What Causes Turnover? Evidence from an Industrial Park in Ethiopia*

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This version: May, 2026

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Abstract

We study the causes of high turnover rates in a flagship industrial park in Ethiopia with detailed administrative records for 58,530 applicants during 2018–23. (1) Leveraging exogenous price shocks, we find that better outside options reduced the likelihood that applicants would take any jobs in the industrial park but did not induce current workers to separate from the industrial park. We use a standard search model to show that applicants' rejection rate can be inefficiently low. (2) Using productivity data from individual firms, we find correlational evidence that workers with lower productivity were more likely to separate. We further provide causal evidence using an information treatment that separation can be explained by learning on the job. Our model demonstrates that workers' separation rate can be inefficiently high. Our policy discussion implies a tension between improving matching efficiency and decreasing turnover.

*We are very grateful to Francis Annan, Philipp Barteska, Rob Garlick, Florian Grosset-Touba, Andreas Kotsadam, Maximiliano Lauletta, Christian Meyer, Edward Miguel, Deresse Fekadu Nigussie, and Ritwika Sen for helpful conversations, comments, and feedback. We gratefully acknowledge funding and support from Center for Global Action, Center for African Studies at UC Berkeley, International Growth Center, Structural Transformation and Economic Growth, and the UC Berkeley Strandberg Fund. The information treatment was approved by UC Berkeley Committee for Protection of Human Subjects and is registered at the AEA RCT Registry (AEARCTR-0006998).

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1 Introduction

Labor markets in low-income countries feature frequent flows between jobs (Donovan et al., 2023). Workers often transition between "marginal jobs" such as self employment and informal, low-earnings wage work. Unlike workers in high-income countries where job flows reflect climbing job ladders, labor market flows in low-income countries do not result in wage growth, which implies the lack of formal wage work and the volatility of labor income.

In response, many low-income countries are actively pushing to transition away from subsistence-agriculture to formal wage work in manufacturing. Many industrial policies provide amenities and subsidies to attract large-scale, often multinational, manufacturing firms to start production in the country. Although these manufacturing firms generally offer comparatively good formal job opportunities, turnover rates are still high (Groh et al., 2016; Blattman and Dercon, 2018). However, we have little evidence of what causes turnover in these manufacturing firms. Without understanding the underlying causes, we are unable to understand whether turnover rates are too high or too low, and whether these industrial policies are an efficient tool of creating good jobs in low-income countries.

This paper focuses on Hawassa Industrial Park (HIP), a flagship project in Ethiopia that received 58,530 applicants between 2018–23 and uniquely suited to study the causes of high turnover rates. We discuss two main hypotheses. First, a worker may quit because she finds a better outside option. We leverage exogenous price shocks in coffee, a major cash crop in the region, to examine the effect of outside options on turnover. Second, a worker may quit because she updates negatively on the match quality. We collect productivity from individual firms to first show the negative correlation between individual productivity and separation and leverage an information treatment to obtain causal evidence. Our evidence draws a connection between turnover and market tightness in a standard equilibrium search model. With this, we discuss the efficiency implications of turnover and policy implications.

HIP is the largest employer of garment industry in the Sidama region. One unique feature of HIP is the centralized hiring system. In 2018, shortly after the HIP was established, the Ethiopian government set up an office next to the HIP to facilitate the hiring for entry-level workers. All applicants were required to register in the hiring office and would wait for an assignment to one of the firms in HIP. We obtained administrative records from the hiring office between 2018–23, with details on each worker's date of registration, origins, dates of all assignments and terminations if any.

We define two types of turnover in HIP. First, applicants might decline an assignment and never work in HIP. This type of turnover is similar to rejecting a job offer in a job search model. In other settings where large manufacturing firms conduct hiring by themselves, entry-level job seekers are usually hired on the spot and wait for further assignments, and many would quit on the first day of work (see Blattman and Dercon (2018) for an example), which potentially reflects this type of turnover. In HIP, we observe that 34% of all applicants never took up a job, suggesting that a large proportion of them might have declined the first assignment. This is unlikely to be only driven by potential lack of jobs: on average, we observe 66 applicants per day, including those who re-entered the pool, and 53 hires per day.

Second, among the hires, some separated after staying on the job for a period of time. This type of turnover is the conventional definition. Of all applicants, 43% accepted a job assignment and separated before the end of the study period. Of these workers, 42% never showed up in the record again. Given that HIP is the largest recruiter of garment industry in Sidama region, this is a strong indicator that workers switched to a different industry after separation. We thus refer to it as industry-specific separation. For the rest of workers who separated from the previous job but accepted another assignment later in HIP, we refer to it as firm-specific separation.

We now examine the first hypothesis that turnover is driven by better outside options. We first use Ethiopian Socio-Economic Panel Survey between 2021–22 to characterize potential outside options in nearby regions.[1] More than 40% of working-age survey respondents worked in agricultural production, 10% in non-wage self employment, and only less than 10% in wage employment, suggesting that agriculture is still the main employment sector. One of the most salient cash crop in Sidama region is coffee, which remains one of the largest export goods in Ethiopia. The average imputed monthly revenue from coffee production is 9,934 ETB, higher than the average monthly salary from wage employment (8,967 ETB) with large standard deviation. Given its economic saliency, we use coffee production to capture outside options in our context.

Our empirical strategy leverages shocks in coffee prices that are orthogonal to turnover

[1] They include Southern Nations, Nationalities, and Peoples' Region, or SNNP, of which Sidama was a part but separated since 2020, and Oromia region.

decisions. We obtain local coffee prices from Ethiopia Commodity Exchange and global coffee prices from International Monetary Fund. We first show a strong correlation between local and global coffee prices. Because local price shocks can potentially reflect local supply shocks and thus possibly endogenous to workers' turnover decisions, we use global coffee prices to tease out exogenous demand shocks. We further assume that not all workers have complete information about outside options due to high transportation costs, and that workers from a coffee producing district are more likely to react to increasing labor demand for coffee production. Using the Agricultural Sample Survey conducted by Central Statistical Agency during 2018–19, we define coffee producing districts as those where the share of coffee producing fields is above median (10.5%). For each worker, we interact the log price of global coffee one month after her application date with whether a worker originally came from a coffee producing district, control for the global coffee price one month before to capture potential selection, and regress her turnover outcomes on the interaction to obtain a causal estimate of the effect of outside options.

We find a significant effect on whether a worker never took up a job in HIP. For applicants from coffee producing districts, one standard deviation increase in coffee prices leads to a 5.0 percentage points increase in the likelihood of never working in HIP. The effect is only significant during harvesting season and remains unchanged in various specifications. This suggests that a large portion of early turnover can be explained by applicants still looking for better job opportunities. For workers who accepted a job assignment, we do not find any significant impact of coffee price shocks on separation. This suggests that workers do not use HIP jobs as an insurance against temporary income shocks, which is consistent with anecdotes that many workers are indeed seeking for a career in garment industry.

Our empirical evidence thus suggests that we can use standard search model to understand turnover in HIP, where job seekers are matched with a job in HIP and accept it if the value of job is higher than that of "unemployment", which is captured by all outside options in this setting. The first type of turnover has a one-to-one mapping with the market tightness in a standard equilibrium search model (Diamond, 1982; Mortensen, 1977; Pissarides, 2000). In this framework, when workers enter job search, they would create a search externality by decreasing the chance of other job seekers being matched with a job. With Nash bargaining, the search externality can be perfectly internalized only when workers' bargaining power equals the elasticity of the matching function (Hosios, 1990).

We attempt to evaluate matching inefficiency with this equilibrium search framework. Using our administrative data, we estimate the elasticity of the matching function to be 0.77, consistent with most estimates from the literature. For workers' bargaining power, we estimate that for entry-level workers, a 100% increase in the percentage of targets met is correlated with around 1,000 ETB increase in monthly salary. If we approximate 100% increase in targets with 100% of export earnings in HIP, this gives us an estimate of workers' bargaining power close to zero, far below the elasticity of the matching function. This suggests that the first type of turnover, the percentage of applicants who reject a job in HIP, might be inefficiently *low*. Because of low workers' bargaining power, firms create too many vacancies that overcompensate the search externality, while some workers would have been better off if they had been employed in a different sector.

We now examine the second hypothesis where a worker quits because she updates negatively on the match quality. Jovanovic (1979) formulated that when workers learn about their productivity on the job over time, those with low-level productivity would choose to quit. Inspired by this, we collected detailed personnel and productivity data from five firms in HIP. One difficulty is that almost all firms collect productivity data only at the production line level. However, assuming firms assign a new worker quasi-randomly to a production line, we can compare the productivity for the given production line before and after the worker was assigned to it, which will reflect individual-level productivity for the new worker especially at the beginning of her tenure. Using this methodology, we impute individual-level productivity within 45-day probation period for 2,294 workers.

We observe a negative correlation between individual productivity and separation. One standard deviation increase in imputed individual productivity is correlated with 3.2–4.0 percentage points decrease in separation. This is consistent with the prediction from Jovanovic (1979). We only observe significant correlation for industry-specific separation, not firm-specific separation, possibly because workers learn about their productivity in the garment industry, not just about idiosyncratic matches with specific firms.

We further provide causal evidence using an information treatment on 1,203 female applicants between March and May 2023. After measuring their baseline perceptions, we provided a subset of respondents with accurate information on upper-level salary, which is difficult for workers to learn before joining HIP. Leveraging the exogenous shock to workers' perceptions conditional on their baseline perception level, we find that one standard deviation increase in the belief about upper-level salary does not affect applicants' take-up of a job or firm-specific separation, but significantly increases industry-specific separation by about 12.3 percentage points. We leave detailed discussions on the learning mechanism to a separate paper (Wu and Lauletta, 2026) and simply use this as supporting evidence that on-the-job learning can cause industry-specific separation.

We introduce on-the-job learning in the equilibrium search model and show that search externality would be amplified because of a positive option value of learning about their true productivity. With low workers' bargaining power, this would further worsen matching inefficiency. However, it also implies that the second type of turnover, separation from the job, is potentially inefficiently *high* because workers are more tempted to forego the option value of learning and re-enter job search due to too many vacancies in the garment industry.

Last, we discuss the implications on matching efficiency and turnover of three sets of policies. Policies that reduce search frictions can potentially decrease applicants' rejection rate but exacerbate matching inefficiency because turnover is already inefficiently low. Policies that reduce information frictions, such as subsidized apprenticeship program, can alleviate matching inefficiency but increase both types of turnover. Policies that increase workers' bargaining power, such as establishing worker unions, can improve matching efficiency and reduce workers' separation rate but potentially increase applicants' rejection rate. Our policy discussion thus demonstrates the tension between improving matching efficiency and lowering turnover.

Our paper first contributes to understanding the causes of high turnover rates in manufacturing industries. The early literature documented high turnover in the early stage of industrialization (Montgomery, 1989; Beckert, 2015) or among young workers in the United States (Farber, 1994, 1999). More recent work has found high turnover rates in developing countries (Groh et al., 2016; Blattman and Dercon, 2018). The understanding of causes are mostly speculative, mainly because of lack of personnel records of individual workers and the difficulty of identifying workers' outside options. Our paper leverages the rich personnel data available in HIP as well as the significance of coffee production as a major outside option in the nearby regions to causally identify the underlying causes. Our evidence implies a connection between turnover and standard search model, which allows us to use off-the-shelf methods to analyze the efficiency implications of turnover.

Second, our policy discussion sheds light on the effectiveness of active labor market policies in developing countries. Current literature has documented that interventions that simply reduce search costs do not often improve job seekers' employment outcomes meaningfully (McKenzie, 2017; Abebe et al., 2021; Bandiera et al., 2023; Caria et al., 2024; Franklin, 2018; Kelley et al., 2023; Fernando et al., 2023; Hensel et al., 2024; Wu and Wang, 2026). Meanwhile, interventions that reduce information frictions are often more successful (Abebe et al., 2024; Abel et al., 2020; Alfonsi et al., 2023; Banerjee and Chiplunkar, 2022; Banerjee and Sequeira, 2023; Bassi and Nansamba, 2022; Beam, 2016; Carranza et al., 2023). Using our equilibrium search framework with on-the-job learning, we demonstrate how reducing search frictions may exacerbate matching inefficiency in the context where workers' bargaining power is low, while reducing information frictions can alleviate it.

Third, this paper provides insight on structural transformation. An extensive literature documents the misallocation across sectors in low- and middle-income countries (Lewis et al., 1954; Hsieh and Klenow, 2009; Gollin et al., 2014). However, our efficiency discussion suggests that simply attracting large manufacturing firms to operate in these countries at the expense of workers' bargaining power may not be efficient, and simply reducing turnover or increasing employment in manufacturing industries does not necessarily improve misallocation across sectors. We caution policymakers and scholars to take into account the labor market effects when evaluating industrial policies.

The rest of the paper is structured as follows. Section 2 describes the context and the turnover data. Section 3 discusses search hypothesis. Section 4 discusses learning hypothesis. Section 5 presents policy discussion. Section 6 concludes.

2 Turnover in HIP

2.1 Hawassa Industrial Park

Ethiopia is a low-income country in east Africa, with a GDP per capita of 944 US dollars in 2021. Starting from the early 2000s, the government endeavored to attract foreign investment opportunities, predominantly in the light manufacturing sector, in hope to transition the economy from agriculture-based to industrialization. In particular, many East Asian companies, state-owned or private, have invested in many infrastructure projects and the light manufacturing sector, mainly because of the relatively low labor cost in Ethiopia and the large subsidies promised by the government.

One of the major government-led project is the Hawassa Industrial Park (HIP), a flagship project in Ethiopia and one of the largest industrial parks in sub-Saharan Africa. It is located in Sidama region, traditionally an agrarian society featuring cash crops such as coffee beans. Around 20 firms operated in the industrial park between 2018–2023, all but one in the garment sector.[2] Within the years where we can observe turnover statistics, HIP has registered 58,530 applicants, actively making itself the major recruiter of the garment sector in southern Ethiopia (Hardy et al., 2022). There is no other competitor of similar size in the region; all other industrial parks are located at least 200km away from the region.

One unique feature of the HIP is the centralized hiring system. To support the hiring process of entry-level workers, the Ethiopian government established a hiring office next to HIP to facilitate the hiring process. Job seekers in the nearby area can directly walk in and register for a job. In addition, the government set up ten recruitment centers within 60km around HIP and recruited workers from outside of Hawassa. After registration, job seekers would be randomly assigned to one of the firms requesting for workers. This centralized hiring system essentially formed a monopsony in the labor market, as firms in HIP agreed to only use the centralized hiring system to hire entry-level workers and not poach from each other. Importantly, it is difficult for an entry-level worker to choose their employer based on better job aspects because they have to re-enter the labor pool and wait for a new draw. If a worker leaves HIP, given the dominant size of HIP in the garment industry in Sidama region, it is likely that the worker would be employed in a different industry.

The criteria for applying for a job in the HIP are very low. Anyone at least 18 years old with eighth grade education is qualified for a job in the HIP. Firms tend to prefer female workers, but they accept over 95% of the first-assigned workers. In fact, 89% of all applicants are female. The ones rejected by firms are usually the ones who used to work in the firm and were already fired by the firm once before, or because firms requested workers for specific tasks for which they have more stringent criteria.

[2]Since 2021, the civil war and the termination of African Growth and Opportunity Act (AGOA) agreement in Ethiopia heavily affected the exporting industries, especially firms who predominantly exported to the United States and Europe. Nevertheless, many companies are from East and South Asia whose main exporting markets are not in the US or Europe, therefore less affected as of September 2023.

2.2 Turnover Data

We collected administrative records from the hiring office between 2018–2023. The data include all 58,530 applicants who registered in HIP between 2018–2023. Each record includes the date of registration, basic demographics (age, gender, education), whether the worker self-applied or was sourced from the nearby recruitment centers, and the origin of the worker. If a worker was ever allocated to or fired from a company, we observe the date of allocation or termination and which company.

We use this data to define two types of turnover in this context. First, applicants may have registered but then chose to decline a job assignment. This type of turnover is closer to rejecting a job offer in a standard job search model. It is potentially relevant to many other settings where large manufacturing firms conduct hiring themselves (e.g. Blattman and Dercon (2018)). Job seekers would be "hired" on the spot and wait for task assignments; meanwhile, they can easily leave and seek for another job before committing to the first assignment. We do not directly observe whether an applicant rejected an assignment in our data. However, 34% applicants never took up a job during the study period. This number goes up to 36% if we only include applicants who we can observe for at least one year during the study period. This suggests that a substantial share of job seekers might have declined the first job assignment.

Could it be because applicants simply did not get a job assignment? Our data suggests unlikely. On average, we observe 66 applicants per day in the hiring office, including those re-entering the labor pool, and 53 hires per day, which indicates potentially sufficient labor demand. Figure 1, Panel A shows the percentage of first-time applicants who haven't taken a job within a certain period. Almost 40% first-time applicants took a job within one day of application, but this number quickly plateaus after the first week. Suppose a worker shows up five days a week with a 40% likelihood to get a job assignment per day, the probability of getting a job assignment within one week is 92%. We therefore believe that the 34% of applicants never taking up a job mainly reflects applicants' rejection of a job assignment.

Second, among job seekers who accepted the first job assignment, some separated after working on the job for some time. This is the conventional definition of turnover (Farber, 1994). Figure 1, Panel B shows the percentage of workers separating from the first job within one day to within one year. 4.6% workers separated within one day, 14.5% within one month, 32.3% within one year. These two statistics are less than half the magnitudes as in Blattman and Dercon (2018). Overall, 43% workers separated from the first job within the observation window.

Among the workers who separated, some eventually came for another job assignment. We refer to it as firm-specific separation, as these workers may not enjoy the previous firm-specific match but still value another job in a different HIP firm. The rest is referred to as industry-specific separation, as these workers never returned for another job assignment and likely employed in a different industry elsewhere. Figure A1 shows the percentage of industry-specific separation within one day to within one year. Only 0.9% workers separated permanently within one day, 1.7% within one month, 8.0% within one year. Overall, 18% workers separated from the first job within the observation window and never returned.

In summary, of the 58,530 applicants, we observe that 34% never took up a job assignment, 43% separated from the first job, among which 42% (=18%/43%) never returned to HIP. The two types of turnover statistics add up to 77%, close to the statistics observed in Blattman and Dercon (2018), potentially with different causes and implications.

2.3 Can Labor Demand Shocks Explain Turnover?

Before we examine the two supply-side hypotheses of turnover, we briefly discuss whether labor demand shocks potentially cause turnover. Although anecdotally, firms rarely fired workers after the probation period before Covid-19, there are more such occasions after 2020. Figure A2, Panel A shows the monthly trend of separation during the study window. We see a spike shortly after the lockdown in March 2020, and a few more spikes during Ethiopian civil war, especially around the end of 2021 when Ethiopia was no longer included in the African Growth and Opportunity Act (AGOA). The volatility in firm production could potentially lower the labor demand and cause involuntary turnover.

We choose not to focus on involuntary turnover for three reasons. First, under certain hypotheses, involuntary turnover has the same efficiency implications as voluntary turnover. Jovanovic (1979) famously pointed out that if workers quit because they realize a bad match component, such a signal would also be observable to firms. Whether workers quit or are fired by the firm due to a bad match is essentially equivalent. Another example is that firms may not open many vacancies when they expect workers to not take the job. This, however, is an equilibrium behavior in response to workers' voluntary turnover.

Second, there is no consistent data on termination reasons. We only observe termination reasons for applicants before 2020. Even so, sometimes a worker is "fired because of absences". It is both difficult to classify whether this is involuntary or voluntary turnover and unnecessary, as we discuss above.

Third, mass layoff events are only occasional during the study period. Figure A2, Panel B shows the distribution of the number of daily separations. The median is eight separations a day across all firms in HIP. In one of the robustness checks, we will drop the observations during the mass layoff episodes, defined as above 95 percentile in Figure A2, Panel B, and results remain largely unaffected.

3 Search Hypothesis

Is turnover driven by workers seeking for better job opportunities? We first characterize outside options in nearby regions with Ethiopian Socio-Economic Panel Survey between 2021–22. We then describe our empirical strategy using global coffee prices to proxy exogenous demand shocks outside of HIP. We further discuss the implications of search hypothesis on the matching efficiency of turnover.

3.1 Outside Options in Nearby Regions

We use 3,984 survey respondents aged between 15 and 64 from Southern Nations, Nationalities, and Peoples' Region and Oromia for the descriptive statistics. Figure 2 shows the percentage of respondents engaged in different types of employment in the last seven days. The majority of respondents (45%) reported income-generating activities in agriculture, some in non-wage employment including self-employment (10%). Only 7.7% respondents reported any wage employment in the last seven days, 10% in the last year. Figure A3 further shows the types of employment for male and female, separately for urban and rural respondents. In general, male respondents had higher labor force participation. More urban respondents were engaged in wage employment (22% for male, 12% for female). Very few rural respondents, however, reported any wage employment (3.9% for male, 1.8% for female). This suggests that the majority of outside options are still in agriculture production, especially for the first-time job seekers from rural area.

We further show the distribution of occupations and industries in Table 1, Panel A and B. Notably, very few respondents worked in manufacturing-related industry (5.1%) or occupation (4.3% as plant and machine operators and assemblers). The majority of occupations are service-related such as sales and office clerks. This further confirms that HIP is uniquely one the most influential recruiters in manufacturing sector, not just in garment industry.

How attractive are these outside options? We attempt to provide an estimate of average monthly income for each employment type in Table 1, Panel C. Average monthly salary for wage employment is 8,967 ETB for male, 3,832 ETB for female, with large standard deviations. An average worker in HIP during 2021–22 can earn 2,301 ETB every month, which is roughly 24 percentile for male workers and 47 percentile for female workers. For non-wage employment, the average monthly revenue is 9,314 ETB, but the median revenue (2,180 ETB) is lower than the average salary in HIP. For agricultural production, we impute monthly revenue for crops that we can find price data from Ethiopia Commodity Exchange (maize, teff, coffee). For all three crops, the average monthly revenue is 5,388 ETB, median 1,939 ETB, lower than the average salary in HIP. However, if we only look at coffee yield, the average monthly revenue and median are much higher (9,934 ETB and 4,343 ETB). In general, these statistics suggest that although salary from HIP is comparable to the median level in the labor market, workers can potentially find more lucrative outside options half the time, especially in coffee production. This is consistent with anecdotes that some workers in HIP quit for coffee production during harvesting seasons.

3.2 Specification

Our empirical strategy leverages exogenous global price shocks to coffee production, one of the most salient outside options in the nearby regions. We first show that positive global price shocks are potentially correlated with higher labor demand for coffee production. We collect prices on local washed and unwashed coffee from Ethiopia Commodity Exchange (ECX), as well as global prices on coffee Robusta and other mild Arabica coffee from the International Monetary Fund (IMF). Figure 3 presents monthly price trend of each type of coffee and shows that local prices largely comove with global prices. Table A1, Panel A shows the correlation between log prices. The global prices of coffee Arabica have higher explanatory power for both local washed and washed coffee, consistent with the fact that Ethiopia mainly produces coffee Arabica. We will use global prices for coffee Arabica for most specifications.

Table A1, Panel B further shows the correlation of global coffee prices and the trading values of local coffee. The price elasticity of local washed coffee is significantly greater than one, suggesting that demand for local washed coffee is more responsive to global price shocks. This is consistent with the fact that washed coffee is primarily produced for export and subject to international competition. The price elasticity of local unwashed coffee is significantly less than one, suggesting that demand for local unwashed coffee is less responsive to global price shocks. This is consistent with the fact that unwashed coffee is mainly for domestic consumption, and the prevalent culture of coffee drinking in Ethiopia contributes to the inelastic demand. These correlations thus suggest that global price shocks translate to price shocks in local washed coffee, possibly generating positive labor demand for coffee production, especially during harvesting season. Using global coffee prices can address the endogeneity of local coffee prices potentially reflecting local supply shock.

We further assume that it is costly for job seekers to obtain information about the opportunities of coffee production in nearby regions. Transportation costs are already high in urban area and prevent job seekers and employers from exchanging information (Franklin, 2018; Abebe et al., 2024; Wu and Wang, 2026). It is potentially even costlier for job seekers to search for opportunities in coffee production unless they come from a coffee producing district. We obtained data from the Agricultural Sample Survey conducted by Central Statistical Agency during 2018–19. The survey sampled around 27,000 farming households and 240,000 fields from 579 local districts ("woredas") across the country. Figure 4 presents the geographical distribution of workers' origins as well as the share of fields that produce coffee. Figure A4 shows the number of workers per district observed in the grading center data. There is no clear geographical pattern of coffee production, and its distribution does not coincide with the distribution of workers' origins. This provides sufficient geographical variations to examine the effect of exogenous coffee price shocks.

The following is our main specification to causally estimate the effect of coffee price shocks on turnover:

$$Y_{ijt} = \alpha_j + \alpha_t + \beta C_j \cdot \log P_{t+1} + \gamma C_j \cdot \log P_{t-1} + X_{ijt} + \epsilon_i \tag{1}$$

Y_{ijt} is the turnover outcomes for worker i originated from district j registering at time t. C_j indicates whether district j is a coffee-producing district, defined as origins with above-median share of fields producing coffee (the median is 10.5%). P_{t+1} is the global price of coffee Arabica one month after application. To capture potential selection induced by coffee price, we control for P_{t-1} the global price of coffee Arabica one month before application. X_{ijt} captures other observable worker's characteristics, including gender, education, and age. We control for fixed effects for workers' origin districts j and the month of application t. β is the coefficient of interest, interpreted as the magnitude change in outcome Y_{ijt} caused by a 100 percentage change in global coffee prices in coffee-producing districts.

3.3 Results

Table 2, Panel A presents the main results. We observe a significant effect in Column 1: For applicants from coffee producing districts, a 100% increase in global coffee prices leads to 23.5 pp increase in the likelihood of an applicant never taking a job in HIP. If we look at one standard deviation increase in coffee prices (mean \$89.9, sd \$19.3), this translates into a 5.0 pp increase. Among applicants who took a job in HIP, we do not observe any significant effects on any separation outcomes (Column 2–4). For a subset of applicants, we observe them multiple times in the turnover records. After controlling for applicant fixed effects in Column 5, we still do not see a significant impact on separation, suggesting that within the selected sample of applicants who took a job, the effect on separation cannot be explained by individual characteristics. Panel B further interacts the main independent variable with whether an applicant applied one month before the harvesting seasons (October to December). We only see a significant effect during the harvesting seasons, consistent with our hypothesis that applicants may have chosen a more lucrative outside option in coffee production especially during harvesting seasons.

To examine whether global price shocks can increase local demand for coffee production, Table A2 replicates the main result in Table 2, Column 1, by replacing global price shocks with local price shocks. Column 1 shows that price increases in local washed coffee would increase the likelihood of a worker never taking a job, although insignificant, possibly because local price shocks may reflect endogenous supply shock in the nearby regions. Column 2 shows a zero effect of price shocks of local unwashed coffee, consistent with the above discussion that unwashed coffee is mainly for domestic consumption and subject to inelastic demand. Column 3 instruments prices of local washed coffee with global prices of coffee Arabica and recovers the significant impact with larger magnitude. Column 4 uses global prices of coffee Robusta as the instrument and finds a similar result with slightly less precision, consistent with the above discussion that Sidama region mostly produces coffee Arabica. Together, our evidence suggests that global prices especially of coffee Arabica, can generate price shocks in local washed coffee with an elastic demand, potentially resulting in an increase in labor demand for coffee production.

One may worry that our main specification does not capture the potential impact on separation because we only use the coffee price one month after application. Table A3, Panel A replicates the results with average coffee prices between 2–12 months after application. We do not see any significant impact on any separation outcomes. Together with the main result, our evidence suggests that once applicants took a job, they were unlikely to separate because of better outside options.[3] The impact on whether an applicant worked in HIP also becomes insignificant, possibly because applicants made decisions quickly within the first two months.

We conduct other specification tests in Table A3, Panel B to examine the robustness of the main result in Table 2, Column 1. Column 2 and 3 use logit and probit regressions and find similar results. Column 4 uses price level instead of log of price. The result is significant despite the estimated magnitude halved — for one standard deviation increase in price, Column 4 suggests a 2.5 pp increase in the likelihood of a worker never taking a job. Column 5 uses a 0-1 indicator of price increase as the independent variable and shows a very similar magnitude of effect (4.4 pp). Column 6 uses global price of coffee Robusta instead of coffee Arabica and shows a positive effect, albeit less significant. Column 7 drops mass layoff episodes and finds a similar although less significant effect. In general, our evidence

[3] Some firms also developed strategies to deal with potential turnover during harvesting seasons. One firm mentioned during qualitative interview that they introduced additional bonus if a worker did not leave for coffee harvesting during the busiest weeks. Some firms allow workers to leave temporarily for harvesting and return afterwards.

suggests a robust estimate of the effect on worker never taking a job in HIP.

To summarize, we leverage exogenous shock in coffee prices and find causal evidence that applicants potentially rejected a job in HIP for better outside options. This provides basis for us to use a simple search model to characterize turnover. We will outline the model and establish the connection of turnover and search model in the next subsection.

3.4 Using Search Model to Characterize Turnover

Suppose there is a continuum of risk-neutral workers with mass normalized to 1, and infinite number of identical, risk-neutral firms. There are two types of jobs, garment and outside options. Each garment firm pays c to open a vacancy and needs to match with one and only worker to produce. Upon a successful match, the pair would produce μ units of goods with no information asymmetry. The matching is random; the likelihood of a worker being matched with a garment job is a function of the market tightness θ, where market tightness a ratio between the mass of workers in outside options u ("unemployment rate" in the standard model) and number of vacancies v. The total number of matches is $m(u, v)$. If a worker takes the job, she would engage in a Nash bargaining process with bargaining power π. If a worker decides not to take the job, she would take an outside option that pays b ("unemployment benefit" in the standard model), which follows a certain distribution $F(\cdot)$. Once a match is formed, a worker would separate at the rate s.

With this set-up, given random matching, the first type of turnover, that is, an applicant rejects the job after matching with a garment job, can be characterized as the following:

$$T_1 = 1 - F(\mu + c\theta) \tag{2}$$

With Equation 2, we establish a direct connection between the first type of turnover and market tightness in search model, with unemployment explicitly modeled by outside options. $c\theta$ enters the expression because firms are willing to compensate average hiring cost per unemployed worker in addition to avoid an idle vacancy. We can thus use the efficiency implications of equilibrium search model to understand the efficiency of the first type of turnover. The second type of turnover is simply equal to the separation rate. Standard framework usually assumes exogenous separation; our evidence so far also does not provide strong evidence of on-the-job search to justify endogenous separation yet.

3.5 Efficiency Discussion: First Type of Turnover

Hosios (1990) provides a condition where matching efficiency can be reached in an equilibrium search model:

$$\pi = \frac{u\partial m}{m\partial u} \tag{3}$$

The right hand side is the elasticity of matching function with regard to unemployment, which captures the search externality of an additional worker entering job search. The left hand side is workers' bargaining power, the share of match surplus accrued to workers. The matching efficiency can only be reached when workers perfectly internalize the search externality. If π is too high, workers are overly incentivized to enter job search without enough jobs to be matched with. If π is too low, workers are not incentivized enough to enter job search, while firms open too many vacancies without enough job seekers to be matched with.

To estimate the elasticity of matching function, We can observe the number of matches per day, but we cannot observe the number of workers in outside options u. With the assumption of random matching, however, we can replace u with the number of applicants A divided by job finding likelihood, and rewrite Equation 19:

$$\pi = \xi \equiv \frac{\partial \log m}{\partial \log A} \tag{4}$$

Figure A5, Panel A shows that log number of daily matches and log number of daily applicants and highly linearly correlated, with the slope estimated to be 0.77. We thus use this to be the estimate of the elasticity of matching function, which is close to other estimates in the literature. For workers' bargaining power, Figure A5, Panel B shows the correlation of first month of salary and imputed individual productivity for a subset of workers. We will discuss the detailed estimation of individual productivity in Section 4.1; here, we use the percentage of targets met ("efficiency") as the productivity measure, which is a comparable measure across all firms in HIP. The graph shows that a 100% increase in targets met is associated with 1,063 ETB increase in monthly salary. We then approximate 100% increase in targets met with 100% export earnings in HIP ($436.3 million between 2018–23). Assuming the total number of workers to be 66% of all 58,530 applicants who took a job in HIP, our estimate of workers' bargaining power is close to zero, nowhere close to the estimated elasticity of matching efficiency.

Therefore, using Hosios' condition, the standard search model indicates that market tightness is inefficiently high. Firms tend to open many vacancies to leverage workers' low bargaining power, while some workers would have been better off if they had taken an outside option. With Equation 2, our efficiency discussion thus suggests that the first type of turnover, the percentage of applicants who reject a job in HIP, might be inefficiently low.

4 Hypothesis 2: Learning

Did workers quit working in the HIP because they learn about their low productivity on the job? Inspired by a classic paper by Jovanovic (1979), we first examine whether high productivity is correlated with less separation from the job, the main prediction from Jovanovic (1979). We then provide causal evidence that separation from the job can be explained by negative update on the job. We then discuss the efficiency implications of separation, the second type of turnover.

4.1 Estimating Individual Productivity

We collected detailed personnel and productivity data from nine firms in the HIP during July–August 2025. Eight of these nine firms record productivity daily for each production line. However, when a new worker just joined a company and was assigned to a production line, we can compare team-level productivity before and after the worker joined the production line and deduce individual-level productivity for a subset of workers at the beginning of the tenure. Specifically, we use the following specification, similar to an AKM model, to impute individual-level productivity:

$$Y_{j,i,t} = \alpha_j + \alpha_i + \alpha_t + e_{ijt} \quad (5)$$

$Y_{j,i,t}$ is the productivity for production line j where worker i worked on day t. For the most part of the analysis, we use the same productivity measure for all firms, that is, the percentage of target production met, or "efficiency". α_j are the production line fixed effects, α_i are the individual fixed effects, α_t are the day fixed effects, and e_{ijt} is the idiosyncratic error term. Assuming the production line assignment is orthogonal to individual productivity, we interpret α_i as the imputed individual productivity of worker i.

Using this method, we are able to impute individual-level productivity within probation period for 2,294 individuals, within one year for 3,371 individuals, and within two years for 3,834 individuals. Note that the imputed individual productivity within probation period is potentially more accurate because when the firm gets more information about workers' productivity, they may assign workers to different production lines based on their productivity and thus affect the causal interpretation of α_i. Figure A6 shows a large variation in the imputed individual productivity during probation.

4.2 Correlation between Turnover and Productivity

Figure 5 first shows the average imputed individual productivity within probation period, within one year, and within two years. We see an increase in individual productivity from 38% to 46% within the first year, about 20% increase, and stay at the similar level within two years. This is consistent with one of the predictions in Jovanovic (1979): Over time, as more low-productivity workers realize their real productivity and quit, the remaining workers present higher-level productivity on average.

Table 3 examines the correlation between individual productivity and the likelihood of separation; keep in mind that we will not observe the first type of turnover because all workers here have already accepted the job assignment. Column 1 and 2 show that one standard deviation increase in individual productivity during probation is correlated with 3.2–4.0 percentage points decrease in the separation likelihood (standard deviation of imputed individual productivity 0.20). This is consistent with the main prediction from Jovanovic (1979), that workers may observe a negative match component on the job and separate as a result. Column 3 and 4 show that the negative correlation mainly exists in industry-specific separation, that workers separated and never returned to HIP. This suggests that these entry-level workers may learn about their comparative advantage of working in garment industry in general, not just whether they are a good match to a specific firm. In general, we find supportive correlational evidence that separation can be explained by on-the-job learning.

4.3 Causal Evidence: Information Treatment

We further use an informational treatment to provide causal evidence about on-the-job learning and separation. We conducted a survey among 1,203 female workers sampled from the grading center between March and May 2022. We collected a series of demographic characteristics (age, marital status, origin, languages, religion), educational attainment, prior work experience, social network information, career plans, reasons of joining the industrial park, and measured workers' cognitive and dexterity ability. We further collected a comprehensive set of respondents' impressions on quantifiable job aspects, with a focus on career incentives. Figure A7, Panel (a) shows the distribution of baseline perceptions about the salary after promotion, and Panel (b) shows the distribution for the perceived likelihood of being promoted to an upper-level position. The dashed vertical line indicates the benchmark values. In both panels, although workers on average have roughly correct perceptions of career ladder, there is substantial variation with some workers being overly-optimistic and some overly-pessimistic.

We then conducted a clustered information treatment; more details in Wu and Lauletta (2026). We randomly select 26 out of 42 survey days (63%) for the information treatment. For each of the treated days, 82% of the sampled workers received the benchmark information on career progression collected by us from the confidential survey of Ethiopian Investment Commission. In total, 53% of the sampled workers received benchmark information of career ladder at the end of the baseline survey. Table A4 compares treated workers and control workers regarding all baseline characteristics. We do not observe systematic pattern of potential selection into treatment.

To causally identify the effect of misperceptions of career incentive on turnover, we use the interaction of cluster treatment and baseline perceptions as the main instrumental variable for causal inference. Specifically, we follow Cullen and Perez-Truglia (2022) and adopt the following instrumental variable approach:

$$Y_i = \pi + \delta \log(P_i^x) + \eta \log(P_i^{x,0}) + A_i\phi + u_i \tag{6}$$

$$\log(P_i^x) = \kappa + \gamma_t T_{c(i)} \cdot \big(\log(P_i^{x,0}) - \log(P_i^{x,s})\big) + \zeta \log(P_i^{x,0}) + A_i\psi + v_i \tag{7}$$

Equation 7 corresponds to the first stage of the IV regression. Equation 6 is the second stage of the IV regression. In particular, the main parameter of interest is δ, interpreted as the magnitude change in turnover outcomes caused by a 100 percentage change in perception P_i^x, worker i's updated perception on job aspect x. We then use the interaction of treatment status and baseline misperceptions as the instrument for P_i^x.

Table 4 presents the main results from this specification. Panel A reports the reduced form estimates; Panel B reports the IV estimates. Column 1 shows no significant impact of the information treatment on the first type of turnover, that applicants rejected a job in HIP. Column 2–4, however, show that information treatment may potentially affect industry-specific separation. One standard deviation increase in the posterior belief of average salary after promotion causes 12.3 pp increase in the likelihood of separating. Our preferred interpretation is that workers with over-optimistic baseline beliefs are potentially positively self-selected, and for those who did not correct over-optimism before starting a job, after controlling for baseline selection, the behavioral reaction is higher when they discovered the true upper-level salary on the job. In this paper, we will simply use this as evidence that on-the-job learning can explain separation and leave the detailed discussions on the behavioral channels to Wu and Lauletta (2026).

Interestingly, unbeknownst to us during the survey, 30% of the workers sampled from the grading center had actually worked in the HIP previously. Table A5 examines treatment heterogeneity regarding whether the worker had worked in the HIP before, and finds that the information treatment mainly decreases the likelihood of quitting for new workers. This confirms that information treatment mainly induces new workers to learn about jobs in the HIP and make turnover decisions accordingly, further supporting the learning hypothesis.

4.4 Introducing On-the-job Learning to Search Model

Both the correlational and causal evidence suggests that separation, or the second type of turnover, can be explained by on-the-job learning. In the following, we will introduce endogenous separation to the standard search model a la Fujita and Ramey (2012), where workers may receive a negative signal about their true productivity on the job and choose to separate from the job.

Suppose in a discrete time model with infinite periods, all agents have a discount rate β for future return. Upon a successful match, the worker-firm pair would produce x units of goods, and the match quality, or worker's true ability x follows a given distribution $G(\cdot)$. Assume firms have perfect information about the distribution of x.[4] For a given worker, we assume that worker's initial perception is on average accurate but with noise. For workers on the job, we still assume an exogenous separation rate s to capture firm-specific separation. For those who did not leave exogenously, with probability λ, a worker would observe their true ability and stay accurate for all future periods.

With this set-up, Appendix B shows that the second type of turnover, separation from the job, can be written as the following, where $\underline{x}(\theta) < b$ is the threshold (a function increasing in θ) where a worker stays indifferent between separating or staying on the job:

$$T_2 = s + (1 - s)\lambda G(\underline{x}(\theta)) \tag{8}$$

With Equation 8, we establish another direct connection between the second type of turnover and market tightness in search model with endogenous separation and on-the-job learning.

4.5 Efficiency Discussion Under On-the-job Learning

With on-the-job learning, the new search model introduces an option value of learning: there is a chance to receive a positive signal of ability on the job. Appendix B illustrates how this option value of learning can exacerbate search externality when workers' bargaining power

[4] Wu and Wang (2025) discusses the possibility of violation of this assumption in a more general labor market in Ethiopia. In the context of Hawassa Industrial Park, where entry-level workers are more homogeneous and there are many applicants every day, we believe it is less likely that firms would have substantial misperceptions of the distribution of workers' productivity.

is sufficiently low. When a worker separates from the job and enters job search, she would decrease the chance of other job seekers being matched with a garment job. Because of the option value of learning, the opportunity cost of not getting a job in garment industry becomes higher, thus the search externality of a worker entering job search is amplified. When workers' bargaining power is sufficiently low and market tightness is already inefficiently low as we discussed in Section 3.5, allowing on-the-job learning would further increase the market tightness away from the efficient level.

However, this implies that the second type of turnover, especially the industry-level turnover, is potentially too high. Because garment firms post too many jobs inefficiently, it becomes more tempting for workers to separate from the current job and get a new match, instead of staying on the job and learning about their true ability. In an efficient search economy, social planner would prefer a higher percentage of applicants rejecting a job in HIP so that they can be employed in more lucrative outside options, but for those who choose to stay in HIP, social planner would prefer a lower separation rate so that workers can fully leverage the option value of learning.

5 Policy discussions

We first discuss the implications on turnover and efficiency of active labor market policies that reduce search frictions. The establishment of the hiring office in HIP is an example of such policies. Our evidence and model suggest that given low workers' bargaining power, some workers would have been better off if they were employed elsewhere. Further alleviating search frictions to match more job seekers to HIP may potentially lower both types of turnover, but it would further exacerbate the matching inefficiency in this context.

A second set of policies that reduce information frictions may potentially improve both matching efficiency and turnover. This type of policies may include providing information of HIP jobs to applicants, or subsidized apprenticeship program for workers who are interested in garment industry. These policies alleviate the information asymmetry before applicants took a job, which would decrease the option value of learning and improve matching efficiency. However, this would potentially increase applicants' rejection rate because there are fewer inefficiently created vacancies in the labor market. For those who stay on the job, there is no option value of learning, and thus workers' separation rate would also increase.

A third set of policies is to increase workers' bargaining power, such as establishing workers' unions or lowering firms' monopsony power in the labor market. This would decrease the number of inefficiently created vacancies, increase matching efficiency. Workers' separate rate would be lower because they would enjoy higher wages. However, applicants' rejection rate would still increase because of fewer inefficiently created vacancies.

Our policy discussions thus illustrate the tension between improving matching efficiency and lowering turnover. If policymakers aim to improve matching efficiency, they would expect a higher turnover, especially applicants' rejection rates. If policymakers aim to alleviate turnover, they would need to bear the consequences of matching inefficiency, especially for workers who would have been better off if they were employed in other outside options.

6 Conclusion

We study the causes of high turnover rates in the context of a flagship industrial park in Ethiopia. Combining data from multiple sources and using various causal inference techniques, we find that applicants' rejecting a job in HIP can be explained by workers seeking for better outside options, and that workers' separating from the job can be explained by on-the-job learning. We use a standard search model with endogenous separation and on-the-job learning to demonstrate that applicants' rejection rate might be inefficiently low, while workers' separation rate might be inefficiently high. Our policy discussion suggests a tension between improving matching efficiency and reducing turnover.

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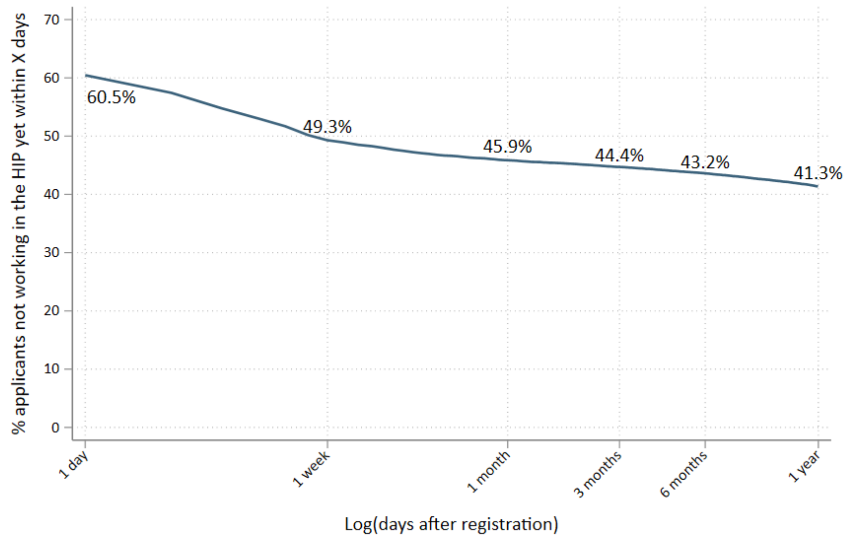
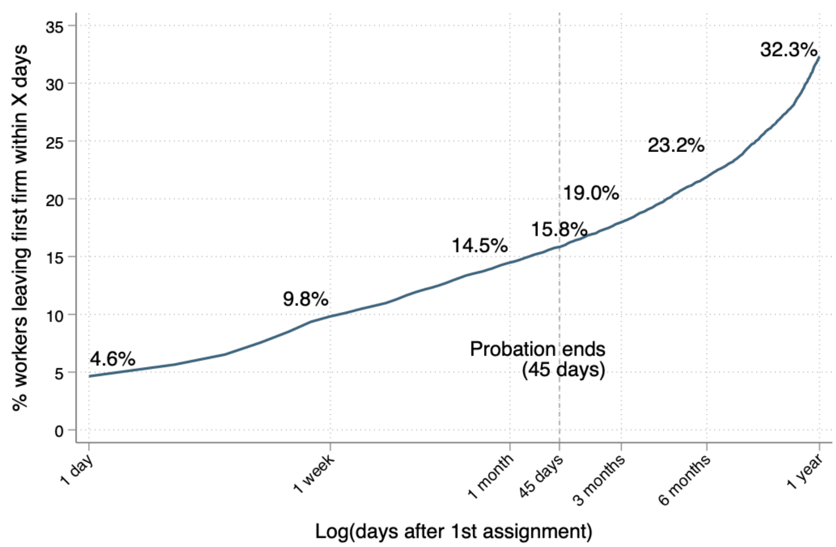
FIGURES

Figure 1: Turnover Patterns in the Industrial Park

Panel A. Percentage of Workers Not Taking A Job Yet

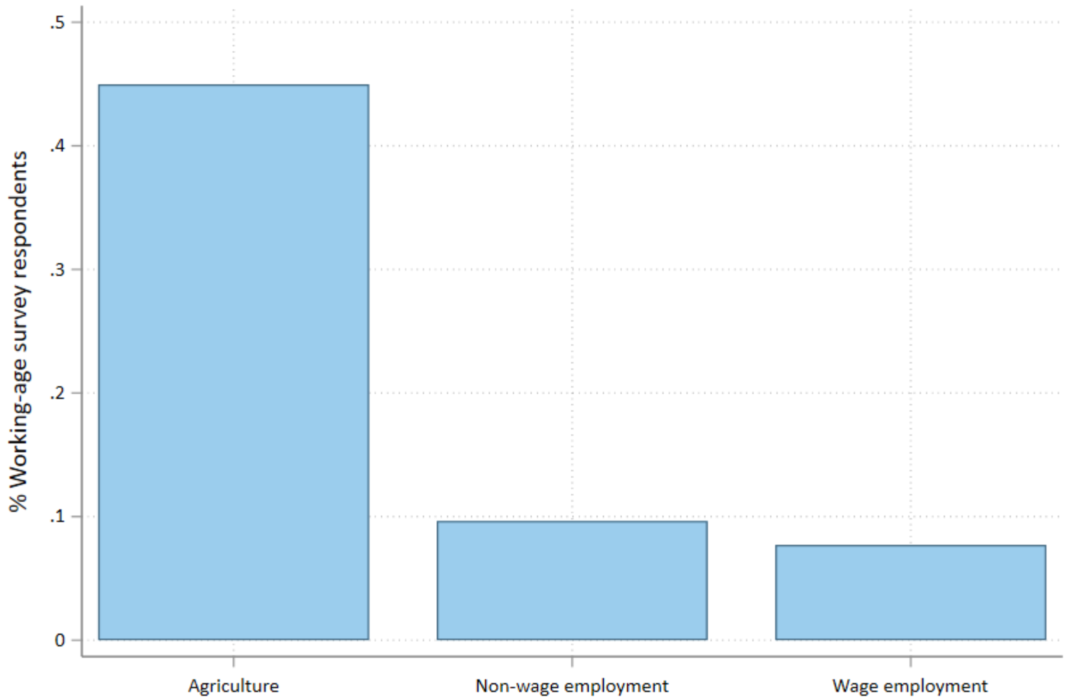


Panel B. Percentage of Workers Separating From the Job



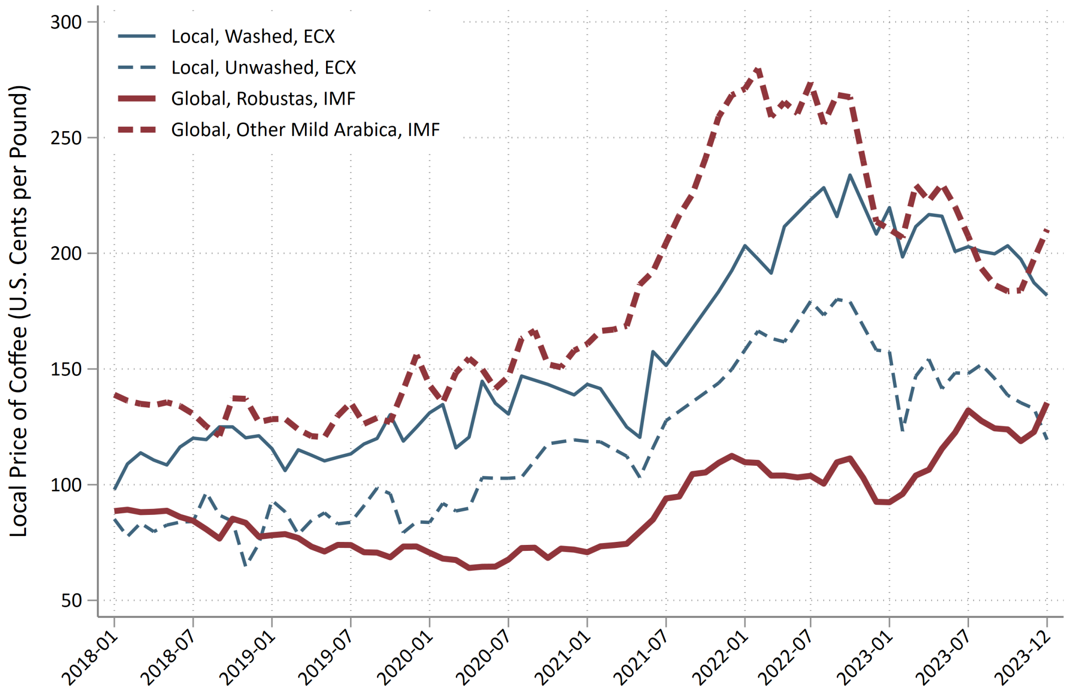
Notes: This figure shows the distribution of the turnover in the industrial park between August 2018 and September 2023. We show the key statistics of turnover within one day, one week, one month, 45 days when the probation period ended, three months, six months, and one year.

Figure 2: Distribution of Types of Employment in Nearby Regions



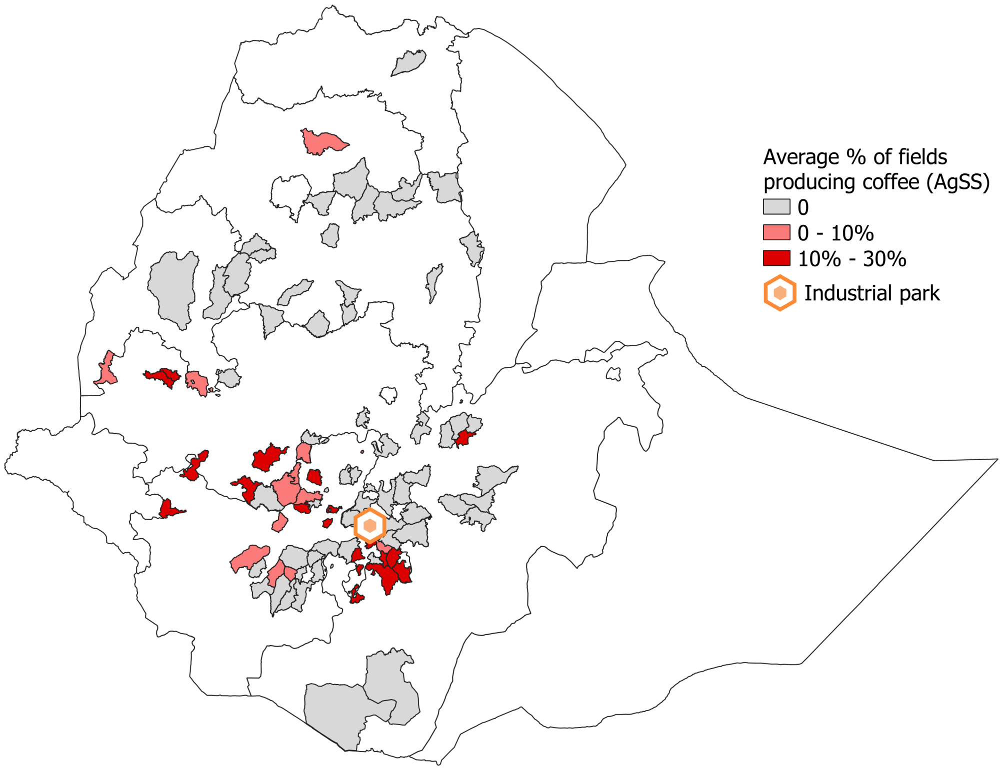
Notes: We use Ethiopian Socio-Economic Panel Survey 2021–22 to describe the distribution of types of work in SNNPR and Oromia regions. Only individuals aged above 15 and below 64 are included.

Figure 3: Time Trend of Coffee Prices



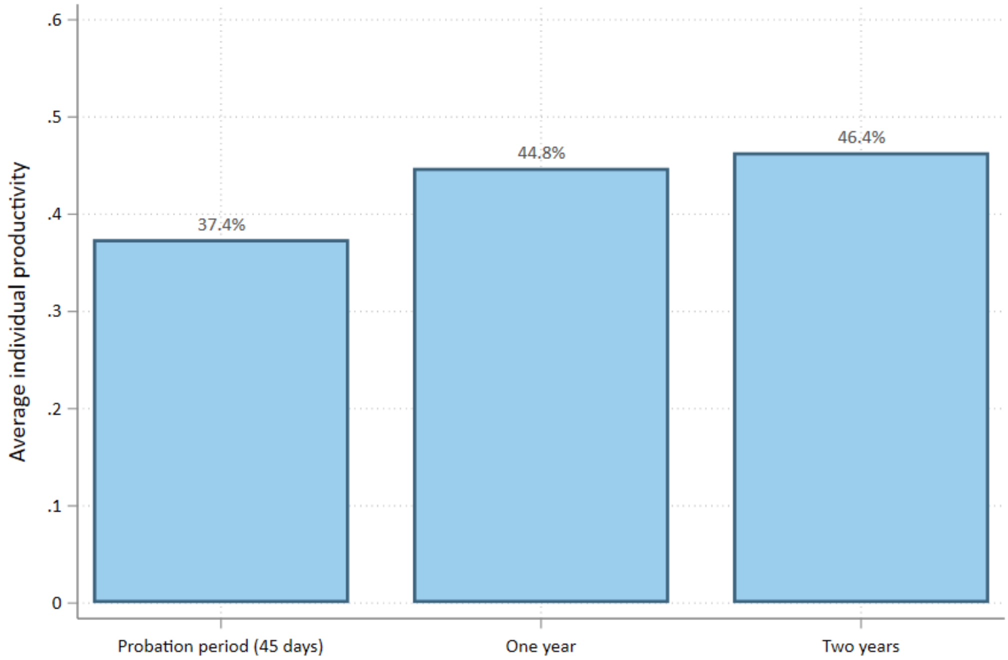
Notes: This figure shows coffee price trend between 2018 and 2023 (unit: US cents per pound). The local coffee prices are obtained from Ethiopia Commodity Exchange. The global coffee prices are obtained from International Monetary Fund.

Figure 4: Distribution of Coffee Producing Districts



Notes: This figure shows the distribution of coffee producing districts. A coffee producing district is defined by whether the share of coffee-growing fields in the Agricultural Sample Survey is above median. We only show the districts from which at least one worker in the industrial park was originated.

Figure 5: Average Imputed Productivity of Individual Workers



Notes: This figure shows average productivity measured within probation period (45 days), within one year, or within two years. Individual productivity is imputed using Equation 5 with personnel data collected from nine firms in the industrial park. Productivity is measured by the percentage of targets met daily.

TABLES

Table 1: Descriptives of Outside Options in SNNP and Oromia Regions

Panel A. Occupations in Wage Employment

	Male	Female	Total
1. Legislators, Senior Government Officials and Managers	4.07	0.00	2.57
2. Professionals/ Physical, Mathematical and Engineering Science Professionals	13.57	17.83	15.14
3. Technicians and Associate Professionals/ Physical and Engineering Science Associate Professionals	8.14	10.08	8.86
4. Clerks, Office clerks	12.22	17.05	14.00
5. Service Workers and Shop and Market Sales Workers/ Personal and Protective Service workers, Travel attendants and related workers	16.74	13.95	15.71
6. Market-Oriented Skilled Agricultural and Fishery Workers	8.14	7.75	8.00
7. Craft And Related Trades Workers, Extraction and Building Trades Workers	9.05	3.88	7.14
8. Plant and Machine Operators and Assemblers, Stationary-Plant and Related Operators	4.98	3.10	4.29
9. Elementary Occupations, Sales And Services Elementary Occupations	22.62	26.36	24.00
10. Army/ Member of the Armed Forces	0.45	0.00	0.29

Panel B. Industries in Wage Employment

	Male	Female	Total
1. Agriculture, Hunting, Forestry and Production of Related Products and Services	5.43	8.53	6.57
2. Mining and Quarrying	2.26	4.65	3.14
3. Manufacturing, Including Food Products Processing, Caning and Preserving	4.98	5.43	5.14
4. Electricity, Gas, Steam and Hot Water Supply	2.71	0.00	1.71
5. Construction, Site Preparation, Land Clearing	11.76	4.65	9.14
6. Wholesale and Retail Trade, Repair of Vehicles, Personal and Household Goods/ Sale, maintenance and Repair of Motor Vehicles and Motorcycles; Retail, Sale of Automotive Fuel.	9.05	2.33	6.57
7. Hotels and Restaurants/ Hotels (With Hotel Rooms); Camping Sites and Other Provision of short-Stay Accommodation	4.52	5.43	4.86
8. Transport, Storage and Communications/ Land Transport – People and Merchandise	2.71	4.65	3.43
9. Financial Intermediation (Except Insurance and Pension Funding)	13.57	17.83	15.14
10. Real Estate, Renting and Business Activities)	14.48	15.50	14.86
11. Public Administration and Defence , Compulsory Social Security	3.62	7.75	5.14
12. Education	12.67	11.63	12.29
13. Health and Social Work	9.95	8.53	9.43
14. Private Households with Employed Persons	0.90	0.00	0.57
15. Extra-Territorial Organizations and Bodies including International Organizations and NGOs	1.36	3.10	2.00

Panel C. Monthly Income (ETB)

	Mean	SD	P25	P50	P75	P99
Agriculture: Imputed monthly revenue from crop yields	5388	9357	869	1939	6949	52761
Agriculture: Imputed monthly revenue from coffee yields	9934	14329	869	4343	12160	52114
Non-wage employment: Average monthly revenue	9314	26469	600	2180	8160	100000
Wage employment: Monthly salary (Male)	8967	16156	2400	4500	7371	84480
Wage employment: Monthly salary (Female)	3832	5079	1100	2500	4609	35280

Notes: We use Ethiopian Socio-Economic Panel Survey 2021–22 to describe workers' outside options in SNNP and Oromia regions. For wage employment, we report average monthly salary for individuals aged between 15–64 in SNNP and Oromia. Both agricultural and non-wage employment income are summarized at the household level. In Panel C, agricultural income is imputed by yields from three main crops (maize, teff, coffee) interacting with average market prices in 2021–22. We use closing prices for maize and teff from World Bank monthly food price estimates in SNNP and Oromia regions, and closing prices for coffee from Ethiopia Commodity Exchange.

Table 2: Causal Effect of Coffee Price Shocks on Turnover

Panel A. Main Specification

	(1)	(2)	(3)	(4)	(5)
	Never worked	Separated			
	in HIP	All	Not returned	Returned	All
$C_j \times \log P_{t+1}$	0.235**	0.0835	-0.00956	0.0930	-0.0737
	(0.0977)	(0.139)	(0.0975)	(0.0915)	(0.225)
	[0.0194]	[0.550]	[0.922]	[0.313]	[0.744]
Observations	15,596	10,112	10,112	10,112	2,162
R-squared	0.403	0.135	0.144	0.072	0.687
Control mean	0.405	0.197	0.0816	0.115	0.197

Panel B. By Seasonality

	(1)	(2)	(3)	(4)	(5)
	Never worked	Separated			
	in HIP	All	Not returned	Returned	All
$C_j \times \log P_{t+1} \times$ harvest	0.319***	0.0862	0.0467	0.0394	-0.0713
	(0.115)	(0.152)	(0.126)	(0.0904)	(0.302)
	[0.00747]	[0.572]	[0.712]	[0.664]	[0.813]
$C_j \times \log P_{t+1} \times$ lean	0.109	0.0806	-0.122	0.203	-0.228
	(0.357)	(0.231)	(0.108)	(0.190)	(0.378)
	[0.762]	[0.729]	[0.264]	[0.289]	[0.545]
Observations	15,596	10,112	10,112	10,112	2,162
R-squared	0.403	0.135	0.144	0.072	0.688
Control mean	0.405	0.197	0.0816	0.115	0.197

Notes: This table reports the effect of coffee price shocks on turnover. Coffee district is defined as whether the worker's origin reports to have above-median producing fields (10.5%) in the agriculture census. Post price is defined as global prices of coffee Arabica one month after the application date. Global coffee prices are collected from International Monetary Fund. Dependent variables: Column 1 —the applicant never took up a job in HIP. Column 2 and 5 — the worker separated from the job. Column 3 — the worker separated from the job and never returned to HIP. Column 4 — the worker separated from the job and returned to HIP. All regressions control for demographics (gender, education, age), worker's origin fixed effects and cohort fixed effects (the month of application), cluster two-way at worker's origin and cohort. Panel A further controls for the interaction of coffee district and the log price one month before application; Panel B controls for the interaction of coffee district, the log price one month before application, and $t+1$ is during harvesting season (October - December). Standard errors are clustered two-way at the cohort level and at the district level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 3: Correlation Between Productivity Measure and Turnover

	(1)	(2)	(3)	(4)
	Separation			
VARIABLES	All	All	Not returned	Returned
Productivity during probation	-0.168	-0.200***	-0.127*	-0.0734
	(0.0895)	(0.0318)	(0.0530)	(0.0562)
	[0.157]	[0.00814]	[0.0969]	[0.283]
Data source	Personnel	HIP	HIP	HIP
Observations	2,305	1,236	1,236	1,236
R-squared	0.360	0.048	0.044	0.042
Firm FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Cluster at firm	Yes	Yes	Yes	Yes
Cluster at month	Yes	Yes	Yes	Yes
Control mean	0.401	0.346	0.165	0.181

Notes: This table reports the correlation between individual productivity within the probation period and the likelihood of quitting the industrial park. Individual productivity is imputed using Equation 5 with personnel data collected from nine firms in the industrial park. Productivity is measured by the percentage of targets met daily. Dependent variables: Column 1 and 2— the worker separated from the job. Column 3 — the worker separated from the job and never returned to HIP. Column 3 — the worker separated from the job and returned to another firm in HIP later. Column 1 uses personnel records from individual firms; Column 2–4 uses administrative records on turnover for those who can be matched. All regressions control for firm fixed effects and cohort fixed effects (the month when the worker first joined to the firm). Standard errors are clustered two-way at the production line level and at the cohort level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 4: Causal Effect of Misperceptions on Turnover

Panel A. Reduced Form

	(1)	(2)	(3)	(4)
	Never worked		Separated	
VARIABLES	in HIP	All	Not returned	Returned
Treated cohort	-0.049	-0.086	-0.282**	0.196
× Baseline update potential	(0.144)	(0.202)	(0.134)	(0.178)
	[0.733]	[0.672]	[0.042]	[0.278]
Observations	1,127	628	628	628
R-squared	0.001	0.004	0.014	0.003
Cluster	Cohort	Cohort	Cohort	Cohort
Dep var mean	0.477	0.222	0.0906	0.131

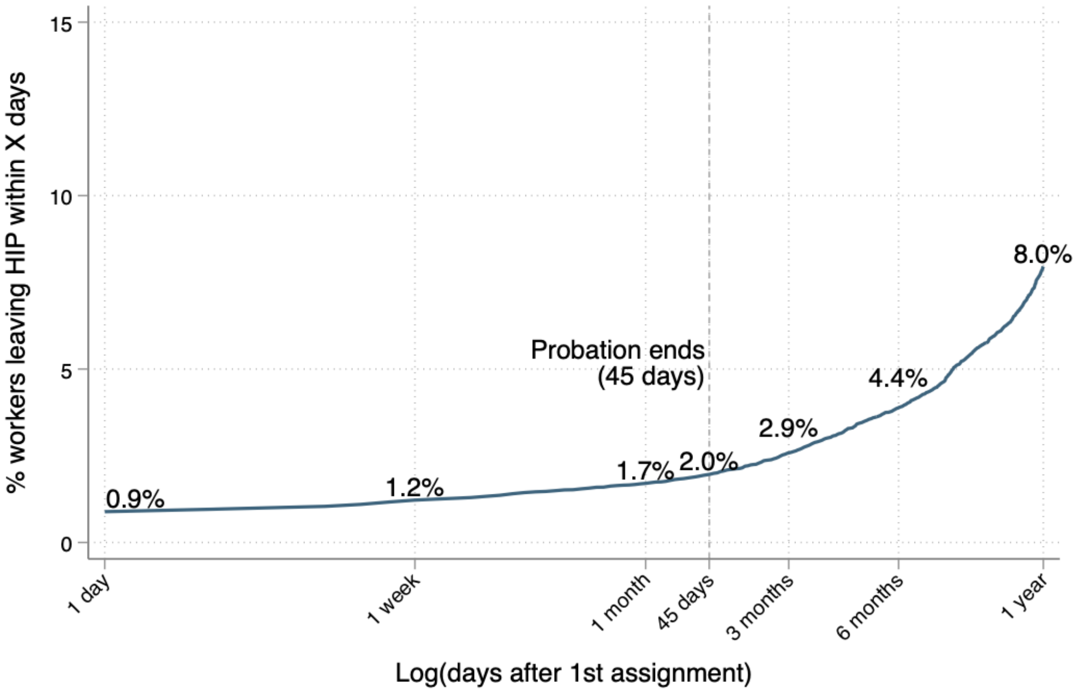
Panel B. IV Estimates

	(1)	(2)	(3)	(4)
	Never worked		Separated	
	in HIP	All	Not returned	Returned
Posterior belief of	0.082	0.166	0.535**	-0.369
upper-level salary	(0.228)	(0.399)	(0.264)	(0.281)
	[0.721]	[0.677]	[0.043]	[0.189]
Observations	1,126	627	627	627
R-squared	0.003	0.002	-0.001	0.001
Cluster	Cohort	Cohort	Cohort	Cohort
Dep var mean	0.477	0.222	0.0906	0.131
F-stat	27.40	10.52	10.52	10.52

Notes: This table shows the impact of information treatment on upper-level salary on turnover outcomes. Dependent variables: Column 1 —the applicant never took up a job in HIP. Column 2 — the worker separated from the job. Column 3 — the worker separated from the job and never returned to HIP. Column 4 — the worker separated from the job and returned to HIP. Baseline bias is the distance between the natural logarithm of the prior belief and the natural logarithm of the benchmark. The independent variable in Panel B, updated belief of upper-level salary, is the natural logarithm of the posterior belief of the after-promotion salary, instrumented by the interaction of treatment status and baseline update potential, defined as the distance between baseline perception and benchmark. Standard errors are clustered at the cohort (day of hire) level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

A Appendix Figures and Tables

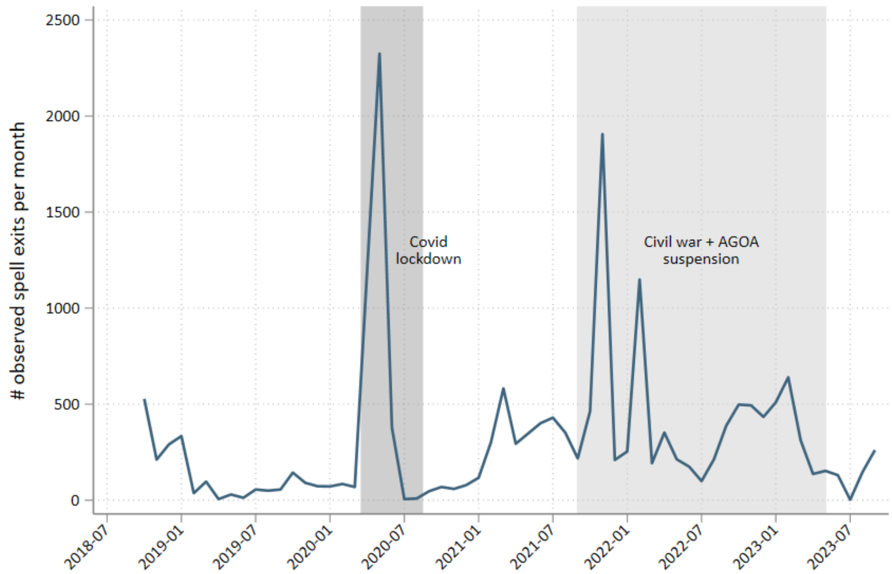
Figure A1: Percentage of Workers Separating From the First Job and Never Returning



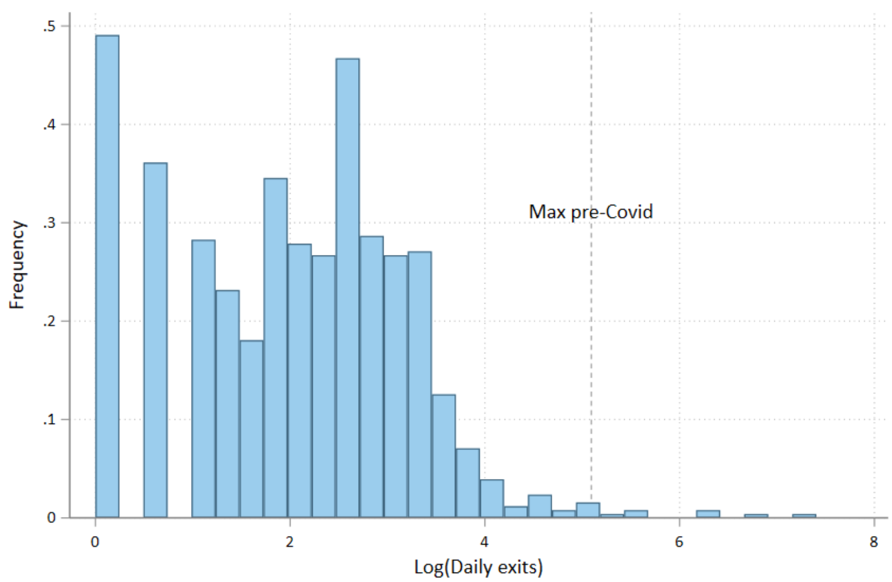
Notes: This figure shows the distribution of the turnover in the industrial park between August 2018 and September 2023. We show the key statistics of turnover within one day, one week, one month, 45 days when the probation period ended, three months, six months, and one year.

Figure A2: Mass Layoff in HIP

Panel A. Monthly Trend of Separation



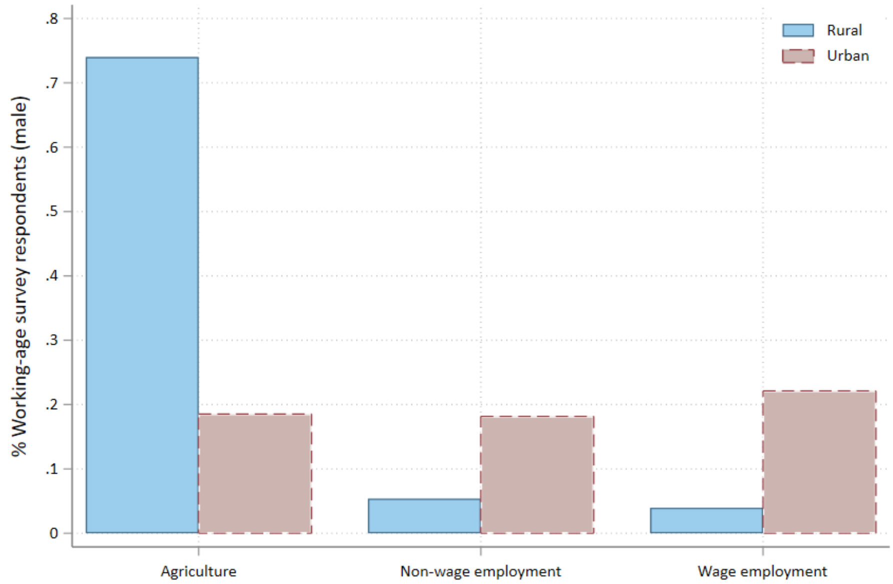
Panel B. Histogram of the Number of Daily Separations



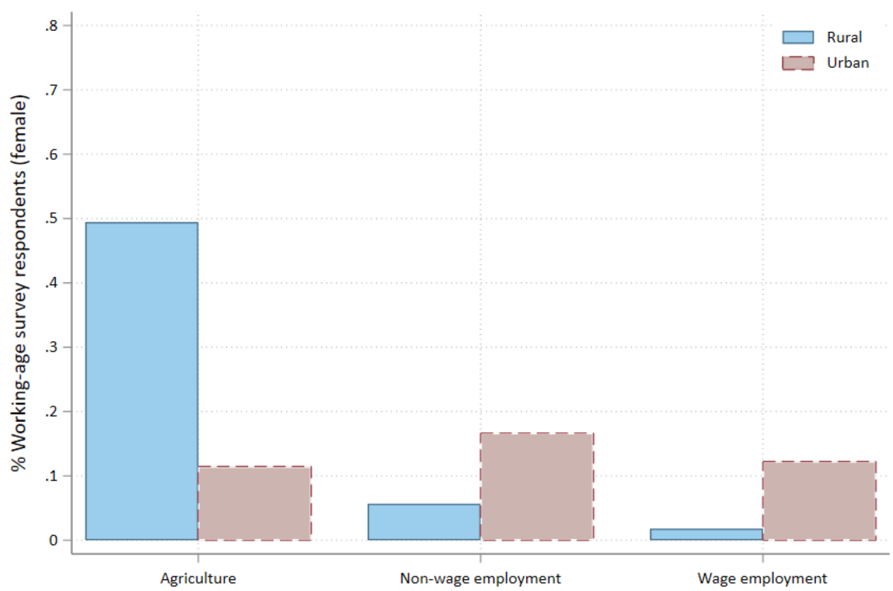
Notes: This figure shows the trend of monthly separation between August 2018 and September 2023 (Panel A) and the histogram of the number of daily separations (Panel B). Panel A indicates two major periods of mass layoffs (Covid, civil war and AGOA suspension). The gray line in Panel B indicates the maximum daily separation before Covid.

Figure A3: Distribution of Types of Employment, By Rural and Urban

Panel A. Male workers

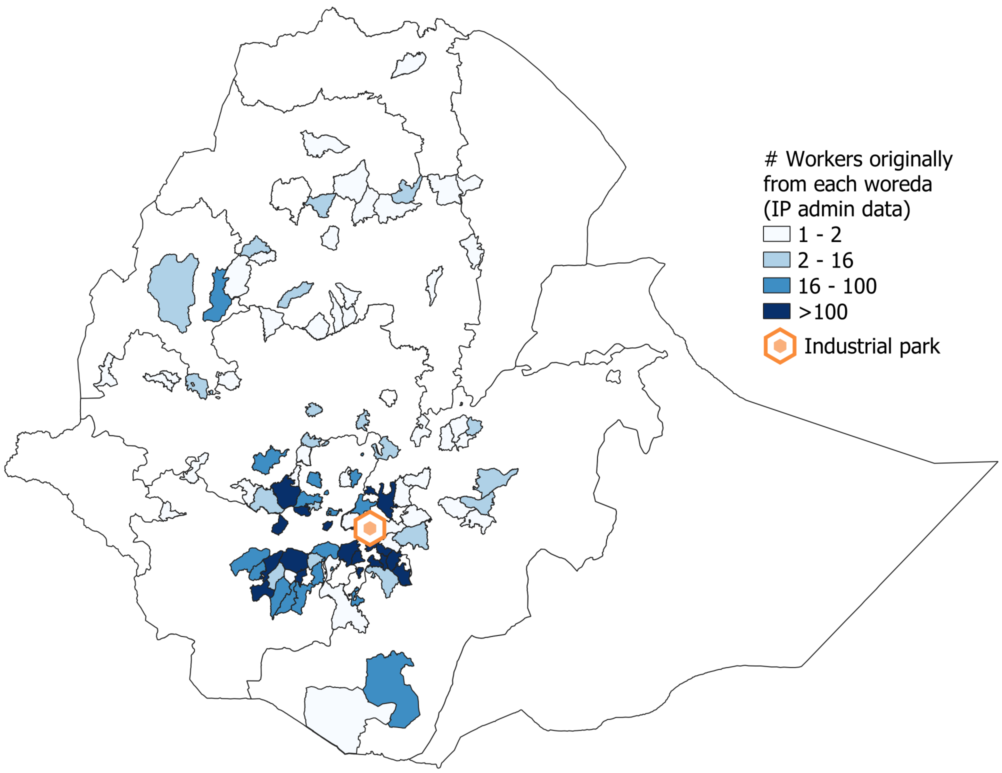


Panel B. Female workers



Notes: This figure shows the distribution of types of work in SNNP and Oromia from LSMS data. Only individuals aged above 15 and below 64 are included.

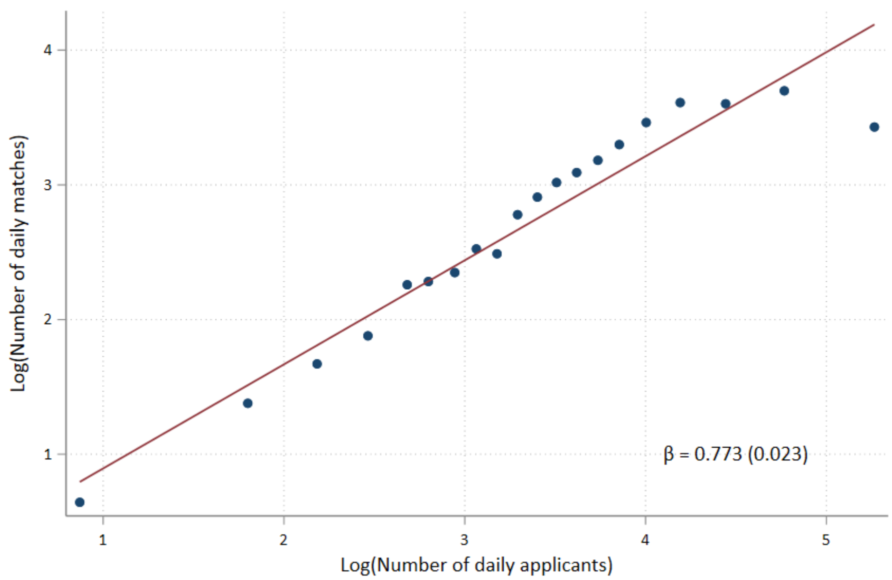
Figure A4: Distribution of Workers' Origins



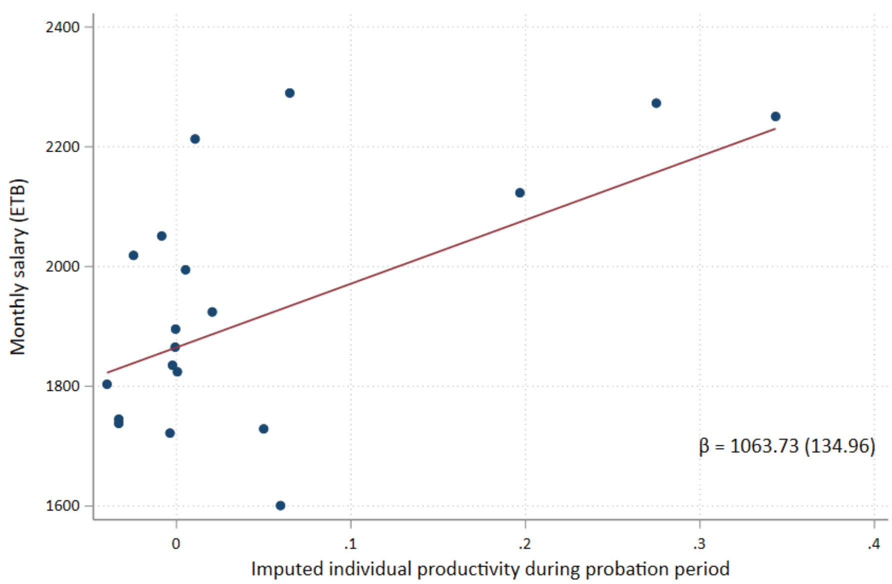
Notes: This figure shows the distribution of workers' origins. We only show the districts from which at least one worker in the administrative data was originated.

Figure A5: Visualization of Key Parameters Estimation in Matching Efficiency

Panel A. Elasticity of Matching Function

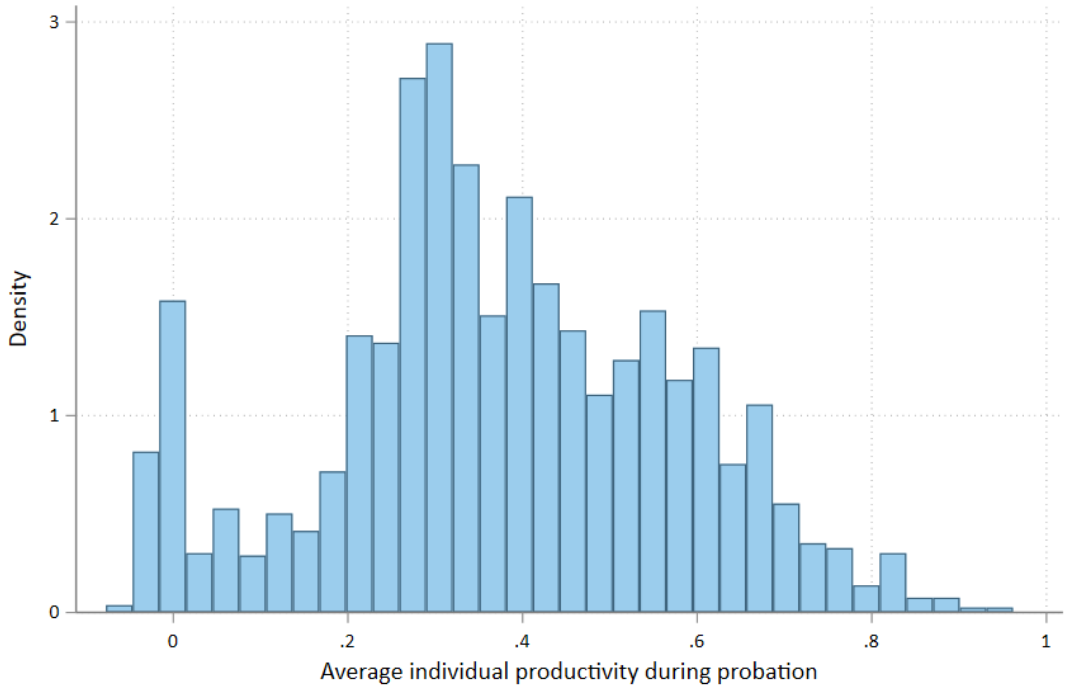


Panel B. Wage Sharing



Notes: This figure shows the estimation of key parameters in matching efficiency discussion. Panel A shows the correlation between log number of daily matches and log number of daily applicants to estimate the elasticity of matching function. Panel B shows the correlation between the first month salary and imputed individual productivity during probation period to estimate workers' bargaining power.

Figure A6: Productivity Measure Histogram

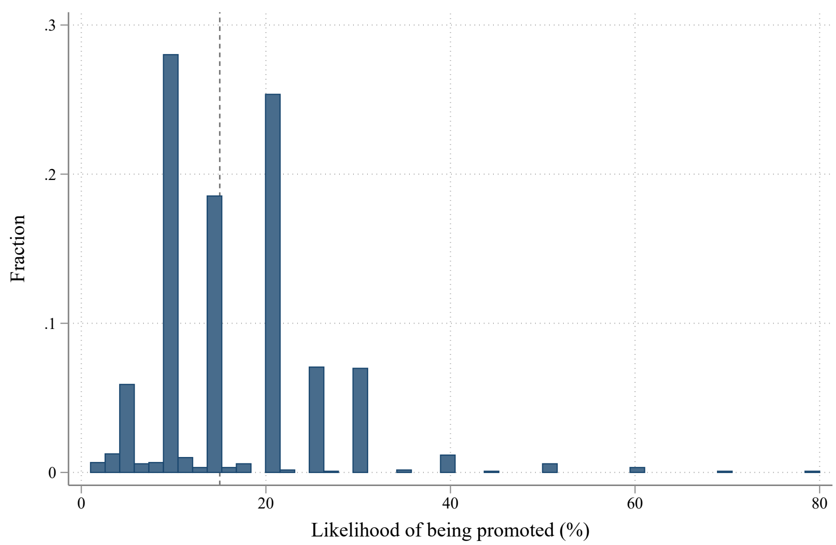


Notes: This figure shows the histogram of individual productivity imputed within probation period (45 days). Individual productivity is imputed using Equation 5 with personnel data collected from nine firms in the industrial park. Productivity is measured by the percentage of targets met daily.

Figure A7: Baseline Perceptions of Career Incentives

(a) Belief about salary after promotion

(b) Belief about likelihood of being promoted



Notes: This figure shows histograms of the prior beliefs reported in the survey. Panel (a) shows the histogram of prior beliefs about the after-promotion salary (measured in US dollars) and panel (b) shows the histogram for prior beliefs about the probability of being promoted to an upper-level position (measured as a percentage). The dashed vertical line indicates the true value in both plots.

Table A1: Predicting Local Coffee Prices Using Global Coffee Prices

Panel A. Correlation between local prices and global prices

	(1)	(2)	(3)	(4)
	Log price: Local coffee			
	Washed	Washed	Unwashed	Unwashed
Log price: Global, Robustas	0.984***		1.049***	
	(0.121)		(0.145)	
Log price: Global, Other Mild Arabica		0.816***		0.932***
		(0.0452)		(0.0453)
Observations	53	53	53	53
R-squared	0.478	0.830	0.425	0.846
P-value: coefficient = 1	0.894	0.000	0.738	0.138

Panel B. Correlation between local trading volumes and global prices

	(1)	(2)	(3)	(4)
	Log trading values: Local coffee			
	Washed	Washed	Unwashed	Unwashed
Log price: Global, Robustas	-1.667***		-0.356	
	(0.516)		(0.216)	
Log price: Global, Other Mild Arabica		-1.449***		-0.158
		(0.261)		(0.125)
Observations	53	53	53	53
R-squared	0.210	0.401	0.047	0.023
P-value: coefficient = 1	0.000	0.000	0.000	0.000

Notes: This table reports the correlation between local coffee prices, local trading volumes, and global coffee prices. The local coffee prices and trading volumes are obtained from Ethiopia Commodity Exchange. The global coffee prices are obtained from International Monetary Fund. Standard errors are clustered two-way at the cohort level and at the district level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table A2: Causal Effect of Coffee Price Shocks on Turnover: IV Specification

	(1)	(2)	(3)	(4)
	Dependent variable: Never worked in HIP			
$C_j \times \log P_{t+1}$, Local Washed	0.0892		0.396**	0.101
	(0.0991)		(0.165)	(0.0638)
	[0.372]		[0.0197]	[0.120]
$C_j \times \log P_{t+1}$, Local Unwashed		-0.0206		
		(0.116)		
		[0.860]		
Observations	15,596	15,596	15,596	15,596
R-squared	0.403	0.403	0.032	0.032
Control mean	0.405	0.405	0.405	0.405
F-stat			10.60	16.63

Notes: This table reports the effect of coffee price shocks on turnover. Coffee district is defined as whether the worker's origin reports to have above-median producing fields (10.5%) in the agriculture census. Post price is defined as coffee price one month after the application date. The local coffee prices and trading volumes are obtained from Ethiopia Commodity Exchange. The global coffee prices are obtained from International Monetary Fund. Dependent variable: the applicant never took up a job in HIP. Specification: Column 1 — OLS, local washed coffee price. Column 2 — OLS, local unwashed coffee price. Column 3 — IV, local unwashed coffee price instrumented by the global coffee price (Coffee Arabica). Column 4 — IV, local washed coffee price instrumented by the global coffee price (Coffee Robusta). All regressions control for demographics (gender, education, age), worker's origin fixed effects and cohort fixed effects (the month of application), the interaction of coffee district and the log price one month before application (global coffee price), and cluster two-way at worker's origin and cohort. Standard errors are clustered two-way at the cohort level and at the district level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table A3: Causal Effect of Coffee Price Shocks on Turnover: Robustness

Panel A. Using average coffee prices 2–12 months after application

	(1)	(2)	(3)	(4)	(5)
	Never worked	Separated			
	in HIP	All	Not returned	Returned	All
$C_j \times \log P_{[t+2,t+12]}$	0.0848	-0.0374	-0.0760	0.0386	0.0865
	(0.100)	(0.118)	(0.117)	(0.0935)	(0.251)
	[0.400]	[0.753]	[0.519]	[0.681]	[0.730]
Observations	15,596	10,112	10,112	10,112	2,162
R-squared	0.403	0.135	0.144	0.071	0.687
Control mean	0.405	0.197	0.0816	0.115	0.197

Panel B. Other specification tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Never worked in HIP						
$C_j \times \log P_{t+1}$	0.235**	0.257*	0.257*				0.190*
	(0.0977)	(0.134)	(0.132)				(0.111)
	[0.0194]	[0.0562]	[0.0508]				[0.0926]
$C_j \times P_{t+1}$				0.00132**			
				(0.000591)			
				[0.0292]			
$C_j \times 1(P_{t+1} > P_{t-1})$					0.0442**		
					(0.0169)		
					[0.0115]		
$C_j \times \log P_{t+1}$, Robusta						0.196*	
						(0.117)	
						[0.0991]	
Observations	15,596	14,814	14,814	15,596	15,596	15,596	13,794
R-squared	0.403			0.403	0.403	0.403	0.372
Control mean	0.405	0.405	0.405	0.405	0.405	0.405	0.405

Notes: This table reports the effect of coffee price shocks on turnover. Coffee district is defined as whether the worker's origin reports to have above-median producing fields (10.5%) in the agriculture census. Global coffee prices are collected from International Monetary Fund. Panel A: Post price is defined as average global coffee price between 2–12 months after the application date. Panel B: Post price is defined as global coffee price one month after the application date. Dependent variable is whether the applicant never took up a job in HIP. Specification: Column 1 — main specification. Column 2 — Logit regression. Column 3 — Probit regression. Column 4 — replace log price with price level. Column 5 — replace log price with whether global coffee price in $t + 1$ is higher than $t - 1$. Column 6 — use global prices of coffee Robusta. Column 7 — drop mass layoff episodes. All regressions control for demographics (gender, education, age), worker's origin fixed effects and cohort fixed effects (the month of application), the interaction of coffee district and the log price one month before application, and cluster two-way at worker's origin and cohort. Standard errors are clustered two-way at the cohort level and at the district level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table A4: Balance Table of Information Treatment

	All	Mean outcomes				Difference	
		Control		Treated		T-C	
Observations		566		637			
A. Demographics							
Age	21.53	21.62	(2.07)	21.44	(2.11)	-0.17	(0.12)
Married	0.12	0.11	(0.32)	0.12	(0.33)	0.01	(0.02)
From Hawassa	0.38	0.34	(0.47)	0.41	(0.49)	0.07**	(0.03)
Speaks Sidamagna	0.76	0.74	(0.44)	0.78	(0.42)	0.03	(0.04)
Speaks Amharic	0.24	0.25	(0.44)	0.23	(0.42)	-0.03	(0.03)
Protestant	0.91	0.90	(0.30)	0.91	(0.29)	0.01	(0.02)
B. Education and experience							
TVET or college educated	0.31	0.31	(0.46)	0.31	(0.46)	-0.00	(0.03)
High school graduate	0.31	0.28	(0.45)	0.34	(0.47)	0.06*	(0.03)
Has work experience	0.17	0.16	(0.37)	0.19	(0.39)	0.02	(0.03)
Has work experience in garment	0.11	0.09	(0.29)	0.13	(0.33)	0.04	(0.02)
C. Skill measures							
Memory score	5.32	5.32	(1.05)	5.32	(1.02)	-0.00	(0.05)
Raven score	3.90	3.91	(2.12)	3.90	(2.09)	-0.01	(0.17)
Game: When Abiy got Nobel Prize	0.46	0.48	(0.50)	0.44	(0.50)	-0.03	(0.04)
Game: How many regions in Ethiopia	0.39	0.37	(0.48)	0.40	(0.49)	0.02	(0.03)
Cognitive score (normalized)	0.00	0.01	(1.00)	-0.01	(1.00)	-0.01	(0.06)
Game: Finger coordination	34.80	34.83	(9.15)	34.76	(8.54)	-0.07	(0.58)
Game: Threading needles	11.78	11.56	(4.79)	11.97	(4.53)	0.41	(0.36)
Dexterity score (normalized)	0.00	-0.03	(1.02)	0.02	(0.98)	0.05	(0.08)
D. Social network							
Number of friends who worked in HIP before	2.30	2.35	(5.33)	2.24	(4.95)	-0.11	(0.44)
Number of friends who apply together	2.98	3.30	(4.98)	2.70	(4.08)	-0.60*	(0.36)
Number of the treated workers she knows	0.06	0.07	(0.35)	0.05	(0.28)	-0.01	(0.02)
Network score (normalized)	-0.00	0.02	(1.09)	-0.02	(0.91)	-0.04	(0.08)
E. Career plan and motivations							
Plans to start their own business	0.54	0.54	(0.50)	0.53	(0.50)	-0.01	(0.03)
Number of years planned to stay in HIP	3.75	3.77	(1.92)	3.73	(1.80)	-0.04	(0.12)
Cares about long-run salary	0.62	0.64	(0.48)	0.60	(0.49)	-0.04	(0.03)
Applies for HIP b/c she wants to learn skills	0.89	0.90	(0.29)	0.88	(0.32)	-0.02	(0.02)
Applies for HIP b/c the future salary is good	0.48	0.47	(0.50)	0.49	(0.50)	0.02	(0.03)
Applies for HIP b/c the job is interesting	0.80	0.83	(0.38)	0.77	(0.42)	-0.06***	(0.02)
Intrinsic motivation score (normalized)	0.00	0.02	(0.98)	-0.02	(1.01)	-0.04	(0.06)

Notes: This table shows balance between the baseline characteristics of treated and control workers. Standard deviations in brackets. We compute the difference in the last column; standard errors are clustered at the cohort (day of hire) level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table A5: Treatment Heterogeneity of the Effects of Misperception

	(1)	(2)	(3)	(4)
	Never worked	Separated		
	in HIP	All	Not returned	Returned
Treated cohort * Baseline salary bias * Old worker	-0.007	0.089	-0.244*	0.339
	(0.153)	(0.170)	(0.141)	(0.231)
	[0.964]	[0.605]	[0.091]	[0.150]
Treated cohort * Baseline salary bias * New worker	-0.113	-0.106	-0.328**	0.017
	(0.203)	(0.156)	(0.156)	(0.168)
	[0.578]	[0.502]	[0.041]	[0.921]
Observations	1,127	1,127	628	628
R-squared	0.002	0.076	0.030	0.127
Cluster	Cohort	Cohort	Cohort	Cohort
Dep var mean	0.477	0.222	0.0906	0.131

Notes: This table shows the treatment heterogeneity of the impact of information treatment on upper-level salary on turnover outcomes. Dependent variables: Column 1 —the applicant never took up a job in HIP. Column 2 — the worker separated from the job. Column 3 — the worker separated from the job and never returned to HIP. Column 4 — the worker separated from the job and returned to HIP. Baseline bias is the distance between the natural logarithm of the prior belief and the natural logarithm of the benchmark. We interact the treatment status, baseline update potential, defined as the distance between baseline perception and benchmark, and whether a worker had worked in HIP previously. Standard errors are clustered at the cohort (day of hire) level. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

B Model

We follow the endogenous separation set-up a la Fujita and Ramey (2012). Suppose there is a continuum of risk-neutral workers with mass normalized to 1, and infinite number of identical, risk-neutral firms. Time is discrete; all agents have a discount rate β for future return. In a search economy, each firm needs to match with one and only one worker to produce. Upon a successful match, the pair would produce x units of goods. We assume that x follows a given distribution $G(\cdot) = N(\mu, \sigma^2)$. We would also refer x as match quality throughout the model.

In each period, each firm pays c up front to post a vacancy. Define the mass of unemployed workers v, the mass of vacancies v, and market tightness $\theta = v/u$. Assume the total number of matches follows $m(u, v) = Au^{\alpha}v^{1-\alpha}$. The probability of each firm receiving one worker is $q(\theta) = m(u, v)/v = A\theta^{-\alpha}$. The probability of a worker being matched with a firm is $\theta q(\theta)$. The pair would engage in Nash bargaining; workers' bargaining power is π.

Initial beliefs. Assume firms have perfect information about the distribution of x.[5] For a given worker i, denote x^i as the true match quality whenever she gets a match, $x_t^i = \mathbf{E}_t^i(x)$ as her perception of average match quality. x^i is a constant because firms are identical. We further assume $x_0^i = x^i + \epsilon$, $\epsilon \sim N(0, \sigma_\epsilon^2)$, that is, worker i's initial perception is on average accurate but with noise. For workers on the job, with probability λ, a worker would observe their true match quality x^i and stay accurate for all future periods.

Bellman equations. Denote the value function for unemployment is U_t^i for worker i in period t, the value function for a vacancy V_t. For a given match quality x, the total value function is $M_t^i(x)$, and the worker gets a share π from the surplus $S_t^i(x) = M_t^i(x) - U_t^i - V_t$. Workers enjoy b when they are unemployed.

Value function for unemployment, notice there is no uncertainty for match surplus be-

[5] Wu and Wang (2025) discusses the possibility of violation of this assumption in a more general labor market in Ethiopia. In the context of Hawassa Industrial Park, where entry-level workers are more homogeneous and there are many applicants every day, we believe it is less likely that firms would have substantial misperceptions of the distribution of workers' productivity.

cause of homogeneous firms:

$$U_t^i = b + \beta \left[\theta_t q(\theta_t)\pi S_{t+1}^i(x_t^i) + U_{t+1}^i\right] \tag{9}$$

Value function for vacancy posting, where $\mathbf{E}_t$ without superscript is an operator with accurate belief of x:

$$V_t = -c + \beta \left[q(\theta_t)(1-\pi)\mathbf{E}_t S_{t+1}^i(x) + V_{t+1}\right] \tag{10}$$

Assuming free entry, firms would stop entering the search market when $V_t = 0 \ \ \forall t$. From Equation 10:

$$q(\theta_t)(1-\pi)\mathbf{E}_t S_{t+1}^i(x) = c \tag{11}$$

For the matched pair with match quality x, denote $M_t^{i,c}(x)$ as the continuation value if the worker decides to stay on the job, $S_t^{i,c}(x)$ the continuation surplus. A share s of all matches will exogenously terminate without any belief update.[6] Among the rest, with probability λ, a worker with the belief x_t^i will learn about her true match quality and stop learning for any future period.

Suppose worker i already realizes her true match quality: $x_t^i = x^i$. Denote $M_t^{i,NL}(x_t^i)$ as the match value with no learning, and $S_t^{i,NL}$ the match surplus. We have:

$$M_t^{i,NL}(x_t^i) = \max\{x_t^i + \beta(1-s)M_{t+1}^i(x_t^i) + \beta s(U_{t+1}^i + V_{t+1}), 0\}$$

With the free entry condition, the match surplus without learning follows:

$$S_t^{i,NL}(x_t^i) = \max\{x_t^i - b + \beta(1-s)S_{t+1}^{i,NL}(x_t^i) - \beta\theta_t q(\theta_t)\pi S_{t+1}^{i,NL}(x_t^i), 0\} \tag{12}$$

Suppose now worker i has not realized her true match quality yet. Ex ante, the worker

[6] This reflects firm-specific separation, where workers may quit because of reasons irrelevant to overall match quality (for example, management styles of individual firms).

would expect the match value after learning as follows:

$$\int M_{t+1}^{i,NL}(x_t^i - \epsilon)\phi(\frac{\epsilon}{\sigma_\epsilon})d\epsilon$$

Therefore, the continuation value for a worker with belief x_t^i:

$$M_t^{i,c}(x_t^i) = x_t^i + \beta(1-s)\left[\lambda \int M_{t+1}^{i,NL}(x_t^i - \epsilon)\phi(\frac{\epsilon}{\sigma_\epsilon})d\epsilon + (1-\lambda)M_{t+1}^i(x_t^i)\right] + \beta s(U_{t+1}^i + V_{t+1})$$

With the free entry condition, the continuation surplus follows:

$$\begin{aligned} S_t^{i,c}(x_t^i) = x_t^i - b + \beta(1-s)S_{t+1}^i(x_t^i) - \beta\theta_t q(\theta_t)\pi S_{t+1}^i(x_t^i) + \\ \beta(1-s)\lambda\left[\int S_{t+1}^{i,NL}(x_t^i - \epsilon)\phi(\epsilon/\sigma_\epsilon)d\epsilon - S_{t+1}^i(x_t^i)\right] \end{aligned} \tag{13}$$

Workers choose to break the match if the continuation surplus is not greater than zero:

$$S_t^i(x_t^i) = \max\{S_t^{i,c}(x_t^i), 0\} \tag{14}$$

Note on steady state equilibrium. There is no conventional steady state solution to this model because at any given period t, there are always some workers who would observe their true match quality and update on all value functions. Ex ante, a worker would have a probability of $p_t \equiv \theta_t q(\theta_t)(1-s)\lambda$ to update their beliefs permanently. A modified definition of steady state equilibrium should satisfy these two conditions. (i) For workers with correct beliefs, $S_{t+1}^{i,NL} = S_t^{i,NL}$. (ii) For workers before belief correction, $p_t S_{t+1}^{i,NL} + (1-p_t)S_{t+1}^{i,c} = p_t S_t^{i,NL} + (1-p_t)S_t^{i,c}$, which is equivalent to $S_{t+1}^{i,c} = S_t^{i,c}$. From now on, we only discuss the features of the model in this modified equilibrium definition and ignore the time dimension for the value functions.

Characterization of match surplus. With this modified equilibrium definition, x_t^i becomes a sufficient statistic of $S_t^{i,c}(x_t^i)$ because workers at different bias levels would undergo the same belief update process; denote $S(\cdot) = S^i(\cdot)\ \forall i$, etc.

Lemma 1. *$S(x_t^i)$ is weakly increasing in x_t^i.*

Proof. For any given level of belief x, we first examine $S^{NL}(x)$ from Equation 12 when positive:

$$S^{NL}(x) = x - b + \beta(1-s)S^{NL}(x) - \beta\theta_t q(\theta_t)\pi S^{NL}(x)$$
$$\Rightarrow S^{NL}(x) = \frac{1}{1-\beta(1-s)+\beta\theta_t q(\theta_t)\pi}(x-b) \equiv \frac{1}{h_t}(x-b)\ \forall x > b$$

Suppose $S^c(x_t^i) > 0$ for a given worker i. Rearrange Equation 13:

$$S(x_t^i) = x_t^i - b + \beta(1-s)S(x_t^i) - \beta\theta_t q(\theta_t)\pi S(x_t^i) +$$
$$\beta(1-s)\lambda\int_b \frac{x-b}{h_t} d\Phi(\frac{x-x_t^i}{\epsilon}) - \beta(1-s)\lambda S(x_t^i)$$

Solve for $S(x_t^i)$:

$$S(x_t^i) = \max\{\frac{1}{h_t+\beta(1-s)\lambda}(x_t^i - b) + \frac{\beta(1-s)\lambda}{h_t[h_t+\beta(1-s)\lambda]}\left[\int_b (x-b)d\Phi(\frac{x-x_t^i}{\epsilon})\right], 0\} \quad (15)$$

Thus, $S(x_t^i)$ is a monotonic function because $0 < \beta(1-s) < 1$ and $\theta_t q(\theta_t) \geq 0$.

□

Notice that for some $x_t^i < b$, match surplus can be positive because there is a chance that the worker learns about their true match quality to be higher. Because $S(x_t^i)$ is monotonic increasing, there exists a threshold belief level such that a worker is indifferent between staying and quitting:

$$\underline{x}_t = b - \frac{\beta(1-s)\lambda}{1-\beta(1-s)+\beta\theta_t q(\theta_t)\pi}\int_b (x-b)d\Phi(\frac{x-\underline{x}_t}{\epsilon}) \quad (16)$$

For $x_t^i > b$, one can also rewrite the match surplus as a combination of $S^{NL}(x_t^i)$, match surplus without learning, and the option value of learning $L(x_t^i)$:

$$S(x_t^i) = \underbrace{\frac{1}{h_t}(x_t^i - b)}_{S^{NL}(x_t^i)} + \underbrace{\frac{\beta(1-s)\lambda}{h_t[h_t+\beta(1-s)\lambda]}\left[\int_b (x-b)d\Phi(\frac{x-x_t^i}{\epsilon}) - (x_t^i - b)\right]}_{L(x_t^i)} \quad (17)$$

When a worker enters unemployment and decreases market tightness θ_t, she would first incur a search externality by decreasing unemployment value and increasing on-the-job match surplus $S^{NL}(x_t^i)$. This would further incur a *learning* externality because match surplus under all potential belief updates would increase. Introducing on-the-job learning can thus further persuade workers to stay on the job and reduce separation.

Steady-state separation. To close the model, the employment-unemployment flow should equal unemployment-employment flow:

$$(1-u)\left[s+(1-s)\lambda\Phi(\frac{x_t}{\epsilon})\right]=u\theta_t q(\theta_t) \tag{18}$$

Efficiency. Social planner would maximize the total values in the search market:

$$\max_{u,v}(1-u)\mathbf{E}S(x^i)+\mathbf{E}U^i+(1-u+v)V$$

In steady state equilibrium, we have:

$$(1-\beta)\mathbf{E}U^i=b+\beta\theta_t q(\theta_t)\pi\mathbf{E}S(x^i)$$
$$(1-\beta)V=-c+\beta q(\theta_t)(1-\pi)\mathbf{E}S(x^i)$$

The maximization problem is simplified as:

$$\max_{u,v}\frac{b}{1-\beta}-\frac{c}{1-\beta}(1-u+v)+\underbrace{\left[\frac{\beta}{1-\beta}\theta q(\theta)\pi+\frac{\beta}{1-\beta}(1-u+v)q(\theta)(1-\pi)+1-u\right]}_{J(u,v)}\mathbf{E}S(x^i)$$

First order conditions:

$$J(u,v)\frac{\partial\mathbf{E}S(x^i)}{\partial u}+\frac{\partial J(u,v)}{\partial u}\mathbf{E}S(x^i)=-\frac{c}{1-\beta}$$
$$J(u,v)\frac{\partial\mathbf{E}S(x^i)}{\partial v}+\frac{\partial J(u,v)}{\partial v}\mathbf{E}S(x^i)=\frac{c}{1-\beta}$$

Adding the two equations:

$$J(u,v)\left(\frac{\partial\mathbf{E}S(x^i)}{\partial u}+\frac{\partial\mathbf{E}S(x^i)}{\partial v}\right)+\left(\frac{\partial J(u,v)}{\partial u}+\frac{\partial J(u,v)}{\partial v}\right)\mathbf{E}S(x^i)=0$$

This can be further simplified into the following:

$$\frac{\partial \mathbf{E}S(x^i)}{\mathbf{E}S(x^i)\partial\theta} = -\frac{\partial J}{J\partial\theta}\left(\frac{\partial\theta}{\partial u} + \frac{\partial\theta}{\partial v}\right) + \frac{1}{J} \tag{19}$$

Notice that under free entry condition,

$$\frac{\partial \mathbf{E}S(x^i)}{\mathbf{E}S(x^i)\partial\theta} = -\frac{q'(\theta)}{q(\theta)} \tag{20}$$

These two conditions are generally different. Similar to Hosios (1990), the matching efficiency depends on the relation between worker's bargaining power π and features of matching function. One can prove from Equation 19 that $|\frac{\partial \mathbf{E}S(x^i)}{\mathbf{E}S(x^i)\partial\theta}|$ decreases in π. If π is sufficiently small, when a worker enters unemployment and decreases market tightness, the marginal increase in match surplus at the efficient level of market tightness would be smaller than at the free entry condition, suggesting that under free entry condition, workers forego too much match surplus and quit too much because of the lack of private incentives.

Theorem 1. *When workers' bargaining power is sufficiently low, matching efficiency in the search economy worsens under endogenous separation with on-the-job learning.*

Proof. Using the notations from Equation 17, for a given belief $x > b$, when there is no endogenous separation,

$$\frac{\partial S^{NL}(x)}{S^{NL}\partial\theta} = -\frac{h'(\theta)}{h(\theta)}$$

Under endogenous separation, for any belief $x > \underline{x}$,

$$\begin{aligned}\frac{\partial S(x)}{S(x)\partial\theta} &= -\frac{h'(\theta)}{h(\theta)}\cdot\frac{S^{NL}(x)}{S(x)} - \frac{(2h+\beta(1-s)\lambda)h'(\theta)}{(h+\beta(1-s)\lambda)h(\theta)}\cdot\frac{L(x)}{S(x)}\\ &= -\frac{h'(\theta)}{h(\theta)}\cdot\left(\frac{S^{NL}(x)}{S(x)} + \frac{2h+\beta(1-s)\lambda}{h+\beta(1-s)\lambda}\cdot\frac{L(x)}{S(x)}\right)\\ &= \underbrace{-\frac{h'(\theta)}{h(\theta)}\cdot\frac{S^{NL}(x)+L(x)}{S(x)}}_{\frac{\partial S^{NL}(x)}{S^{NL}\partial\theta}} - \frac{h'(\theta)}{h(\theta)}\cdot\frac{h}{h+\beta(1-s)\lambda}\cdot\frac{L(x)}{S(x)}\end{aligned}$$

Take integration:

$$\frac{\partial \mathbf{E}S(x^i)}{\mathbf{E}S(x^i)\partial\theta} = \frac{\partial \mathbf{E}S^{NL}(x^i)}{\mathbf{E}S^{NL}(x^i)\partial\theta} - \int_{\underline{x}} \frac{h'(\theta)}{h(\theta)} \cdot \frac{h}{h+\beta(1-s)\lambda} \cdot \frac{L(x)}{S(x)} - \int_{\underline{x}}^{b} \frac{h'(\theta)}{h(\theta)}$$
$$> \frac{\partial \mathbf{E}S^{NL}(x^i)}{\mathbf{E}S^{NL}(x^i)\partial\theta}$$

When π is sufficiently low, the efficient market tightness is already lower than θ^* with no endogenous separation, so matching efficiency with endogenous separation is worse off. □

Theorem 1 illustrates how the learning externality exacerbates the matching inefficiency in a classic DMP model by two margins. (i) Because learning externality is caused by increased match surplus under all potential belief updates, learning externality goes in the same direction as search externality. (ii) More matches were affected by the two externalities because $\underline{x} < b$.