects move monotonically with the changes in local commodity prices.

Interestingly, comparing the effects estimated from positive and negative changes in endowment indicate that the effects on local economic outcomes are mostly symmetric. For instance, as reported in the third row of Table A.4, when defining a negative endowment shock to be in the bottom 10% of the distribution of \hat{u}_{jt} in equation 11 (a particularly negative shock), we find a 6.5% decline in local employment and a 6.8% decline in local income. When defining the shock to be in the top 10% of the distribution (a particularly positive shock), we find a 6.9% increase in local employment and a 7.8% increase in local income. We find a similar symmetric response in terms of number of firms, as well as when we focus on shocks in the top and bottom 25th percentiles. These results illustrate that our findings are not driven by the choice of using a log-log specification and provide evidence for only weak non-linearities in the effects of the shock.

5.2.3. *Persistence of Treatment Effects*

Finally, we explore the persistence of the effects generated by the local endowment shocks. We find that the response of new firm creation, and economic activity more generally, to local economic shocks is persistent but decreases gradually over time. Table A.5 reports our main results for different *lagged* definitions of the treatment variable. While the response is strongest in the year of the shock, local economic activity continues to respond positively one to four years after the commodity endowment shocks, gradually declining over time.

5.2.4. *The Informal Sector*

The analysis up until this point has focused exclusively on firm creation responses in the formal sector. In many emerging countries, including Brazil, a significant share of economic activity occurs in the informal sector (Ulyssea, 2018). This raises the question of whether the informal sector is also important in driving the entrepreneurial response we observe, which is challenging to test due to the obvious limitations of measuring informality. To address this issue, we utilize an alternative data source, namely the Brazilian National Household survey (PNAD), which is an annual survey representative at the national level. This survey aims to capture various labor market statistics and, importantly, contains information on both formal and informal firms and workers. As a result, the survey allows us to study the responsiveness to local commodity price shocks of both the formal and informal sectors. Since the survey is at the state-level, counts of formal and informal employers and employees are assigned to municipalities based on population shares in the state.²⁵

Table A.6 reports the elasticity of the number of formal and informal firms and employees to the local demand shock. In column 1, we find that the number of firms in the formal sector is highly responsive to local demand shocks, with an elasticity equal to 7.3%. The effect is highly statistically significant. In contrast, in column 2, when we explore how the number of firms in the informal sector changes, we find that the coefficient is statistically insignificant and of extremely small magnitude, equal to -0.1%. In columns 3 and 4, we explore the elasticity of number of workers (including self-employed). Again, we find a highly statistically significant elasticity in the formal sector equal to 4%. In contrast, we find no response in the informal sector, with the elasticity statistically insignificant and close to zero.

5.2.5. *Outlier Municipalities*

The distribution of the value of commodity production relative to local income is quite skewed, as shown in Panel B of Table 1. We therefore test the robustness of our main results to the exclusion of municipalities in the far right tails of this distribution. These tests are reported in Tables A.7 and A.8, where we show that our results are largely similar in both magnitude and statistical significance after removing municipalities in the top 5% and 1%, respectively.

6. Individual-Level Analysis

The model in Section 2 highlights the importance of individual heterogeneity in driving the magnitude of the entrepreneurial responsiveness to economic shocks. Motivated by this theory, we now

²⁵This assumption may impose measurement error that may lead to a downward bias of our estimated elasticities. As long as the bias similarly affects the formal and informal samples, it will allow us to explore the relative importance of the two sectors to firm creation in response to the local income shocks.

move to our primary empirical analysis and attempt to identify the key characteristics of those individuals who respond to local demand shocks by creating new firms. We conduct this analysis at the individual, rather than municipality, level so as to fully exploit the richness of our micro data and run regressions with batteries of demographic controls, which is not feasible with the municipality-level analysis.

We model the decision to start a business using a binary choice linear probability model. Let the binary indicator variable T_{ijt} denote the decision in year t of an individual i in municipality j to become an entrepreneur, as defined in Section 3.²⁶ Analogous to the previous analysis, we again let $\ln(CI_{jt})$ denote an exogenous increase in local demand in municipality j , as proxied for by the local agricultural endowment index described earlier. We estimate the following linear probability model:

$$T_{ijt} = \alpha_j + \delta_t + \beta \cdot \ln(CI_{jt}) + \gamma X_{ijt} + \varepsilon_{ijt}, \quad (13)$$

where α_j denotes municipality fixed effects, and δ_t denotes year fixed effects. Here, β captures the direct effect of the local endowment shock on the individual’s choice to form a new firm, and X_{ijt} controls for individual-specific characteristics.²⁷ Standard errors are clustered at the municipality level. Importantly, in this analysis, we focus on individuals who are already working in the municipality, rather than individuals who migrate from elsewhere, so as to cleanly identify the individuals who experience the change in local demand and investment opportunities. That is, consistent with our theoretical framework, we focus on the individual decisions of local wage workers to switch to entrepreneurship.

Motivated by prior work on the importance of lifecycle considerations for entrepreneurial choice, we begin our analysis by studying heterogeneity in entrepreneurial responsiveness by age.²⁸ We then study how the presence of various skills, such as those acquired through both education and prior employment, impacts the decision of whether to start a firm in the face of new economic opportunities. In both cases, we additionally examine whether the “responsive” entrepreneurs of our study, namely those responding to changing market conditions, differ in meaningful ways from the average new entrepreneur. The procedure for doing this, which hinges on simple econometric insights and is described Section A.2 in the Appendix, allows us to characterize and compare the unique distributional features of both populations precisely.

²⁶The dependent variable T_{ijt} is a dummy that takes value 1 for individual i working in firm j if i is the top paid individual in the firm, and firm j is observed for the first time in year t . We multiply the variable by 1,000, to ease the interpretation of the coefficients.

²⁷We sequentially add various individual-specific controls to the empirical specifications. These include education dummies equal to 1 if the individual has a high-school diploma or higher, occupation dummies equal to 1 if the previous occupation is in a white collar position, a control for the skill level required in the job (i.e., non-routine cognitive occupations versus others), and a variable ranking individual experience within the firm. Finally, we also control for the rank of the individual within the income distribution in a given municipality.

²⁸See [Parker \(2018\)](#) for a comprehensive survey of the literature on factors that determine individual transitions to entrepreneurship.

6.1. The Firm Creation Response by Age

Table 5 illustrates that young individuals are more likely to become entrepreneurs when there is a shock to the value of the local agricultural endowment. Column 1 shows the simple entrepreneurial responsiveness to the shock, controlling only for year and municipality fixed effects. A one-standard-deviation (13%) positive change to the Index increases the probability of becoming an entrepreneur by 0.032 out of 1,000. This corresponds to a 1.1% increase in entrepreneurial activity compared to the average flow of entrepreneurs (2.91 out of 1,000, as per Table 1). In column 2, we add an interaction term between the treatment variable and the Young indicator, which is equal to 1 in the bottom quartile of the age distribution.²⁹ Young individuals exhibit a striking responsiveness, more than three times as large than that of the rest of the population.³⁰ In columns 3-5, we sequentially add individual controls, which we discuss below. A more stringent specification is presented in column 6, where we control for municipality-by-year fixed effects, effectively comparing individuals subject to exactly the same municipality-year shock, but who differ in age. The resulting coefficient, albeit smaller than in the previous specifications, remains positive and strongly statistically significant. The inclusion of such fixed effects addresses a number of standard Bartik concerns by controlling for any municipality-wide increase in entrepreneurial opportunities shared across all demographics.

We next compare the distributional characteristics by age of the responsive entrepreneurs to the average new entrepreneurs in the population, and show that the former are indeed different than the latter. To perform this exercise, we adopt a modified version of the econometric framework outlined earlier, by relying on a binary rather than a continuous shock, and where we estimate the following specification:

$$T_{ijt} = \alpha_j + \delta_t + \beta \cdot Z_{jt} + \gamma X_{ijt} + \varepsilon_{ijt}, \quad (14)$$

where α_j denotes municipality fixed effects, δ_t denotes year fixed effects and Z_{jt} is an indicator variable that equals 1 if the residual \hat{u}_{jt} from equation 11 falls in the top 10 percent of the distribution. Here, β captures the direct effect of the local endowment shock on the individual's choice to form a new firm, and X_{ijt} controls for individual-specific characteristics. Figure 2 shows that using a binary shock does not affect our main finding: it is young individuals – those in the bottom quartile of the age distribution – who respond strongly to the shock.³¹ Following the procedure described

²⁹We also interact municipality fixed effects with the Young indicator to allow greater flexibility in capturing unobserved characteristics.

³⁰Specifically, the magnitude is obtained as: $\frac{0.151+0.353}{0.151} \approx 3.337$.

³¹The figure reports the increase in entrepreneurial rates in response to the shock, estimated with model (14), for different age quartiles. The 25th percentile of the age distribution in the analysis sample is 27, the median is 34, and the 75th percentile is 43. As discussed earlier, the sample is restricted to individuals between 18 and 65 years old. Our main results of Table 5 are robust to various binary treatment definitions, not just the shock in the top 10th percentile. In Appendix Table A.9, we explore positive and negative economic shocks separately, defining a municipality to be subject to a positive (negative) shock if the residual \hat{u}_{jt} from equation 11 falls in the top (bottom) 10th or 25th percentile of the commodity price change distribution within a municipality. These results illustrate that young individuals are particularly responsive to changes in local opportunities, both when such opportunities arise and when they decline.

in Appendix Section A.2, which relies on the binary shock, we find that the average individual who starts a business tends to be younger relative to the overall population, but that this feature is significantly more pronounced among responsive entrepreneurs.³² As Figure 3 illustrates, roughly 40 percent of individuals who start a new business are in the bottom quartile of the age distribution. However, more than 60 percent of entrepreneurs who respond to the demand shocks are in this same quartile of age. Figure 3 shows that the entire age distribution of the responsive entrepreneurs is tilted towards younger demographics, when compared to the average new entrepreneur in the economy.

6.2. *Lifecycle Considerations*

The disproportionate response of the young to new entrepreneurial opportunities is perhaps surprising. First, according to standard models such as Lucas (1978), ability is the relevant dimension along which individuals sort into entrepreneurship. In this type of model, to the extent that ability is an innate characteristic, the age profile of the population does not matter per se. On the other hand, individuals may accumulate general business and managerial skills over time, and to the extent that such skills are necessary to take advantage of changes in local opportunities, one might have expected older individuals to be more responsive (Lazear, 2005; Evans and Leighton, 1989). Similarly, to the extent that financing constraints affect the ability to start a new business, we may once again have expected that older individuals would be more responsive to new opportunities, having had more time to develop the necessary personal wealth (Quadrini, 1999).

Instead, we find that it is the young who generate, almost entirely, the firm creation response. Existing studies have proposed a variety of lifecycle mechanisms that could potentially explain why the young may be more able and willing to respond to new economic opportunities. For example, young individuals may have a greater tolerance for risk or an overall higher degree of flexibility in their personal and family circumstances, thus allowing them to seize opportunities quickly as they arise.³³

Of course, it is difficult to say with certainty that the higher responsiveness of the young is driven purely by lifecycle considerations. For instance, our results could potentially reflect other characteristics influencing the entrepreneurial response, but which are themselves correlated with age. While it is admittedly challenging to identify precisely the mechanism underlying the disproportionate

³²The calculation of the age distribution of the “responsive” entrepreneurs is described in detail in Section A.2 in the Appendix. Intuitively, the methodology uses Bayes’ Rule to show that the proportion of responsive entrepreneurs that are young, divided by the fraction of the total population that is young, is equal to the firm creation response of the young, divided by the overall firm creation response. Since the distributional age characteristics of the overall population can be calculated, this relationship allows the distributional age characteristics of the responsive entrepreneurs population to be determined as well.

³³See, for example, Miller 1984a; Reynolds and White 1997; Delmar and Davidsson 2000; Uusitalo 2001; Arenius and Minniti 2005; Rotefoss and Kolvereid 2005; Wagner 2006; Levesque and Minniti 2006; Bergmann and Sternberg 2007.

response of the young, we attempt to shed light on the importance of lifecycle considerations by relying on the highly granular individual-level data available in our setting.

Specifically, we show that when gradually adding a battery of individual-level characteristics, the estimates of the entrepreneurial responsiveness of the young remain essentially unchanged. For example, in column 3 of Table 5, we add controls for educational achievement, including indicator variables for whether the individual has a high school diploma, or postsecondary education. In column 4, we additionally control for the occupational characteristics of the previous job (e.g., whether she was a white collar worker, or was working in an occupation requiring non-routine cognitive skills), as well as years of experience within the firm. Finally, in column 5, we also control for the wage in the previous job. Remarkably, including all these additional controls has essentially no impact on the estimated effect of age. Even when adding these controls to the specification with municipality by year fixed effects, in column 7, the estimates remain mostly unchanged relative to column 6. In sum, this evidence strongly suggests that lifecycle-specific features, such as individual risk aversion and flexibility, are important driving forces in our results on age. For instance, column 5 rules out an alternative explanation in which younger individuals earn lower wages, and it is this lower outside option that is truly driving the disproportionate firm creation response. Overall, our results are consistent with the notion that the ability to respond quickly to new economic opportunities depends crucially on traits disproportionately possessed by the young, such as flexibility, and tolerance of risk.

An important final consideration is that the results may be mechanically driven by compositional changes in the set of potential entrepreneurs that occur over time: older individuals may appear to be less responsive to changes in local opportunities simply because they have already responded to previous opportunities by starting a business. To explore whether this can explain our findings, we directly control for past entrepreneurial experience. Specifically, we add an indicator variable that equals 1 if the individual was ever a founder in the past. The results are reported in Table A.10. We first find that the coefficients on past-entrepreneur are positively correlated with the likelihood to become an entrepreneur, and the effects are statistically significant. This immediately goes against the attrition story, since it relies on older individuals who have already started a business being less likely to respond. Table A.11 further shows that, even when comparing young and old individuals of similar past entrepreneurial experience, the point estimates of the young interaction term remain largely unchanged when compared to Table 5. This strongly suggests that having been an entrepreneur in the past is not driving the relative increased responsiveness of the young.³⁴

³⁴In Panel B of Table A.10 we add an indicator variable that equals 1 if the individual was an entrepreneur in the past 5 years. The results are robust to this specification as well.

6.3. *Do Skill and Experience Matter?*

So far we have illustrated that young individuals are disproportionately more likely to start a business in response to local economic shocks. In this section, we show that age in itself is not sufficient to account for the firm creation response. Motivated by a large literature on the nature of entrepreneurs, we show that skills also strongly affect an individual’s entrepreneurial responsiveness to local economic opportunities (e.g., [Evans and Leighton \(1989\)](#) and [Lazear \(2004\)](#), among others). To show this, we explore heterogeneity in the firm creation response *within* the population of young individuals, focusing on several proxies for an individual’s skill set.

Panel A of Table 6 shows that skill and experience are significant determinants of individual responsiveness within the population of young individuals. We estimate the main specification in equation (13) across various sample splits, including year and municipality fixed effects. The aim is to characterize skilled versus unskilled individuals within the young population. First, in columns 1 and 2, we split the population based on the level of education. In column 1, we focus on individuals who have at least a high school diploma. We find that within this population, individuals are highly responsive to the economic shock by forming new ventures, and the effect is highly statistically significant. A 10% increase in the Crops Index increases the likelihood of starting a firm by 0.106 in 1,000 in this group, approximately a 3% increase from the baseline flow of 2.9. Moreover, when we focus on individuals with less than high school education (column 2), we find that this population is not responsive, with the estimate close to zero and insignificant.

In columns 3 and 4, we characterize the skill sets of individuals based on information regarding their previous occupation. We find that individuals who were previously working in occupations that required non-routine cognitive skills are significantly more responsive than others to the rise of local opportunities. Recall that these occupations are those that require creativity and problem-solving and involve tasks related to communication, negotiation, and management. The effects for this subpopulation, documented in column 3, are particularly large, with the estimated elasticity equal to 1.53 and statistically significant at the 1% level. A 10% shock implies an increase in the likelihood of starting a firm of about 0.15, reflecting an increase of 5% relative to the average flow into entrepreneurship. In contrast, the responsiveness to the economic shock in the remaining subpopulation, as shown in column 4, is significantly lower with a coefficient of 0.615, although still statistically significant at the 5% level.

Given these findings, it is natural to ask whether individuals sort into these occupations because they possess these skills, or whether individuals acquire relevant entrepreneurial skills by working in such occupations over time. That is, does experience matter? We test this in columns 5 and 6 by splitting young individuals (within the same firm), above and below the median of number of years of experience. We find that more experienced young individuals are almost four times more responsive than those with less experience. In column 5, the coefficient is equal to 1.26 and it is

highly statistically significant, in contrast to less experienced individuals, for whom we estimate a statistically insignificant coefficient of 0.332. These results are consistent with Lazear (2004) and other empirical studies emphasizing the importance of ability and acquired skills for entrepreneurial responsiveness.³⁵

In Panel B of Table 6 we repeat the analysis for older individuals, by excluding all individuals in the bottom quartile of the age distribution. Strikingly, but conceptually in line with our previous results, we find that there is no statistically significant heterogeneous response when we perform the analogous analysis for older individuals. That is, within individuals in the top three quartiles of the age distribution, we do not find that higher skill levels increase entrepreneurial responsiveness to local economic shocks, in contrast to our findings with respect to the younger population. This result provides further strong support for the joint importance of lifecycle considerations, together with experience and skills, in allowing individuals to form new businesses in response to rapid changes in local opportunities.

Finally, as we did when studying age, we show that the “responsive” entrepreneurs differ in significant and meaningful ways, based on skill characteristics, from the average new entrepreneur. Again, to perform this exercise we modify our main specification to estimate the effects of a binary version of the shock in the different sample split. As our model illustrated, depending on the strength of various forces, one might expect the entrepreneurs driving firm entry to be of higher or lower skill than the average. Our results are shown in Figure 4, focusing on young individuals only.³⁶ We first note that the average young entrepreneur is, in fact, quite similar to the average young individual in the population. While the average young entrepreneur is slightly more educated, she has similar levels of general business, communication, and managerial skills compared to the average individual in the population, as measured by working in occupations that require cognitive non-routine skills, and she is only slightly more experienced. In contrast, all of these traits are significantly more pronounced among those entrepreneurs who specifically create new firms in response to the local demand shocks. For example, while only 18% of all entrepreneurs in the population worked previously in occupations that we classify as non-routine cognitive, almost 50% of the responsive entrepreneurs have done so. Similar findings apply to individual experience. We find that almost 80% of the responsive entrepreneurs have above_ median work experience. In contrast, among all entrepreneurs in the population, this applies to only 62% of individuals.

In summary, within the young population, responsive entrepreneurs are more likely to be experienced and educated, and are more likely to have worked in occupations that require general business and managerial skills. However, skill in itself is not sufficient to enhance individuals’ entrepreneurial

³⁵To ensure correct inference on the heterogeneity, we re-estimate our main specification by interacting the shock with the characteristics capturing individual skills and experience. The results are reported in the appendix Table A.12, where we find that the differences across all sample splits are indeed statistically significant.

³⁶Section A.2 in the Appendix illustrates the calculation of the distribution of “responsive” entrepreneurs. The coefficients used to obtain the estimates are reported in Table A.13.

responsiveness, as we find that among the older population, the more skilled individuals still remain unresponsive. Our findings thus emphasize the joint importance of age, in addition to experience and skill, in driving an individual's ability and willingness to become an entrepreneur in response to exogenous economic shocks.

7. Structural Estimation and Counterfactuals

In this section, we structurally estimate the model presented in Section 2. This exercise will allow us to recover the dispersion parameters of the fixed costs associated with becoming an entrepreneur, defined as κ_j . This parameter influences the magnitude of the firm creation response across different demographics. We will use these estimates to construct counterfactuals that will allow us to study the impact of demographic changes on the entrepreneurial responsiveness of the local economy.

7.1. Identification

We follow a similar strategy to [Suárez Serrato and Zidar \(2016\)](#). In particular, indexing different municipalities by r , we estimate the following reduced-form system of equations:

$$\begin{bmatrix} \Delta \log Y_{r,t} \\ \Delta \log w_{r,t} \\ \Delta \log M_{r,t} \\ \Delta \log M_{j,r,t} \end{bmatrix} = \begin{bmatrix} \beta_Y \Delta \log P_{r,C,t} \\ \beta_w \Delta \log P_{r,C,t} \\ \beta_M \Delta \log P_{r,C,t} \\ \beta_{M_j} \Delta \log P_{r,C,t} \end{bmatrix} + \begin{bmatrix} \Delta \varepsilon_{Y,r,t} \\ \Delta \varepsilon_{w,r,t} \\ \Delta \varepsilon_{M,r,t} \\ \Delta \varepsilon_{M_j,r,t} \end{bmatrix}$$

The first equation measures the log change in local income in response to the commodity bundle price shock. The second equation measures the log change in wages. The third equation measures the log change in the number of nontradable firms, and the fourth equation measures the log change in the number of non-tradable firms run by an entrepreneur of demographic j .

Log differentiating equation (9), we find the elasticity of the number of entrepreneurs of demographic j with respect to P :

$$\frac{\partial \log M_j}{\partial \log P_C} \approx \left(\frac{\partial \log Y}{\partial \log P_C} - \frac{\partial \log M}{\partial \log P_C} - \frac{\partial \log w}{\partial \log P_C} \right) / \kappa_j \quad (15)$$

where we used equation (7) to express firm profits as a function of Y/M .³⁷ We can therefore identify

³⁷We have used the approximation that the baseline probability an individual chooses to be an entrepreneur $p_j \approx 0$, which is true in the data. If we do not make this approximation, the equation (16) actually identifies $\kappa_j / (1 - p_j)$. Whether one makes this approximation or not, none of the counterfactual results are impacted. See the Appendix for a full derivation of equation (16).

κ_j from the reduced-form coefficients as:

$$\kappa_j = \frac{\beta_Y - \beta_M - \beta_w}{\beta_{M_j}}, \quad (16)$$

using the estimated elasticities from above. Note that we can recover these structural parameters directly from the reduced-form estimates and no additional parameter restrictions are required.

7.2. Estimation Results and Robustness

We now turn to the structural estimation results. In the first two columns of Table 7, we break the population into young and old demographics and report κ_j . We find a structural dispersion parameter of 0.975 for the young and 1.95 for the old.³⁸ Consistent with our previous reduced-form results, we find that κ is substantially smaller for younger individuals than older individuals, indicating a much higher responsiveness to the shock. These values imply an elasticity of entrepreneurship to local demand, $d \log M_j / d \log L$, of .584 for the young and .292 for the old.³⁹ That is, a 10% increase in the size of the local population increases the number of young entrepreneurs by 5.84% and the number of old entrepreneurs by 2.92%. Aggregating, a 10% increase in the size of the local population increases the total number of entrepreneurs by 4.31%.

It is worthwhile to first discuss the implicit identification assumptions that were made to derive equation (16). In particular, as discussed previously in Section 2, we have assumed that there is no correlation between shocks to commodity prices $P_{C,t}$ and innovations in fixed costs $\bar{F}_{E,j,t}$. In words, we require that changes in the price of the local commodity bundle only impact a particular demographic's firm creation response through its effect on the local aggregate demand for non-tradable goods αY_t . If such price changes also led to changes in $\bar{F}_{E,j,t}$, we would have an endogeneity problem. Recognizing that $\bar{F}_{E,j,t}$ is a catch-all for the costs associated with starting a new business for a demographic category j , potential issues are, for example, that increases in the commodity bundle price disproportionately relax financing constraints for the young. Alternatively, it could be that the young are particularly well-suited to provide non-tradable services when commodity prices increase, for example, if the main beneficiaries from such changes are young individuals.

To investigate the latter concern, we study whether the increase in employment and income following the commodity price shock is concentrated among the young population. To do so, we re-estimate our main aggregate results, presented in Table 2, separately for different age segments within municipalities. The results are reported in Panels A and B in Table A.14. Interestingly, we

³⁸These numbers are derived from equation 16 using the point estimates from Table 2 (estimated on the common support), as well as the additional required coefficients which are estimated and reported in Table A.15. In other words, the estimates are obtained from specification 13, and specifically the coefficients $\beta_Y = 0.222$ and $\beta_M = 0.076$ as reported in Table 2 columns 2 and 3, and the coefficients $[\beta_w, \beta_{M_{young}}, \beta_{M_{old}}] = [0.017, 0.116, 0.067]$ as reported in Table A.15.

³⁹Recall that $d \log Y - d \log w = d \log L$.

find that the rise in both employment and income following the economic shock are in fact somewhat *less* concentrated among young individuals, relative to the older segment of the population. The elasticity of employment to the shock is lowest in the second age quartile (0.17) and highest in the third (0.21). Similarly, the income elasticity grows from 0.18 to 0.24 between the first and the third age quartiles, declining only slightly to 0.21 in the top quartile. This evidence seems to be inconsistent with the notion that this demand shock leads to changes mostly within the young population, which in turn would allow young entrepreneurs to be better positioned to take advantage of it.

An alternative concern is that the commodity shock itself acts as a financing shock alleviating financial constraints. For instance, the shock might raise local land and home prices, improving collateral values. Then, to the extent that young individuals are more financially constrained than the old, we might expect a larger firm creation response among the young. We believe, however, that such an explanation is quite unlikely in the context of Brazil, where financial instruments like home equity loans are close to non-existent during the sample period. Furthermore, since older individuals are more likely to be home owners, it is surprising that we find no response at all among the old to the shock. Moreover, we would expect the young to be more financially constrained because of other, more fundamental demographic traits, such as having lower income and lower wealth. Yet, as noted previously in Section 6.6.2, when we include a battery of demographic and career characteristics which likely proxy for the severity of individual financing constraints, including income, educational status, and white-collar status, the estimated effect of entrepreneurial responsiveness of the young remains entirely unchanged, suggesting that a relaxation of financing constraints is unlikely to be driving the results.

7.3. Counterfactuals

We finally use our structural estimates to investigate the impact of counterfactual local demographics. One of the significant demographic trends of the past fifty years has been towards aging populations. This trend is widespread, stemming from both declines in fertility rates and increased longevity. We thus use our structural framework to counterfactually study entrepreneurial responsiveness under alternative age compositions of the local population. To perform this counterfactual, in addition to our recovered κ_j structural parameters, we need values for the Cobb-Douglas share α , the CES elasticity of substitution σ , and the Cobb-Douglas labor shares γ for the commodity sector. As is standard in local urban studies, we calibrate these parameters from alternative sources. The values are reported in the final columns of Table 7. In our preferred calibration, we set $\alpha = .3$ from Suárez Serrato and Zidar (2016). We set $\sigma = 6$ from Bilbiie et al. (2012). Finally, we set $\gamma = .5$ from Benguria et al. (2018). We perform sensitivity analysis around these parameter choices.

We finally use our model to recover the elasticity of the commodity shock firm creation response

to the size of the young population, holding total population fixed. That is, since we are interested in compositional changes, we compensate any increase (decrease) in the young population with a commensurate decrease (increase) in the old population so as to keep the total population size fixed. We show how to compute this elasticity in Section A.3 of the appendix. In Figure 5, we report the percentage increase in the firm creation response due to a 10% increase in the size of the young population implied by this elasticity, as we vary the nontradable share α and CES elasticity of substitution σ .⁴⁰

The results are economically significant. At our preferred calibration, with $\alpha = .3$ and $\sigma = 6$, a 10% increase in the size of the young population, holding total population fixed, increases the firm creation response by 1.5%. As seen in Figure 5, the effects are larger for smaller values of σ and higher values of α . Such a combination implies that nontradable consumption is a large part of overall consumption and that goods in the nontradable sector are not very substitutable. Thus, as σ falls and α rises, consumers increasingly benefit from firm entry. Due to perfect mobility, this triggers greater in-migration to the local municipality, higher aggregate income, and even more firm entry. For example, with $\alpha = .5$ and $\sigma = 3$ a 10% increase in the young population increases the firm creation response by 2.5%.

These findings illustrate how aging populations may induce a significant lower entrepreneurial responsiveness to economic shocks. Since the firm entry response is higher in younger populations, this further implies that a greater share of the increase in nontradable output occurs on the extensive margin, there is a smaller increase in per-firm profits, and a larger decrease in the non-tradable aggregate price index. In particular, increasing the size of the young population by 10%, holding total population fixed, amplifies the nontradable price index decline by 1.5% and reduces the increase in firm profits by 1.1%. In the current framework, there is perfect mobility between municipalities, so the decrease in the nontradable price index is perfectly offset by falling wages due to an increase in the local population. However, under limited mobility, wages would not perfectly offset the larger decline in the nontradable index. Thus, under limited mobility, a larger firm creation response implies larger welfare benefits to the local population.

Finally, our reduced-form level results demonstrated that, in addition to age, education and skill also mattered for the entrepreneurial response. Just as we did for age alone, we can recover κ_j by age and education levels.⁴¹ Using those structural estimates, we find that if the increase in the young population occurs among the non-educated, the effect of the demographic change is muted by 32%, highlighting the importance of education to promote a more entrepreneurial and responsive economy.

⁴⁰If young workers constitute 25% of the population, then a 10% increase implies young workers will then constitute 27.5% of the population.

⁴¹The set of reduced-form results used for this structural estimation are unreported but available upon request.

8. Conclusion

In this paper, we examine the characteristics of the individuals who become entrepreneurs when local opportunities arise due to an increase in local demand. We use Brazil as our setting, which allows us to analyze rich individual-level longitudinal data for the entire formal sector. We identify plausibly exogenous shocks to local demand by interacting municipality-level historical production endowments of agricultural crops with contemporaneous changes in global commodity prices. These shocks lead to higher local employment and local income, and increased firm entry in the non-tradable sector.

In our main analysis, we explore the demographic and career characteristics of the individuals leading to the local entrepreneurial response and the creation of new firms. At the individual level, we find that the entrepreneurial response to local economic shocks is almost entirely concentrated among the young, consistent with the idea that early in the lifecycle, individuals have greater flexibility and risk tolerance. However, age alone is insufficient to explain the firm creation response. The most responsive individuals are not only young, but those who also have significant prior industry experience and who have acquired relevant skills through previous engagement in occupations involving nonroutine cognitive tasks.

Our findings have implications for economic dynamism in the long term due to secular demographic trends. One of the most profound demographic transitions of the past fifty years has been towards aging populations, stemming from both declines in fertility rates and increased longevity. We explore the implications of such changes by structurally estimating a two-sector model of a local economy. We find that lowering the proportion of young individuals in the local economy causes a significant decline in their entrepreneurial responsiveness to economic shocks. In fact, the model also suggests that this lower responsiveness could have meaningful ramifications for local welfare as well.

Our results emphasize the importance of age, skill, and experience in driving entrepreneurial responsiveness. While our results suggest that such trends might have contributed to the declining business dynamism observed in the United States in the last twenty years (Decker et al., 2014), unpacking all possible specific economic channels behind our reduced-form and structural evidence is challenging. For example, Liang et al. (2014) argue that, in older populations, young individuals might have a more difficult time moving up the job ladder into more managerial positions and acquiring skill. The difficulty of young individuals to acquire skills in aging populations may further limit the entrepreneurial responsiveness of the economy. While the direct investigation of these types of mechanisms is beyond the scope of this paper, such issues are likely to be central for an interesting future research agenda that could leverage new micro-data and institutional settings to explore in more details the determinants of the responsiveness of individuals, firms, and the broader economy to aggregate shocks.

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Figure 1

Spatial Distribution of Commodities

The map shows the cross sectional variation in the value of crop production relative to the GDP at the municipality level. Darker shades of blue indicate municipalities where crops are more relevant, according to a split by quintiles of the empirical distribution in 2000.

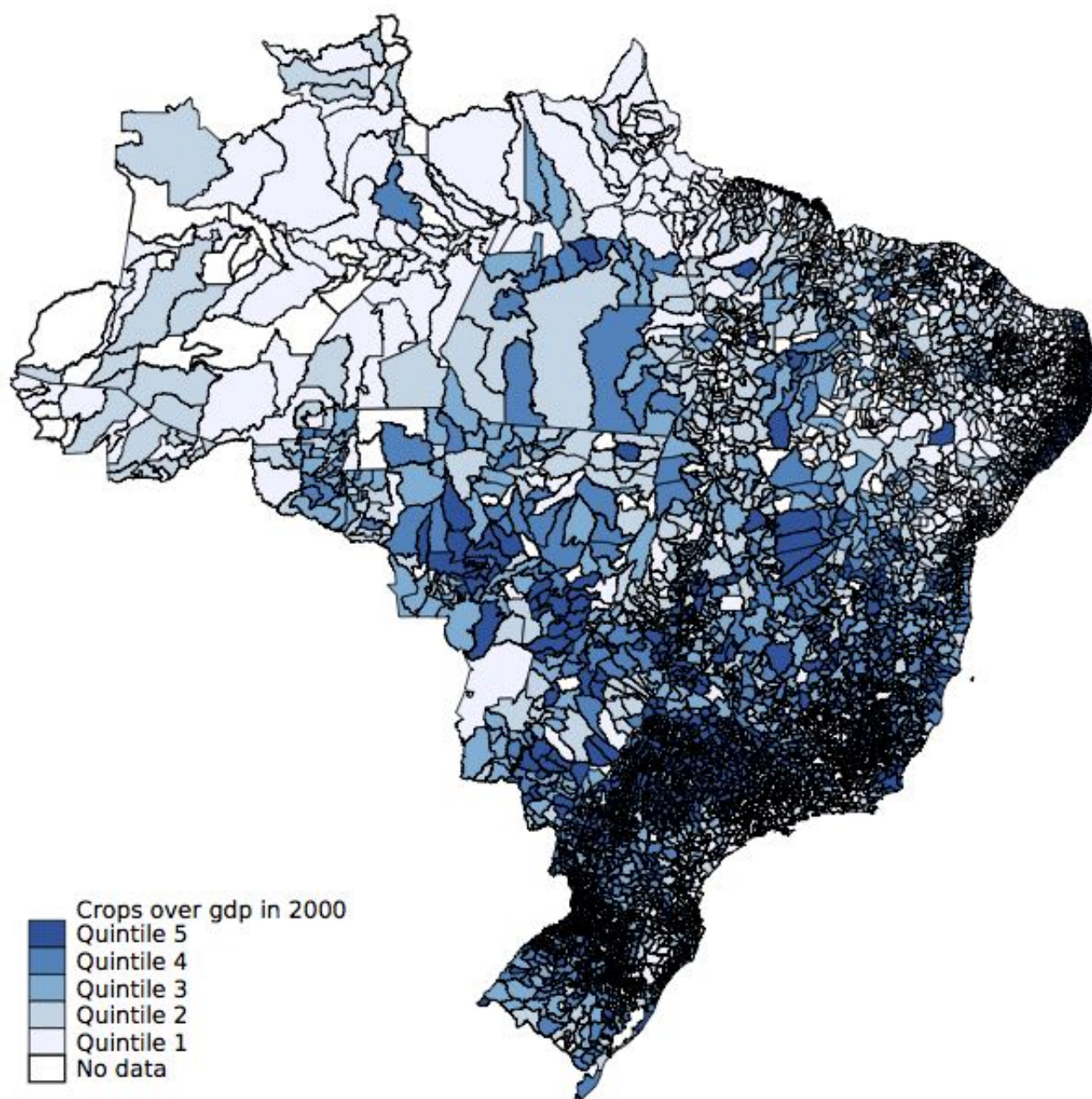


Figure 2
Entrepreneurial Response by Age Group

The coefficients reported in the graphs are estimates of β_n from the model $T_{ijnt} = \alpha_{nj} + \delta_{nt} + \beta_n \cdot Z_{jt} + \varepsilon_{ijnt}$, estimated on different age quartiles n . An observation in the model is an individual i , in age quartile n , municipality j , and year t . T_{ijnt} is an indicator for being a new entrepreneur. Z_{jt} is the commodity shock. Age quartiles are computed within the 10% analysis sample. The standard deviation bands are obtained from standard errors clustered at the municipality level. The magnitudes of the coefficients are in per-thousand points.

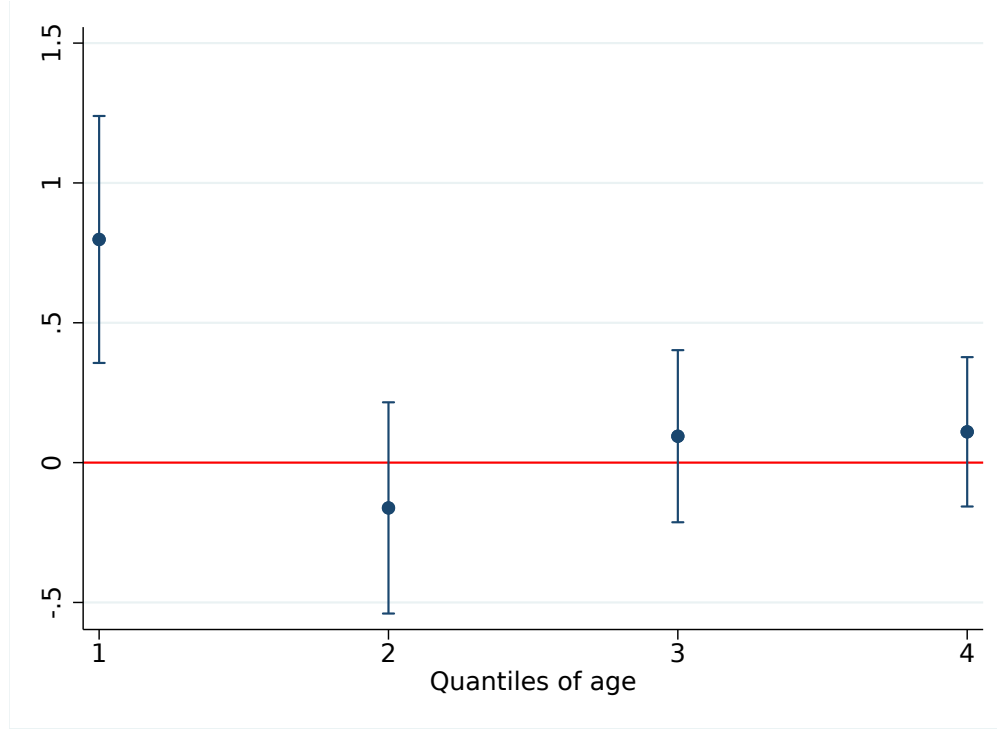


Figure 3

Comparison of Age Distribution

The graph reports the probability of being in each of the four different quartiles of the age distribution for individuals in the group of all workers (blue - population), in the group of individuals who start a new firm in a given year (red - entrepreneurs), and individuals in the group of entrepreneurs who start a firm in response to the commodity shock (green - responsive entrepreneurs). The age quartiles are computed within the 10% analysis sample. The probabilities for the whole population are 0.25 by construction. The probabilities for the group of new entrepreneurs are computed from the data as the share of new entrepreneurs in each age quartile. The probabilities for the group of responsive entrepreneurs are obtained starting from estimates of β_n from the model $T_{injt} = \alpha_{nj} + \delta_{nt} + \beta_n \cdot Z_{jt} + \varepsilon_{injt}$ estimated on the sample of individuals belonging to age quartile n (for $n \in \{1, 2, 3, 4\}$). An observation in the model is an individual i , in subsample n , municipality j , and year t . T_{injt} is an indicator for being a new entrepreneur, α and δ are municipality and time fixed effects, Z_{jt} is the commodity shock. Each probability is then computed as the ratio β_n/β (where β is the coefficient from the model above estimated on the whole population) multiplied by 0.25 (the probability of being in each quartile). More details are discussed in Section A.2 in the Appendix.

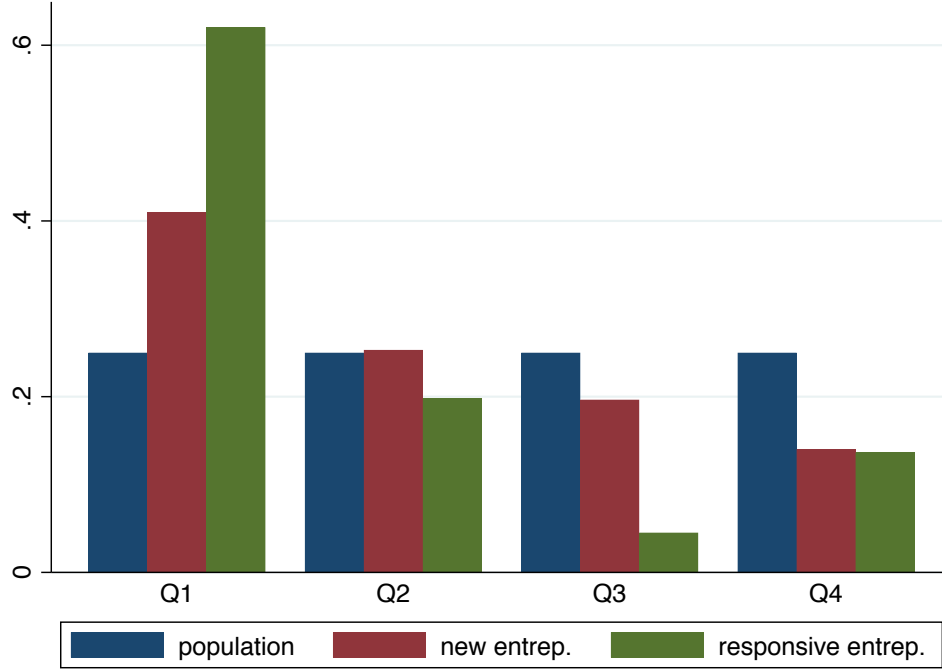


Figure 4

Comparison of Skill Distribution

The graph reports the conditional probability of having the characteristics reported on the y-axis, as discussed in the paper, for individuals in the group of all workers (blue - population), in the group individuals who start a new firm in a given year (red - entrepreneurs), and individuals in the group of entrepreneurs who start a firm in response to the commodity shock (green - responsive entrepreneurs). We focus on the set of “young” individuals only, i.e. in the bottom quartile of the age distribution in the analysis sample. The conditional probabilities are constructed analogously to Figure 3, and as discussed in Section A.2 in the Appendix.

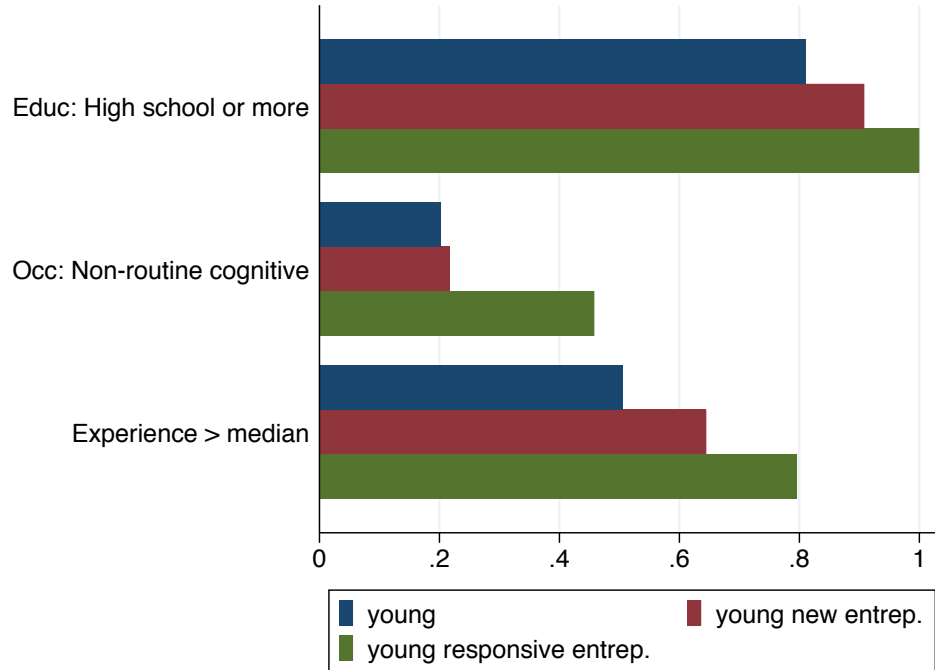


Figure 5
Counterfactual Firm Creation Responses

This figure reports counterfactual changes in the firm creation response to increases (decreases) in the share of the young population. These counterfactuals are generated according to our structural estimates, reported in Table 7.

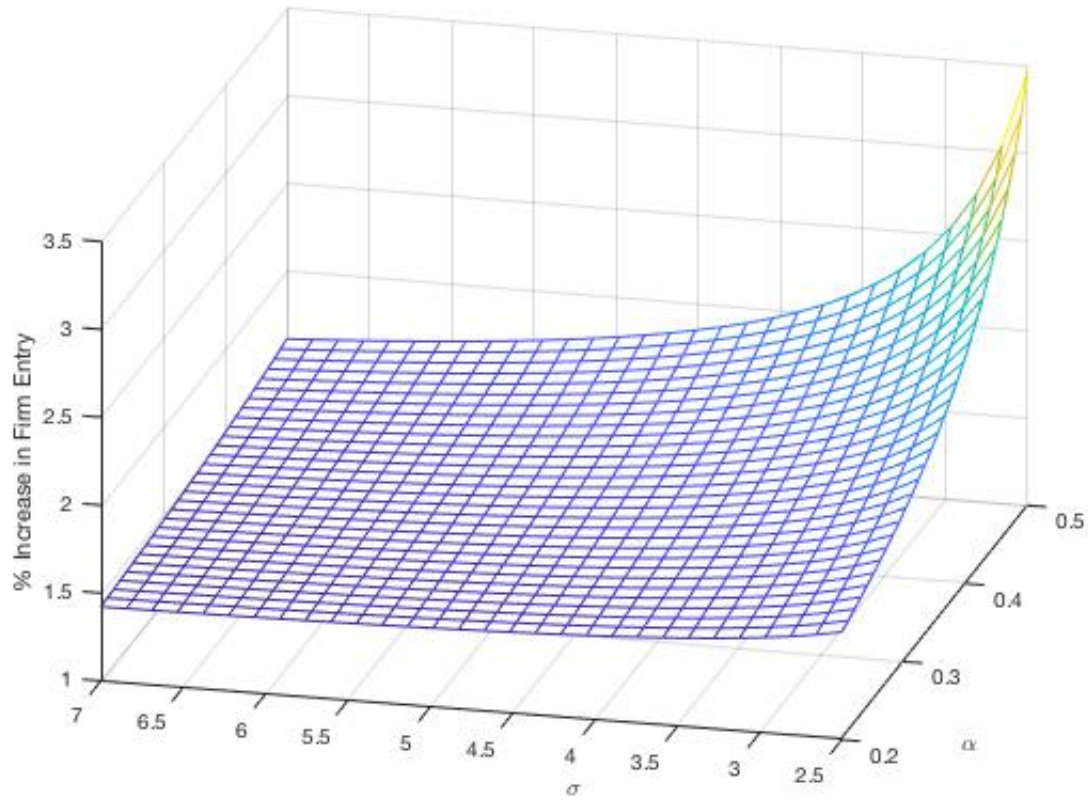


Table 1**Summary Statistics**

This table reports summary statistics on the main analysis samples, as described in Section 3. All averages from RAIS therefore refer to the period 1998-2014. Panel A describes the importance (as shares of firms, employees, and new firms) of each sector in the economy. Panel B describes municipality level data. Panel C describes individual level characteristics for all workers and founders, respectively.

A: Industry Composition - Annual Data (Shares)			
	Firms	Employees	New Firms
Agriculture/Mining	0.068	0.095	0.034
Manufacturing	0.130	0.235	0.116
Non-tradable	0.489	0.248	0.554
Transp./Utilities/Commodities	0.050	0.050	0.055
Services	0.263	0.372	0.242

B: Municipality Composition - Annual Data				
	Obs.	Mean	SD	Median
RAIS				
# Firms	82,463	274.9	761.1	64
# Employees	82,463	4214.5	13197.1	850
# New Firms	82,463	33.5	91.7	7
Other Data Sources				
Population	82,463	23680.8	45180.7	10676
GDP per capita (2000 US)	82,463	3093.8	3764.037	2217.473
Value of Commodities / GDP	5,443	1.2	3.7	0.156
Value of Commodities / Population	5,443	3038.7	10782.5	254.9

C: Individuals - Annual Data			
	Population		Founders
	Obs.	Mean	Mean
Founders of new firm (every 1000)	23,838,803	2.91	-
Males	23,838,803	61%	57%
Age	23,838,803	35.6	31.9
Blue collar worker	23,838,803	48%	40%
White collar worker	23,838,803	42%	50%
Manager	23,838,803	4%	4%
Education dummy: less than High School	23,838,803	32%	17%
Education dummy: High School	23,838,803	47%	64%
Education dummy: more than High School	23,838,803	21%	19%

Table 2**Aggregate Results**

This table reports the estimated effect of commodity price shocks on several municipality-level outcomes. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is $Y_{jt} = \alpha_j + \delta_t + \beta \ln(CI_{jt}) + \gamma X_{jt} + u_{jt}$, as described in Section 5. *Total Employment* is the total number of employees, *Total Income* is the sum of payroll across all firms, *Number of Firms* is the total number of firms, and *Number of Closures* is the total number of firms that exit. All dependent variables are in logs. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Total Employment	Total Income	Number Firms	Number Closures
Treatment	0.206*** (0.020)	0.222*** (0.021)	0.076*** (0.010)	-0.009 (0.017)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	80,902	80,902	80,902	66,090
Municipalities	5,442	5,442	5,442	5,358

Table 3**Aggregate Results by Sector**

This table reports the estimated effect of commodity price shocks on employment and number of firms at the municipality-level across three sectors of the economy (Agriculture and Mining, Manufacturing and Non-tradable/Services). The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is $Y_{jt} = \alpha_j + \delta_t + \beta \ln(CI_{jt}) + \gamma X_{jt} + u_{jt}$, as described in Section 5. *Total Employment* is the total number of employees in the relevant sector, and *Number of Firms* is the total number of firms in the relevant sector in the municipality. All dependent variables are in logs. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: By Sector - Employment

	(1)	(2)	(3)
	Agriculture Mining	Manufacturing	Non-tradable Services
Treatment	0.355*** (0.032)	0.091** (0.036)	0.182*** (0.021)
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	71,926	66,184	80,688
Municipalities	5,107	4,977	5,442

Panel B: By Sector - Number of Firms

	(1)	(2)	(3)
	Agriculture Mining	Manufacturing	Non-tradable Services
Treatment	0.036*** (0.006)	0.032*** (0.009)	0.090*** (0.010)
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	71,844	66,135	80,688
Municipalities	5,106	4,976	5,442

Table 4**New Firms - Ex-Post Outcomes**

This table reports the estimated effects of commodity price shocks on the survival probability of newly created firms. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is $S_{fjt} = \alpha_j + \delta_t + \beta \ln(CI_{jt}) + u_{fjt}$. The dependent variable is a variable that equals 1,000 if the new firm survived more than 1, 2, 3 or 5 years, respectively, and takes value 0 otherwise. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. All specifications include controls for year of entry dummies and municipality fixed effects, and f indicates a firm. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	<i>Survive</i> ≥ 1	<i>Survive</i> ≥ 2	<i>Survive</i> ≥ 3	<i>Survive</i> ≥ 5
Treatment	-.47 (2.56)	6.03* (3.45)	7.58** (3.6)	6.26* (3.47)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Survived every 1000	837	708	626	521
Observations	2,439,964	2,256,611	2,056,887	1,643,609
Municipalities	5,360	5,346	5,322	5,241

Table 5
Young Responsiveness

This table reports the estimated effect of commodity price shocks on the probability of becoming an entrepreneur. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The basic empirical specification (column 1) is $T_{ijt} = \alpha_j + \delta_t + \beta \cdot \ln CI_{jt} + \varepsilon_{ijt}$, as described in Section 6. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. Column 1 includes only municipality and year fixed effects. Columns 2, 3, 4, and 5 add different sets of fixed effects, and include an interaction term constructed as an indicator equal to 1 for individuals in the bottom quartile of the age distribution in the sample. *Sector* controls include dummies for seven different sectors referred to the job in year $t - 1$. *Education Controls* include a binary variable for high school diploma, and a dummy variable for above high school education. *Occupation Controls* include a binary variable that equals one if previous occupation is a white collar worker, a binary variable that equals one if previous occupation is defined as generalist, a control for the type of occupation (i.e., requires non-routine cognitive skills), and a control for experience within the firm. *Wage at Previous Job* control for the rank of the individual within the wage distribution in a municipality. Column 6 includes municipality-by-year fixed effects and Sector controls. Column 7 also includes *Education*, *Occupation* and *Wage at Previous Job* controls. The dependent variable, *Founder*, is an indicator equal to 1,000 if the individual has founded a firm in year t , and 0 otherwise. Variables are defined in Section 3. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Founder	Founder	Founder	Founder	Founder	Founder	Founder
Treatment	.251** (.0984)	.151 (.0968)	.0991 (.0966)	.116 (.0962)	.0128 (.1)		
Treatment X Young		.353** (.148)	.533*** (.149)	.517*** (.148)	1*** (.147)	.0659*** (.0121)	.0724*** (.0101)
Year	Y	Y	Y	Y	Y	N	N
Municipality	Y	N	N	N	N	N	N
Municipality X Young	N	Y	Y	Y	Y	N	N
Municipality X Year	N	N	N	N	N	Y	Y
Sector Controls	N	Y	Y	Y	Y	Y	Y
Education Controls	N	N	Y	Y	Y	N	Y
Occupation Controls	N	N	N	Y	Y	N	Y
Wage at previous job	N	N	N	N	Y	N	Y
Observations (mil)	23.8	23.6	23.6	23.6	23.6	23.8	23.6

Table 6
Heterogeneity Within Municipalities

This table reports the estimated effect of commodity price shocks on the probability of becoming an entrepreneur. Panel A explores individual responsiveness within the sample of young individuals in the bottom quartile of the age distribution. Panel B explores individual responsiveness within the sample of older individuals, in the top three quartiles of the age distribution. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. We estimate the main individual level specification, namely $T_{ijt} = \alpha_j + \delta_t + \beta \cdot \ln CI_{jt} + \varepsilon_{ijt}$, across various sample splits, with the aim of characterizing skilled versus unskilled individuals within the young population. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. The first two columns split the sample into individuals with high school or higher education (column 1) versus others (column 2). The second split is between individuals who engaged in non-routine cognitive occupations in $t - 1$ (column 3) versus others (column 4). The third split is between individuals with above (column 5) or below years of within-firm experience in the $t - 1$ and others (column 6). The dependent variable, *Founder*, is an indicator equal to 1000 in year t if the individual has founded a firm in year t , and 0 otherwise. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Young Individuals (Bottom Age Quartile)

	(1)	(2)	(3)	(4)	(5)	(6)
	Founder	Founder	Founder	Founder	Founder	Founder
Treatment	1.06*** (.269)	-.0849 (.309)	1.53*** (.482)	.615** (.245)	1.26*** (.36)	.332 (.24)
Partition	Education		Non-routine Cognitive		Experience	
Partition Criteria	>=HS	<HS	Yes	No	>median	<median
Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
Observations (mil)	5.342	1.248	1.334	5.256	3.331	3.259

Panel B: Older Individuals

	(1)	(2)	(3)	(4)	(5)	(6)
	Founder	Founder	Founder	Founder	Founder	Founder
Treatment	.0939 (.136)	-.0877 (.114)	-.0161 (.227)	.041 (.104)	.0416 (.143)	.00602 (.119)
Partition	Education		Non-routine Cognitive		Experience	
Partition Criteria	>=HS	<HS	Yes	No	>median	<median
Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
Observations (mil)	11.000	6.296	3.489	13.800	8.664	8.583

Table 7**Structural Parameters**

This table reports our estimated and calibrated structural parameters. The first two columns report the results of estimating equation (16), which recovers the structural dispersion parameters of the idiosyncratic fixed costs distribution for the young and old demographics respectively. The final four columns report our calibrated parameters. Respectively, these are the Cobb-Douglas nontradable share, the CES elasticity of substitution, and the Cobb-Douglas labor shares for the tradable and commodity sectors

κ_y	κ_o	α	σ	γ	ϕ
.975	1.95	.3	6	.5	.5

Appendix

A.1. Model Proofs

To motivate our empirical analysis, we construct a two-period, two-sector model of a local economy which combines the [Lucas \(1978\)](#) insights of entrepreneurial choice with a model of heterogeneous firms and firm entry. The model features exogenous profitability shocks to the local commodity sector in period 2. In the model, the local economy comprises two sectors, producing commodity goods and local non-tradable goods, indexed respectively by $j \in \{C, N\}$. The commodity sector provides a single homogenous good. The local non-tradable sector is comprised of a continuum of differentiated goods, indexed by varieties ω . The model is described in the paper in Section 2. In the propositions below, we study the effects of an exogenous increase in the price $P_{t,C}$ of the commodity good in period 2. We are particularly interested in the effects of such an increase on employment and the magnitude of the firm entry response in the non-tradable sector,.

Proof of Proposition 1

From equations (7) and (8), it is clear that:

$$\frac{d \ln \pi_{t,N}}{d \ln P_{t,C}} - \frac{d \ln w_t}{d \ln P_{t,C}} = \frac{d \ln l_{t,C}}{d \ln P_{t,C}}.$$

It is then easy to check from equation (9) that:

$$\frac{d \ln M_t}{d \ln P_{t,C}} = \Xi \frac{d \ln l_{t,C}}{d \ln P_{t,C}}.$$

for some constant $0 < \Xi < 1$. That is, a change in the commodity price will increase the number of entrepreneurs if it increases the number of workers in the commodity sector. By perfect mobility, we know that:

$$\begin{aligned} 0 &= \frac{d \ln w_t}{d \ln P_{t,C}} - \alpha \frac{d \ln P_{t,N}}{d \ln P_{t,C}} \\ &= (1 - \alpha) \frac{d \ln w_t}{d \ln P_{t,C}} + \frac{\alpha}{\sigma - 1} \frac{d \ln M_t}{d \ln P_{t,C}} \\ &= (1 - \alpha) \frac{d \ln w_t}{d \ln P_{t,C}} + \frac{\alpha}{\sigma - 1} \Xi \frac{d \ln l_{t,C}}{d \ln P_{t,C}}. \end{aligned}$$

By equations (4) we then have

$$0 = (1 - \alpha) \left[1 - \gamma \frac{d \ln l_{t,C}}{d \ln P_{t,C}} \right] + \frac{\alpha}{\sigma - 1} \Xi \frac{d \ln l_{t,C}}{d \ln P_{t,C}}$$

Then:

$$\frac{d \ln l_{t,C}}{d \ln P_{t,C}} = \frac{(1 - \alpha)}{\gamma (1 - \alpha) - \frac{\alpha}{\sigma - 1} \Xi}.$$

Since by assumption $\gamma (1 - \alpha) > \alpha / (\sigma - 1)$, the above expression is positive, which implies that commodity price increases leads to nontradable firm entry.

Derivation of Equation (16)

By equation (9), we have:

$$M_{tj} = \frac{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right)}{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right) + 1} \varphi_j L_{0j},$$

where M_{tj} is the number of entrepreneurs of demographic j . Taking logs we have:

$$\ln M_{tj} = \ln \frac{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right)}{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right) + 1} + \ln \varphi_j + \ln L_{0j}.$$

Differentiating with respect to $\ln P_{t,C}$ gives:

$$\begin{aligned} \frac{d \ln M_{tj}}{d \ln P_{t,C}} &= \left[\frac{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right)}{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right) + 1} - \frac{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right)}{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right) + 1} \right] \left(\frac{d \ln v_{E,jt}}{d \ln P_{t,C}} - \frac{d \ln v_{W,jt}}{d \ln P_{t,C}} \right) / \kappa_j. \\ &= (1 - p_{tj}) \left(\frac{d \ln v_{E,jt}}{d \ln P_{t,C}} - \frac{d \ln v_{W,jt}}{d \ln P_{t,C}} \right) / \kappa_j, \end{aligned}$$

where p_{tj} is the probability an individual in population $\varphi_j L_{0j}$ chooses to become an entrepreneur. By equations (2) and (7):

$$\frac{d \ln v_{E,jt}}{d \ln P_{t,C}} = \frac{d \ln \pi_{t,N}}{d \ln P_{t,C}} = \frac{d \ln Y_t}{d \ln P_{t,C}} - \frac{d \ln M_t}{d \ln P_{t,C}}.$$

By equation (3):

$$\frac{d \ln v_{W,jt}}{d \ln P_{t,C}} = \frac{d \ln w_t}{d \ln P_{t,C}}.$$

Since $(1 - p_{tj}) \approx 1$, putting everything together yields:

$$\frac{d \ln M_{tj}}{d \ln P_{t,C}} \approx \left(\frac{d \ln Y_t}{d \ln P_{t,C}} - \frac{d \ln M_t}{d \ln P_{t,C}} - \frac{d \ln w_t}{d \ln P_{t,C}} \right) / \kappa_j.$$

This immediately yields equation (16).

A.2. Estimating Entrepreneur Characteristics

In this section, we describe how to formally estimate the distributional characteristics of those entrepreneurs who start a firm in response to local demand shocks. This is be useful in comparing the characteristics of these entrepreneurs to the characteristics of the average entrepreneur in the Brazilian population, as discussed in Section 6.

As in the main text, let the binary indicator variable T_{ijt} denote the decision in year t of an individual i in municipality j to become an entrepreneur. We again let $Z_{jt} = 1$ denote a time of exogenous increase in local demand in municipality j , as proxied for by local agricultural endowment shocks. Let T_{1ijt} and T_{0ijt} denote the choice to become an entrepreneur when $Z_{jt} = 1$ and $Z_{jt} = 0$, respectively. Then we focus on the “responsive entrepreneurs”, namely those individuals who start

a business in response to the endowment shock; that is, an individual i for whom $T_{1ijt} = 1$ and $T_{0ijt} = 0$ or, equivalently, $T_{1ijt} > T_{0ijt}$. Our goal is to estimate the size and characteristics of this population.

Towards this end, we investigate heterogeneity in the entrepreneurial response to local demand shocks by sorting on individual characteristics. Specifically, let the variable n index demographic categories (e.g. quartiles) of a characteristic of interest such as age. We then estimate the following linear probability model for each subpopulation indexed by n , in particular for young individuals and then again for old individuals:

$$T_{injt} = \alpha_{nj} + \delta_{nt} + \beta_n \cdot Z_{jt} + \varepsilon_{injt}. \quad (1)$$

where α_{nj} denote municipality fixed effects and δ_{nt} denote time fixed effects. We allow each subpopulation to have its own baseline level of entrepreneurship and to have its own time trend.

Two assumptions are key to our empirical strategy. First, as long as Z_{jt} is uncorrelated with the error term, this specification provides a consistent estimate of β_n . Second, we assume monotonicity, which says that $T_{1ijt} \geq T_{0ijt}$ for all i . This rules out cases where an individual starts a business when economic opportunities are weak, but does not start a business when opportunities are strong.

The assumptions of orthogonality and monotonicity imply that:

$$\begin{aligned} P(T_{1injt} > T_{0injt}) &= E[T_{1injt} - T_{0injt}] \\ &= E[T_{injt}|Z_{jt} = 1] - E[T_{injt}|Z_{jt} = 0] \\ &= \beta_n. \end{aligned}$$

Within this framework, the treatment coefficient β_n reveals not only the increase in the probability to become an entrepreneur, but also the proportion of individuals in demographic category n who are responsive entrepreneurs.

Additionally, we would like to determine the distribution of characteristics *conditional* on being a responsive entrepreneur. This will allow us to compare their characteristics to the overall population of workers and to the overall set of entrepreneurs. We can accomplish this with Bayes's rule. Let X_i be the characteristic of interest. Then, conditional on an individual i being a responsive entrepreneur, the probability that i is in category n can be calculated as follows:

$$\frac{P(X_i = n|T_{1ijt} > T_{0ijt})}{P(X_i = n)} = \frac{P(T_{1ijt} > T_{0ijt}|X_i = n)}{P(T_{1ijt} > T_{0ijt})} = \frac{\beta_n}{\beta}$$

where β is found by estimating equation (1) on the entire population. This implies that the distribution of characteristics of responsive entrepreneurs is given by:

$$P(X_i = n|T_{1ijt} > T_{0ijt}) = \frac{\beta_n}{\beta} P(X_i = n).$$

Statistics for all entrepreneurs in the population are computed directly from the data, as the fraction of individuals who create a new firm in a given year and that are in a particular age quartile.

A.3. Structural Counterfactuals

To study the counterfactual impact of different demographics on the firm entry response to commodity price shocks, we use our structural model to recover

$$\frac{d^2 \ln M_t}{d \ln P_{t,C} d \ln L_{j0}} / \frac{d \ln M_t}{d \ln P_{t,C}},$$

that is how the elasticity of entrepreneurship to commodity prices varies with the size L_{j0} of demographic j in the local population. As shown in Section A.1, we have

$$\begin{aligned} 0 &= (1 - \alpha) \frac{d \ln w_t}{d \ln P_{t,C}} + \frac{\alpha}{\sigma - 1} \frac{d \ln M_t}{d \ln P_{t,C}} \\ &= (1 - \alpha) \left(1 - \gamma \frac{d \ln l_{t,C}}{d \ln P_{t,C}} \right) + \frac{\alpha}{\sigma - 1} \frac{d \ln M_t}{d \ln P_{t,C}} \end{aligned}$$

Furthermore, we have:

$$\begin{aligned} \frac{d \ln M_t}{d \ln P_{t,C}} &= \sum_j \phi_{jt} \frac{\frac{d \ln \pi_t}{d \ln P_{t,C}} - \frac{d \ln w_t}{d \ln P_{t,C}}}{\kappa_j} \\ &= \sum_j \phi_{jt} \frac{\frac{d \ln Y_t}{d \ln P_{t,C}} - \frac{d \ln M_t}{d \ln P_{t,C}} - \frac{d \ln w_t}{d \ln P_{t,C}}}{\kappa_j} \\ &= \sum_j \phi_{jt} \frac{\frac{d \ln l_{t,C}}{d \ln P_{t,C}} - \frac{d \ln M_t}{d \ln P_{t,C}}}{\kappa_j} \end{aligned}$$

where $\phi_{jt} = M_{jt}/M_t$, the share of total entrepreneurs in demographic j , which is observable. This system of equations can be solved for $\frac{d \ln M_t}{d \ln P_{t,C}}$ and $\frac{d \ln l_{t,C}}{d \ln P_{t,C}}$.

It is then clear that the cross partial derivative can be recovered from the system of equations:

$$\begin{aligned} 0 &= -(1 - \alpha) \gamma \frac{d^2 \ln l_{t,C}}{d \ln P_{t,C} d \ln L_{j0}} + \frac{\alpha}{\sigma - 1} \frac{d^2 \ln M_t}{d \ln P_{t,C} d \ln L_{j0}} \\ \frac{d^2 \ln M_t}{d \ln P_{t,C} d \ln L_{j0}} &= \sum_j \phi_{jt} \frac{d \ln \phi_{jt}}{d \ln L_{j0}} \frac{\frac{d \ln l_{t,C}}{d \ln P_{t,C}} - \frac{d \ln M_t}{d \ln P_{t,C}}}{\kappa_j} + \sum_j \phi_{jt} \frac{\frac{d^2 \ln l_{t,C}}{d \ln P_{t,C} d \ln L_{j0}} - \frac{d^2 \ln M_t}{d \ln P_{t,C} d \ln L_{j0}}}{\kappa_j}. \end{aligned}$$

It thus simply remains to determine $\frac{d \ln \phi_{tj}}{d \ln L_{j0}}$.

Recall that:

$$M_{jt} = \sum_j \frac{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right)}{\exp\left(\frac{v_{E,jt} - v_{W,t}}{\kappa_j}\right) + 1} \varphi_j L_{0j}.$$

Then:

$$0 = -(1 - \alpha) \gamma \frac{d \ln l_{t,C}}{d \ln L_{j0}} + \frac{\alpha}{\sigma - 1} \frac{d \ln M_t}{d \ln L_{j0}}$$

$$\frac{d \ln M_t}{d \ln L_{j0}} = \phi_{jt} + \sum_j \phi_{jt} \frac{\frac{d \ln l_{t,C}}{d \ln L_{j0}} - \frac{d \ln M_t}{d \ln L_{j0}}}{\kappa_j}.$$

Solving this system equations, we can then compute:

$$\frac{d \ln \phi_{jt}}{d \ln L_{j0}} = 1 + \frac{\frac{d \ln l_{t,C}}{d \ln L_{j0}} - \frac{d \ln M_t}{d \ln L_{j0}}}{\kappa_j} - \frac{d \ln M_t}{d \ln L_{j0}}.$$

Plugging this into the system equations above allows us to fully solve for our counterfactual simulations.

Figure A.1
Residualized Crops Index

The graph captures the variation in the residuals \hat{u}_{jt} , estimated from equation 11 in the paper. We plot these regression residuals (thin gray lines) for a 10% random sample of all the municipalities in our sample over 1998-2014. The solid lines indicate the median, while the dashed lines indicate the tenth and ninetieth percentiles of the empirical distribution.

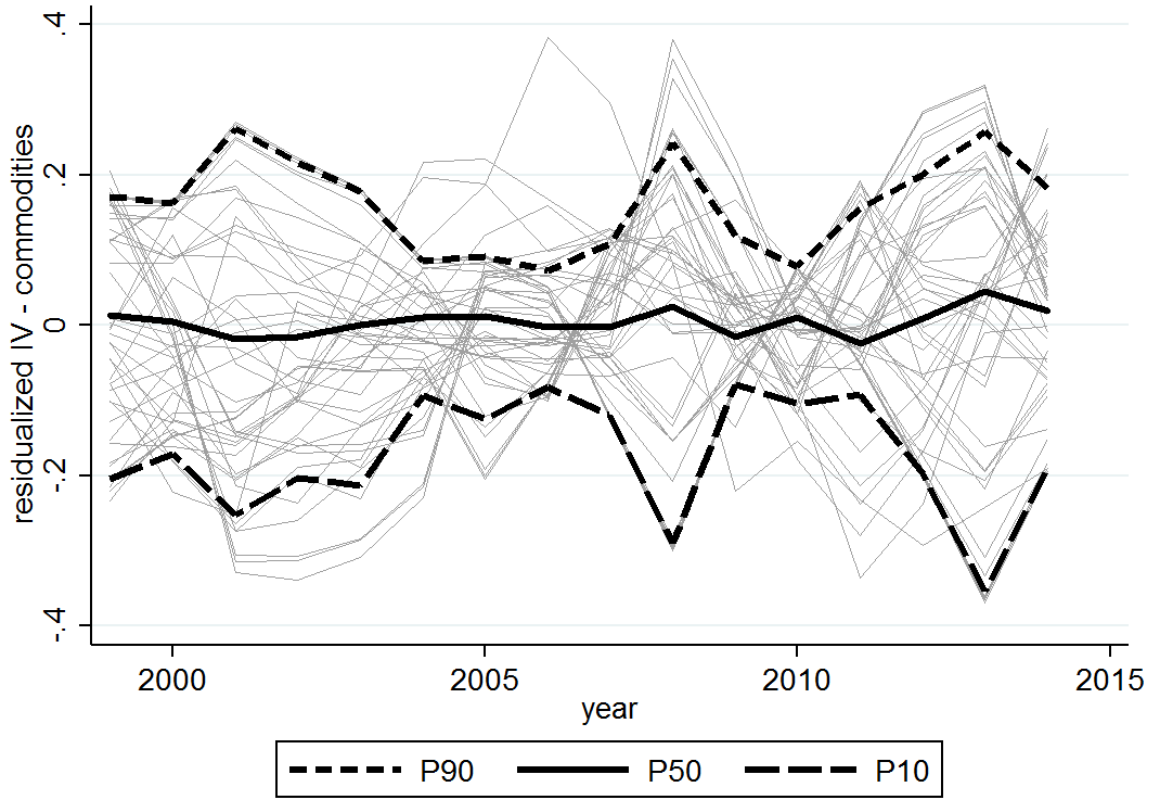


Table A.1**Agricultural Endowments Across Municipalities**

This table provides a breakdown of agricultural crops and the number of municipalities in which they are being produced. We have global commodity prices for 26 crops. Six of these (bean, broadbean, pea, rye, sunflower, triticale) were discarded as we were only able to find a price for generic “grains”. Among the remaining 20, 3 different types of coffee are aggregated into the “Total coffee” category in the table below. Similarly, two types of cotton are aggregated in a unique “total cotton” category. As a result from these aggregation we are left with the 17 types of crops listed below.

Crops	Total Municipalities
Maize	5003
Rice	4045
Banana	3870
Orange	3763
Sugarcanes	3529
Total Coffee	2030
Soybeans	1495
Cotton	1210
Tobaccos	973
Wheat	815
Yerba mate	541
Rubber	421
Oatmeal	411
Sorghums	375
Cocoa	278
Barley	183
Indiantea	7

Figure A.2

Crops Index and Aggregate Income

The graph shows the relationship between the log of the crops index ($\ln CI_{jt}$) and the total payroll in each municipality. Both variables are regressed on local population, year and municipality fixed effects to control for municipality size, aggregate fluctuations and time-invariant differences across municipalities. Then, the residuals from the crops index are collected in 100 bins, and each bin is plotted against the average residual from the payroll regression.

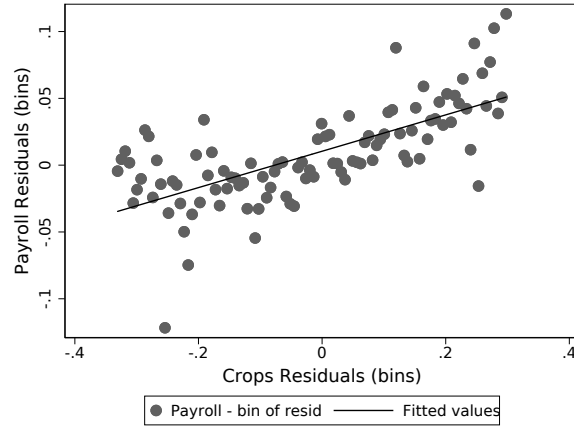


Table A.2

Aggregate Results: Sources of Employment Creation

This table reports the estimated effect of commodity price shocks on several municipality-level outcomes, splitting across sources of employment creation. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is $Y_{jt} = \alpha_j + \delta_t + \beta \ln CI_{jt} + \gamma X_{jt} + u_{jt}$, as described in Section 5. The dependent variable in column 1 is the total number of employees who were either unemployed or informal (i.e. who were not in the RAIS dataset) in $t - 1$. The dependent variable in column 2 is the total number of employees who were working in a different municipality in $t - 1$. All dependent variables are in logs. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
	Employment from:	
	Unemployment / Informality	Different municipality
Treatment	0.202*** (0.021)	0.213*** (0.024)
Year FE	Yes	Yes
Municipality FE	Yes	Yes
Controls	Yes	Yes
Observations	80,455	79,629
Municipalities	5,442	5,442

Table A.3

Aggregate Results: Dropping “World Producer” Municipalities

This table reports the estimated effect of commodity price shocks on several municipality-level outcomes, excluding municipalities who produce a large share of the world production of any crop. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is $Y_{jt} = \alpha_j + \delta_t + \beta \ln CI_{jt} + \gamma X_{jt} + u_{jt}$, as described in Section 5. *Total Employment* is the total number of employees, *Total Income* is the sum of payroll across all firms, *Number of Firms* is the total number of firms, and *Number of Closures* is the total number of firms that exit. All dependent variables are in logs. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. In Panel A (Panel B), the sample excludes municipalities that ever produced 1% (0.5%) or more of the world production of any commodity in any year in the period 1996-2015. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A - Dropping 1% World Producers				
	(1)	(2)	(3)	(4)
	Total Employment	Total Income	Number Firms	Number Closures
Treatment	0.204*** (0.020)	0.220*** (0.021)	0.075*** (0.010)	-0.009 (0.017)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	79,942	79,942	79,942	65,211
Municipalities	5,378	5,378	5,378	5,296

Panel B - Dropping 0.5% World Producers				
	(1)	(2)	(3)	(4)
	Total Employment	Total Income	Number Firms	Number Closures
Treatment	0.206*** (0.020)	0.220*** (0.022)	0.074*** (0.010)	-0.007 (0.017)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	78,403	78,403	78,403	63,761
Municipalities	5,275	5,275	5,275	5,193

Table A.4

Aggregate Results: Heterogeneity by Type of Shock

This table reports the estimated effect of commodity price shocks on several municipality-level outcomes, using different variations of the commodity shock, as defined in Section 5.5.2. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is $Y_{jt} = \alpha_j + \delta_t + \beta Z_{jt} + \gamma X_{jt} + u_{jt}$, as described in Section 5, but where Z_{jt} is either in the top 10% (row 1), top 25% (row 2), bottom 10% (row 3), or bottom 25% (row 4). In row 5, Z_{jt} is the continuous version of the shock $\ln CI_{jt}$, as defined by equation 11. *Total Employment* is the total number of employees, *Total Income* is the sum of payroll across all firms, *Number of Firms* is the total number of firms, and *Number of Closures* is the total number of firms that exit. All dependent variables are in logs. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Employment	Total Income	Number of Firms	Firm Closures
Treatment - Top 10%	0.069*** (0.007)	0.078*** (0.008)	0.027*** (0.010)	-0.008 (0.007)
Treatment - Top 25%	0.057*** (0.006)	0.063*** (0.006)	0.020*** (0.010)	-0.009* (0.005)
Treatment - Bottom 10%	-0.065*** (0.008)	-0.068*** (0.009)	-0.018*** (0.010)	0.004 (0.007)
Treatment - Bottom 25%	-0.047*** (0.005)	-0.048*** (0.006)	-0.019*** (0.010)	-0.001 (0.005)
Treatment - Continuous variable	0.206*** (0.020)	0.222*** (0.021)	0.076*** (0.010)	-0.009 (0.017)

Table A.5

Aggregate Results: Persistence of the Shock

This table reports the estimated effect of commodity price shocks on several municipality-level outcomes, exploring how persistent the effects of the shocks are. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is as described in Section 5. *Total Employment* is the total number of employees, *Total Income* is the sum of payroll across all firms, *Number of Firms* is the total number of firms, and *Number of Closures* is the total number of firms that exit. All dependent variables are in logs. In column 1, $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. Columns 2 to 5 indicate different variations of the main treatment variable, where the shock refers to 1, 2, 3, or 4 years before year t , respectively. Each row indicates a different dependent variable, and therefore each cell represents the coefficient of one single regression. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
Lag treatment	0	1	2	3	4
Total employment	0.206*** (0.020)	0.169*** (0.018)	0.140*** (0.017)	0.121*** (0.015)	0.089*** (0.013)
Total income	0.222*** (0.021)	0.175*** (0.020)	0.147*** (0.018)	0.136*** (0.017)	0.115*** (0.016)
Total number of firms	0.076*** (0.010)	0.078*** (0.010)	0.069*** (0.010)	0.063*** (0.010)	0.052*** (0.010)
Number of closures	-0.009 (0.017)	0.000 (0.017)	0.005 (0.017)	0.011 (0.017)	0.001 (0.017)

Table A.6

Aggregate Results: Formal vs Informal Sector

This table reports the estimated effect of commodity price shocks on the number of formal and informal firms and workers in a given municipality. All the outcomes are obtained starting from PNAD data from 2009-2014, as discussed in the paper. State level counts of formal and informal firms/workers are assigned to municipalities based on population shares. The count of workers in column 3 and 4 include both employees and self-employed. All dependent variables are in logs. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4, so as to capture elasticities. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Firms		All workers	
	Formal	Informal	Formal	Informal
Treatment	0.073*** (0.009)	-0.001 (0.004)	0.040*** (0.003)	-0.001 (0.003)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	21,726	21,726	21,726	21,726
Municipalities	5,435	5,435	5,435	5,435

Table A.7

Aggregate Results: Dropping municipalities above the 95th percentile

This table reports the estimated effect of commodity price shocks on several municipality-level outcomes. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is $Y_{jt} = \alpha_j + \delta_t + \beta \ln CI_{jt} + \gamma X_{jt} + u_{jt}$, as described in Section 5. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. *Total Employment* is the total number of employees, *Total Income* is the sum of payroll across all firms, *Number of Firms* is the total number of firms, and *Number of Closures* is the total number of firms that exit. All dependent variables are in logs. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Total Employment	Total Income	Number Firms	Number Closures
Treatment	0.166*** (0.020)	0.181*** (0.022)	0.086*** (0.010)	0.031* (0.017)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	76,757	76,757	76,757	62,276
Municipalities	5,262	5,262	5,262	5,174

Table A.8

Aggregate Results: Dropping municipalities above the 99th percentile

This table reports the estimated effect of commodity price shocks on several municipality-level outcomes. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is $Y_{jt} = \alpha_j + \delta_t + \beta \ln C_{jt} + \gamma X_{jt} + u_{jt}$, as described in Section 5. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. *Total Employment* is the total number of employees, *Total Income* is the sum of payroll across all firms, *Number of Firms* is the total number of firms, and *Number of Closures* is the total number of firms that exit. All dependent variables are in logs. Z_{jt} Treatment is the log Crop Index $\ln C_{jt}$. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	Total Employment	Total Income	Number Firms	Number Closures
Treatment	0.195*** (0.020)	0.212*** (0.021)	0.079*** (0.001)	0.001 (0.017)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	80,078	80,078	80,078	65,349
Municipalities	5,428	5,428	5,428	5,343

Table A.9

Young Responsiveness: Robustness to Different Shock Definitions

This table reports the estimated effect of commodity price shocks on the probability of becoming an entrepreneur, using different variations of the commodity shock, as defined in Section 6. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The basic empirical specification (column 1) is $T_{ijt} = \alpha_j + \delta_t + \beta \cdot Z_{jt} + \varepsilon_{ijt}$, as described in Section 6, and where Z_{jt} is either in the top 10% (specification 1), bottom 25% (specification 2), bottom 10% (specification 3) or bottom 25% (specification 4), as described in Section 4. Column 1 includes only municipality and year fixed effects. Columns 2, 3, 4, and 5 add different sets of fixed effects, and include an interaction term constructed as an indicator equal to 1 for individuals in the bottom quartile of the age distribution in the sample. *Sector* controls include dummies for seven different sectors referred to the job in year $t - 1$. *Education Controls* include a binary variable for high school diploma, and a dummy variable for above high school education. *Occupation Controls* include a binary variable that equals one if previous occupation is a white collar worker, a binary variable that equals one if previous occupation is defined as generalist, a control for the type of occupation (i.e., requires non-routine cognitive skills), and a control for experience within the firm. *Wage at Previous Job* control for the rank of the individual within the wage distribution in a municipality. Column 6 includes municipality-by-year fixed effects and Sector controls. Column 7 also includes *Education*, *Occupation* and *Wage at Previous Job* controls. The dependent variable, *Founder*, is an indicator equal to 1,000 if the individual has founded a firm in year t , and 0 otherwise. Variables are defined in Section 3. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Founder	Founder	Founder	Founder	Founder	Founder	Founder
Specification 1							
Top 10%	0.145*** (0.046)	0.058 (0.044)	0.055 (0.044)	0.061 (0.044)	0.071 (0.044)		
Top 10% X Young		0.298*** (0.113)	0.304*** (0.113)	0.298*** (0.113)	0.290** (0.113)	0.229*** (0.085)	0.25*** (0.082)
Specification 2							
Top 25%	0.066** (0.032)	0.004 (0.031)	0.0012 (0.0308)	0.00539 (0.0308)	0.014 (0.0311)		
Top 25% X Young		0.227*** (0.077)	0.231*** (0.077)	0.231*** (0.077)	0.220*** (0.077)	0.207*** (0.061)	0.150*** (0.057)
Specification 3							
Bottom 10%	-0.093** (0.042)	-0.031 (0.042)	-0.029 (0.042)	-0.034 (0.042)	-0.049 (0.042)		
Bottom 10% X Young		-0.231** (0.109)	-0.231** (0.109)	-0.234** (0.109)	-0.229** (0.109)	-0.148* (0.081)	-0.201** (0.077)
Specification 4							
Bottom 25%	-0.077*** (0.028)	-0.022 (0.029)	-0.021 (0.029)	-0.025 (0.029)	-0.037 (0.029)		
Bottom 25% X Young		-0.21*** (0.071)	-0.211*** (0.071)	-0.213*** (0.071)	-0.205*** (0.071)	-0.216*** (0.056)	-0.217*** (0.053)
Year	Y	Y	Y	Y	Y	N	N
Municipality	Y	N	N	N	N	N	N
Municipality X Young	N	Y	Y	Y	Y	N	N
Municipality X Year	N	N	N	N	N	Y	Y
Sector	N	Y	Y	Y	Y	Y	Y
Education Controls	N	N	Y	Y	Y	N	Y
Occupation Controls	N	N	N	Y	Y	N	Y
Wage at previous job	N	N	N	N	Y	N	Y
Observations (mil)	23.8	23.6	23.6	23.6	23.6	23.8	23.6

Table A.10

Young Responsiveness: Attrition - Additional Controls (1)

This table reports the estimated effect of commodity price shocks on the probability of becoming an entrepreneur, where we control for previous experience as entrepreneur. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The basic empirical specification (column 1) is $T_{ijt} = \alpha_j + \delta_t + \beta \cdot \ln CI_{jt} + \varepsilon_{ijt}$, as described in Section 6, and where $\ln CI_{jt}$ is the log of the the crops index, described in Section 4. Column 1 includes only municipality and year fixed effects. Columns 2, 3, 4, and 5 add different sets of fixed effects, and include an interaction term constructed as an indicator equal to 1 for individuals in the bottom quartile of the age distribution in the sample. *Sector* controls include dummies for seven different sectors referred to the job in year $t - 1$. *Education Controls* include a binary variable for high school diploma, and a dummy variable for above high school education. *Occupation Controls* include a binary variable that equals one if previous occupation is a white collar worker, a binary variable that equals one if previous occupation is defined as generalist, a control for the type of occupation (i.e., requires non-routine cognitive skills), and a control for experience within the firm. *Wage at Previous Job* control for the rank of the individual within the wage distribution in a municipality. Column 6 includes municipality-by-year fixed effects and Sector controls. Column 7 also includes *Education*, *Occupation* and *Wage at Previous Job* controls. The variable *Previously Founder* in Panel A, is equal to 1 in year t if the individual has founded a firm prior to year t , and 0 otherwise. The variable *Previously Founder (5yr)* in Panel B, is equal to 1 in year t if the individual has founded a firm in the five years prior to year t , and 0 otherwise. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Controlling for Past Experience - Ever Founder

	(1) Founder	(2) Founder	(3) Founder	(4) Founder	(5) Founder	(6) Founder	(7) Founder
Treatment	.251** (.0985)	.0703 (.094)	.0663 (.0937)	.0657 (.0937)	.0577 (.094)		
Treatment X Young		.544** (.231)	.551** (.231)	.548** (.231)	.588** (.232)	.0772*** (.00908)	.0626*** (.00943)
Previously Founder		.12*** (.00124)	.12*** (.00124)	.12*** (.00124)	.122*** (.00128)	.12*** (.00124)	.122*** (.00128)
Year	Y	Y	Y	Y	Y	N	N
Municipality	Y	N	N	N	N	N	N
Municipality X Young	N	Y	Y	Y	Y	N	N
Municipality X Year	N	N	N	N	N	Y	Y
Sector Controls	N	Y	Y	Y	Y	Y	N
Education Controls	N	N	Y	Y	Y	N	Y
Occupation Controls	N	N	N	Y	Y	N	Y
Wage at previous job	N	N	N	N	Y	N	Y
Observations (mil)	23.8	23.6	23.6	23.6	23.6	23.8	23.6

Table A.11
Young Responsiveness: Attrition - Additional Controls (2)

Controlling for Past Experience - 5 Year Founder

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Founder	Founder	Founder	Founder	Founder	Founder	Founder
Treatment	.251** (.0985)	.0191 (.0888)	.0155 (.0887)	.0155 (.0886)	.00223 (.0889)		
Treatment X Young		.551** (.226)	.558** (.226)	.555** (.227)	.599*** (.227)	.0743*** (.00866)	.0596*** (.00906)
Previously Founder (5yr)		.145*** (.00128)	.145*** (.00128)	.145*** (.00128)	.147*** (.00132)	.145*** (.00129)	.147*** (.00132)
Year	Y	Y	Y	Y	Y	N	N
Municipality	Y	N	N	N	N	N	N
Municipality X Young	N	Y	Y	Y	Y	N	N
Municipality X Year	N	N	N	N	N	Y	Y
Sector Controls	N	Y	Y	Y	Y	Y	N
Education Controls	N	N	Y	Y	Y	N	Y
Occupation Controls	N	N	N	Y	Y	N	Y
Wage at previous job	N	N	N	N	Y	N	Y
Observations (mil)	23.8	23.6	23.6	23.6	23.6	23.8	23.6

Table A.12**Heterogeneity Within Municipality: Interactions**

This table reports the estimated effects of commodity price shocks on the probability of becoming an entrepreneur, testing for heterogeneous treatment effects across individuals with different skills, within the set of young individuals (i.e. in the bottom quartile of the age distribution). The empirical specification is $T_{ijt} = \alpha_j + \delta_t + \alpha_{jPV} + \delta_{tPV} + \beta_0 \cdot Z_{jt} + \beta_1 \cdot PV_{ijt} + \beta_2 Z_{jt} PV_{ijt} + \varepsilon_{ijt}$, where Z_{jt} is the log of the Crop Index. PV_{ijt} is an indicator variable that characterizes an individual's skill. In column 1, $PV_{ijt} = 1$ if in $t - 1$ the individual has at least a high school level of education. In column 2, $PV_{ijt} = 1$ if in $t - 1$ the individual was working in an occupation that required cognitive non-routine skills. In column 3, $PV_{ijt} = 1$ if in $t - 1$ the individual had above median within-firm level of experience. The dependent variable, *Founder*, is an indicator equal to 1000 if the individual has founded a firm in year t , and 0 otherwise. All specification includes fixed effects for year, municipality, year by partition variable, and municipality by partition variable. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
	Founder	Founder	Founder
Treatment	-.0849 (.309)	.615** (.245)	.332 (.24)
Treatment X Partition Variable	1.14*** (.402)	.92* (.522)	.927** (.416)
Partition Variable	Education	Non-Routine Cognitive	Experience
Year X PV FE	Y	Y	Y
Municipality X PV FE	Y	Y	Y
Baseline control for PV	Y	Y	Y
Observations	6,590,259	6,590,208	6,590,341

Table A.13**Heterogeneity Within Municipalities: Binary Shock**

This table reports the estimated effect of commodity price shocks on the probability of becoming an entrepreneur. Panel A explores individual responsiveness within the sample of young individuals in the bottom quartile of the age distribution. Panel B explores individual responsiveness within the sample of older individuals, in the top three quartiles of the age distribution. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. We estimate the individual level specification with the binary treatment, namely $T_{ijt} = \alpha_j + \delta_t + \beta \cdot Z_{jt} + \varepsilon_{ijt}$, across various sample splits, with the aim of characterizing skilled versus unskilled individuals within the young population. Z_{jt} (Treatment) is the top 10% local shock indicator generated from the crops index. The first two columns split the sample into individuals with high school or higher education (column 1) versus others (column 2). The second split is between individuals who engaged in non-routine cognitive occupations in $t - 1$ (column 3) versus others (column 4). The third split is between individuals with above (column 5) or below years of within-firm experience in the $t - 1$ and others (column 6). The dependent variable, *Founder*, is an indicator equal to 1000 in year t if the individual has founded a firm in year t , and 0 otherwise. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Young Individuals (Bottom Age Quartile)

	(1)	(2)	(3)	(4)	(5)	(6)
	Founder	Founder	Founder	Founder	Founder	Founder
Treatment	0.468*** (0.126)	-0.022 (0.154)	0.813*** (0.234)	0.242** (0.112)	0.566*** (0.168)	0.147 (0.115)
Partition	Education		Non-routine Cognitive		Experience	
Partition Criteria	>=HS	<HS	Yes	No	>median	<median
Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
Observations (mil)	5.342	1.249	1.334	5.256	3.331	3.259

Panel B: Older Individuals

	(3)	(4)	(1)	(2)	(5)	(6)
	Founder	Founder	Founder	Founder	Founder	Founder
Treatment	0.063 (0.063)	0.053 (0.055)	0.144 (0.110)	0.039 (0.049)	0.0232 (0.067)	0.096 (0.061)
Partition	Education		Non-routine Cognitive		Experience	
Partition Criteria	>=HS	<HS	Yes	No	>median	<median
Year FE	Y	Y	Y	Y	Y	Y
Municipality FE	Y	Y	Y	Y	Y	Y
Observations (mil)	11.000	6.295	3.488	13.800	8.664	8.583

Table A.14**Aggregate Results by Age Quartile**

This table reports the estimated effect of commodity price shocks on income and employment at the municipality level for four quartiles of the age distribution. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is $Y_{jt} = \alpha_j + \delta_t + \beta \ln CI_{jt} + \gamma X_{jt} + u_{jt}$, as described in Section 5. *Total Employment* is the total number of employees in each municipality in the specified age group, *Total Income* is the sum of payroll across all firms paid to employees in the specified age group. All dependent variables are in logs. $\ln CI_{jt}$ (Treatment) is the log of the the crops index, as described in Section 4. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: By Age Quartile - Employment

	(1)	(2)	(3)	(4)
	Total Employment	Total Employment	Total Employment	Total Employment
	Q1	Q2	Q3	Q4
Treatment	0.178*** (0.022)	0.170*** (0.020)	0.214*** (0.019)	0.181*** (0.018)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	80,604	80,747	80,761	80,709
Municipalities	5,443	5,443	5,443	5,443

Panel B: By Age Quartile - Total Income

	(1)	(2)	(3)	(4)
	Total Income	Total Income	Total Income	Total Income
	Q1	Q2	Q3	Q4
Treatment	0.180*** (0.024)	0.195*** (0.023)	0.241*** (0.022)	0.212*** (0.020)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	80,604	80,747	80,761	80,709
Municipalities	5,443	5,443	5,443	5,443

Table A.15**Additional Results for Structural Estimation**

This table reports the estimated effect of commodity price shocks on wages, number of firms created by young individuals, and number of firms created by old individuals. The analysis sample covers the period 1998-2014 and its construction is described in Section 3. The empirical specification is $Y_{jt} = \alpha_j + \delta_t + \beta \ln(CI_{jt}) + \gamma X_{jt} + u_{jt}$, as described in Section 5. *Wages* is the wage per employee in the municipality, *Firms by Young* is the total number of firms in the non-tradable sector in the municipality whose founder is Young the year of firm creation, and *Firms by Old* is the total number of firms in the non-tradable sector in the municipality whose founder is Old the year of firm creation. Young and Old are defined as in Table 6. All dependent variables are in $\log(1+)$ in order to keep the number of observations constant. $\ln CI_{jt}$ (Treatment) is the log of the crops index, as described in Section 4. All specifications include controls for log-population, year dummies and municipality fixed effects. Standard errors are clustered by municipality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
	Wages	Firms by Young	Firms by Old
Treatment	.017*** (.005)	.116*** (.015)	.067*** (.015)
Year FE	Y	Y	Y
Municipality FE	Y	Y	Y
Observations	80,902	80,902	80,902