# Subsistence Wage Employment: Labor Market Dynamics in Urban Ghana

Peter Deffebach

*Boston University*

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**Abstract**

The share of workers in wage employment is low in developing countries. Recent research argues high exit rates out of wage employment, rather than low entry rates, drive low levels of wage work overall. To shed light on the causes of elevated exit rates in low-income labor markets, I conduct a panel survey of job-seekers and a complementary survey of firms in Accra, Ghana. I document three new facts. First, exits are dominated by quits in Ghana while layoffs play a negligible role, in strong contrast to the USA where layoffs dominate and quits are infrequent. Second, workers in Ghana experience income gains after quits, also in strong contrast with the USA, where workers experience substantial income losses following quits. Third, I show quits are most common among job-seekers experiencing a temporary loss in non-wage income at baseline, but by endline have re-gained access to a source of income flows. To quantify the contribution of changing non-wage income in driving exit out of the wage sector, I build a general equilibrium model of job search in which workers face uncertain non-wage income. In the model, workers accept low-quality jobs when non-wage income is low, and quit them when non-wage income improves. When calibrated to match the experience of jobseekers in both the USA and Ghana, my model attributes 25% of the difference in exit rates to differences in the volatility of non-labor income. I conclude in Ghana, wage work is used to cope with risk in the non-wage sector.

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# 1 Introduction

In developing countries, only a small share of workers are engaged in wage employment,[1] and the cause of such low rates of wage work has long been a central question of development economics. Recently Donovan, Lu and Schoellman (2023) collected panel data from countries across the development spectrum and showed elevated exit rates out of the wage sector, rather than low entry rates into the wage sector, drive differences between developed and less-developed countries.

We know little, however, about the causes of such high exit rates. For instance, volatility faced by firms may be driving frequent layoffs. On the other hand, shocks on the worker's side may be driving high quit rates. Existing data sources are not equipped to distinguish between firm and worker-driven exits, that is, quits vs. layoffs, nor equipped to test specific hypotheses about the proximate causes of each type of exit.

The goal of this paper is to shed light on what drives such high rates of exit out of the wage sector in poor countries. To accomplish this, I conduct a new in-depth panel survey of urban job-seekers, along with a complementary survey of firms, in Accra Ghana, a labor market where workers exit the wage sector at elevated rates. Using my surveys, I document three new facts. First, I show quits are the primary driver of exit out of wage work in Ghana, while layoffs play a minor role. This finding stands in stark contrast with patterns of exits in the USA, where layoffs dominate exits out of the wage sector and quits are rare. Second, I show workers in Ghana experience moderate income gains after quitting wage employment, again in stark contrast with the USA, where workers who quit wage employment experience large income losses. Third, changes in the availability of non-wage income are highly predictive of exits out of the wage sector in Ghana.

Taken together, these findings suggest volatility in non-wage income plays an important role in driving high exit rates out of the wage sector in Ghana. To formalize this intuition, I develop and quantify a general equilibrium model with endogenous quits due to volatile non-wage income flows. I calibrate the model to both Ghana and the USA and show that 26% of the difference in exit rates between the two countries can be explained by differences in the volatility of non-wage income.

I conclude that worker-side, rather than firm-side volatility drives high exit rates in Ghana. In particular, I argue that wage work often serves as a means to cope with risk workers face in the non-wage sector: Workers take up some wage jobs when their income outside wage sector is low, then quit such jobs when income opportunities

[1] See Bandiera, Elsayed, Smurra and Zipfel (2022) for an overview of employment rates across the development spectrum. In the poorest countries, 20% of workers are engaged in wage employment. In the richest, 80%.

outside the wage sector improve. I term such jobs "subsistence wage employment." While "subsistence self-employment" refers to income generating activities taken up as a last resort in order to deal with a lack of opportunities in the wage sector, "subsistence wage employment" refers to the opposite phenomenon, wage jobs taken up as a last resort in order to cope with a lack of opportunities in the non-wage sector.[2] In this way, my results are most consistent with the findings of Blattman and Dercon (2018), who similarly argue factory workers in Ethiopia use wage employment as a safety net while cultivating opportunities outside the wage sector. I also join Falco and Haywood (2009), who find self-employment is often a preferred alternative to wage work in urban Ghana, rather than an occupation of last resort.

In Section 2 I describe my new surveys of job-seekers and firms. To conduct my survey, I recruited individuals looking for wage work, whether currently engaged in employment or not, via online advertising, and conducted two surveys eight months apart. The first round of the survey painted a detailed portrait of job-seekers' search strategies, expectations, and outside options. The second round assessed labor market outcomes eight months later, documenting wage employment, self-employment, and earnings. In between the two rounds of job-seeker surveys, I conducted a separate in-person survey with the hiring managers at formal firms, asking about their experience hiring and retaining workers. I compare the experience of my job-seekers in Accra with those in the USA by constructing a weighted sample of workers in the Current Population Survey and the Survey of Income and Program Participation. I compare firms in my sample with firms in the USA using the Job Openings and Labor Turnover Survey (JOLTS).

Due to a lack of worker-level panel data in urban Ghana, little is known about labor market dynamics in my setting. As a consequence, before analyzing the *causes* of exits out of the wage sector, I first ask if, consistent with Donovan, Lu and Schoellman (2023), exit rates really do drive low rates of wage employment overall. They do. I find high exit rates, rather than low entry rates, drive differences between the USA and Ghana. Of job-seekers without wage work in Ghana and the USA, the vast majority of both groups found *some* wage employment over the next eight months. However in Ghana, half the workers who entered the wage sector since baseline were again without wage work at the eight month endline. In the USA, in contrast, workers who entered the wage sector between zero and eight months did not exit, and employment rates at eight months were high. My firm survey confirms these findings: Firms in Ghana reported significantly higher separation rates relative to firms in the USA.

[2]This view of subsistence wage employment dates back to Lewis (1954), and forms the bases of the canonical model of Harris and Todaro (1970). See Schoar (2010) for a discussion on the prevalence of subsistence self-employment. Donovan, Lu and Schoellman (2023) also emphasize how self-employment is an activity of last resort in the absence of formal unemployment insurance.

In Section 3, I explore the causes of high exit rates in Ghana. My central findings consist of three new facts.

First, I document that the majority of these flows out of wage work were voluntary quits, while only a small portion of transitions out of wage work were involuntary layoffs. In the USA, this pattern is reversed: The majority of flows out of wage work were due to involuntary layoffs, and only a small portion were due to quits. This finding is new to the literature. To my knowledge, my study is the first to measure rates of quits and layoffs separations in a developing country, despite these statistics being standard in OECD countries. My firm survey also confirms that quits comprised a higher share of separations in Ghana compared to the USA. I interpret this result to show volatility on the worker side, rather than on the firm-side is the chief cause of exits in Ghana.

Next, I show that quitters had dramatically different experiences in the USA and Ghana. I show that in Ghana, individuals who left the wage sector after a quit saw small income gains. That is, they reported higher non-wage incomes and endline than their earnings at their previous job attained between baseline and endline. In the USA, by contrast, quitters faced steep income losses after leaving wage work. I argue this result is indicative of a process whereby workers quit jobs to avail themselves of opportunities outside the wage sector.

Finally, I document that quits were elevated among job-seekers experiencing a temporary lapse in income at baseline. Specifically, I show job-seekers forced to rely on savings to finance their consumption, as opposed to a stream of income from family support or self-employment, were more likely to quit the wage sector after finding work. Among this group of workers, those who quit appear to have re-encountered income flows at endline. Those who were laid off, on the other hand, were still forced to rely on savings to get by. This finding indicates changes in a worker's outside option play a significant role in driving quits.

These three findings, (1) quits dominate in Ghana, (2) quits are associated with income gains, and (3) quits are concentrated among individuals temporarily without income flows at baseline, indicate volatility in the non-wage sector plays a key role in driving differences in exits between the USA and Ghana. I argue many jobs are taken up solely to help workers deal with bad shocks in the non-wage sector. Workers then quit these jobs when opportunities in the non-wage sector improve. In this way, wage work functions as an insurance device against risk in the non-wage sector.

In Section 4 I benchmark the strength of this explanation with a competing one. I ask if information frictions, that is, the inability of firm and worker to learn about a match before entering into an employment contract, drive high quit rates in Ghana. A wave of recent experimental work has shown reducing information frictions can improve employment outcomes for job-seekers,[3] Poschke (2022), seeking to explain the facts of Donovan, Lu and Schoellman (2023) features noisy signals about match quality in the spirit of Jovanovic (1979).

I leverage my baseline survey's detailed measurement of the level of information job-seekers have about the labor market, as well as their beliefs about the wage and non-wage characteristics of future jobs, to test whether workers with better information or more accurate beliefs are less likely to exit or quit the wage sector. Perhaps surprisingly, I find no heterogeneity in exit along either measure, and conclude information frictions carry little explanatory power in driving exit in my context.

Given income volatility in the non-wage sector appears to drive exit rates, in Section 4 I also ask *what* type of income workers take advantage of when they quit the wage sector. I distinguish between two sources: self-employment income and transfers from friends and family.[4] I show quits out of the wage sector should not be thought of as synonymous with transitions into self-employment.[5] Among both quitters and laid-off workers, less than half of job-seekers who experienced an employment exit are engaged in self-employment. Financial support from friends and family drives income gains after quits just as much as income from self-employment.

Section 5 builds a general equilibrium structural model of unemployment in the spirit of Mortensen and Pissarides (1994) and Diamond (1982). The goal of the model is to quantify the role income volatility outside the wage sector plays in driving differences in exits between the USA and Ghana. The model features two sectors, a wage sector and a non-wage sector. In the wage sector, firms and workers meet according to a frictional matching process and matches differ in productivity. In the non-wage sector, workers face a volatile stream of non-wage income which is not available to workers if they are employed for a wage. As a consequence, workers optimally accept and reject jobs trading off their current level of non-wage income, expectations over future gains or losses in non-wage income, and wage earnings at the job under consideration.

The model features wage rigidity, such that wages are not re-evaluated when a worker's non-wage income opportunities change. As a consequence, when workers see suffi-

[3] Abel et al. (2020), Bassi and Nansamba (2020), Carranza et al. (2020), and Abebe et al. (2020) all show making it easier for workers to signal their strengths improve employment outcomes. Banerjee and Sequeira (2021) highlights the importance of learning about the labor market for employment outcomes. Blattman and Dercon (2018) argues workers accept low-amenity factory jobs partially because they do not know how low-amenity such jobs really are.

[4] Workers do not report government support such as unemployment insurance.

[5] Models of labor market dynamics in developing contexts often treat quits as synonymous transitions to wage employment. See, for example, Feng, Lagakos and Rauch (2021),Rud and Trapeznikova (2021), and Bosch and Maloney (2010), and too a lesser extent Herreño and Ocampo (2023), which features quits to unemployment due to growth of an agent's savings buffer.

ciently large improvements in their non-wage income opportunities, they quit work and enter the non-wage sector. Because the goal of the model is to benchmark the role that non-wage income volatility plays in driving quits, I also feature quits and layoffs driven by exogenous forces.

I calibrate my model to match processes of entry into the wage sector along with quits and layoffs out of the wage sector in the USA and Ghana. Additionally, I match the distribution of wage and non-wage earnings in both the USA and Ghana, and the vacancy rate in the two countries as reported by firms. I show three moments in particular pin down the role of volatility in the non-wage sector in driving quits. First, I estimate volatility in non-wage income directly by measuring correlation in non-wage income across months, and show that non-wage income is more persistent in the USA relative to Ghana. Second, I also demonstrate that the difference in the wages of quit vs. layoff jobs is larger when quits due to non-wage income opportunities are more frequent. Third, I show income changes after a quit are less negative when volatility in the non-wage sector drives quits. In an economy with no volatility, the wages of jobs ending in a quit are identical, and workers see identical drops in income after a quit as after a layoff.

After calibrating the model to match both moments in the USA and Ghana, I conduct counterfactual experiments to understand how eliminating variation in non-wage shrinks the gap in exit rates between the two countries. Approximately 26% of the difference in exit rate can be attributed to volatility in the non-wage sector.

Examining differences in the calibrated structural parameters between the USA and Ghana informs what underlying differences in the labor markets of the two countries drives differences in exit rates. For volatility in the non-wage sector to drive quits, my model requires the non-wage sector be desirable to workers relative to the wage sector. Large and frequent swings in non-wage income matter little if, in all cases, wages are so high that workers always prefer the wage sector to the non-wage sector. This additional mechanism, the relative competitiveness of the non-wage sector on top of its volatility, also drives differences in exit rates between the two countries. My calibrated models indicate the earnings premium of the wage sector is significantly larger in the USA than in Ghana. Additionally, the amenity value of wage employment is significantly higher in the USA relative to Ghana.

My results indicate declining exit rates along the path of development documented by Donovan, Lu and Schoellman (2023) may arise not only from decline in the volatility of non-wage earnings, but also secular improvements in the relative productivity of the wage sector, such as biased structural change discussed in Feng, Lagakos and Rauch (2021) and Vollrath (2009).

## 1.1 Contribution

My project first explores the drivers of low rates of wage work in Sub-Saharan Africa by distinguishing between employment entry and employment exit. I conclude exit, rather than entry, drive low rates of employment in the medium run. In this way my project builds most closely on Donovan, Lu and Schoellman (2023), which compiles labor market surveys from around the world and documents elevated rates of entry as well as exit in less-developed countries. Relative to this work, I trade off breadth for depth, by studying a single context, Accra, Ghana, and painting a more complete picture among my selected sample. In particular, I am able to examine the causes of exit by distinguishing between quits and layoffs and test specific hypothesis related to information frictions and the role non-wage income plays in labor market dynamics. Additionally, Donovan, Lu and Schoellman (2023) says little about labor market flows in Sub-Saharan Africa.[6] In Sub-Saharan Africa, researchers have focused almost exclusively on the margin of entry, where they have tested an array of job search assistance programs (For a review, see Carranza and McKenzie (2023)), with little focus on the role of exit.

My findings that quits dominate layoffs as a cause of employment exit is consistent with Blattman, Dercon and Franklin (2019) and Abebe, Buehren and Goldstein (2024), studying factories in Ethiopia, and Boudreau, Heath and McCormick (2021) studying factories in Bangladesh. Relative to this work, I focus on workers in a broader set of jobs. I find quit rates are high across all occupations, including high-skilled services located in offices, showing physical discomfort alone cannot explain high differences in quit rates in poor countries. Groh, Mckenzie, Shammout and Vishwanath (2015) documents high quit rates among university graduates in Jordan who are given non-factory jobs. Relative to this work, and evidence from experimental evidence more broadly, I focus on "naturally occurring" matches. It is perhaps not surprising to see high levels of quits from matches which would not have existed without researcher intervention.

My project takes seriously the distinction between quits and layoffs, and documents that quits and layoffs in Ghana are *more different* than quits and layoffs in the USA. Workhorse models of job-search do not distinguish between quits and layoffs, with employers and workers always mutually agreeing to part ways (McLaughlin, 1991). My work joins Bagga, Mann, Şahin and Violante (2023) and Blanco, Drenik, Moser and Zaratiegui (2024) which both feature quits to non-employment due to changes in a worker's outside option, with the former featuring shocks to a worker's preference for the non-wage amenities of jobs, and the ladder featuring changers to a worker's

[6]The data set of Donovan, Lu and Schoellman (2023) includes only Rwanda and only in secondary analyses

human capital, prompting them to quit and search for higher-paying jobs.

By documenting employment flows from the firm's perspective, I also build on a small literature studying labor market dynamics from the firm's perspective in developing countries. Research has studied barriers firms face in recruiting workers (Caria and Orkin, 2024), but worker retention has received comparatively little focus. My work compliments Kerr (2018) and Shiferaw and Söderbom (2021) in documenting how firms face significantly higher rates of worker separation in Sub-Saharan Africa relative to the USA. By distinguishing between quits and layoffs, I present the first dis-aggregation of labor market flows from a developing country in the style of the USA's Job Openings and Labor Turnover Survey (JOLTS).

I examine, and reject, information frictions as a cause of employment exits in my setting. Recent years have seen a growth of randomized experiments aiming to improve job-finding and retention by improving mobility and reducing information frictions in Sub-Saharan Africa.[7] In particular, Poschke (2022) builds a structural model of job search and argues that noisily-observed match quality is the primary driver of higher employment exits in poor countries documented by Donovan, Lu and Schoellman (2023).[8] While this mechanism may be salient in other contexts, the fact that information frictions carry little explanatory power in my setting should prompt policymakers and researchers to focus on alternative methods to reduce job destruction.

Finally, the structural portion of my project builds on a large tradition of two-sector labor market models in developing settings (Fields, 2010). I build on this literature by emphasizing two forces. First, I emphasize the dynamics of non-wage income and quantitatively assess it's importance. Second, I emphasize the role transfers from family and friends play worker's non-wage income in addition to self employment earnings. The core mechanism of my model aligns most closely with that of Attanasio, Sánchez-Marcos and Low (2005), which argues women join the labor force in response to negative household shocks, and Falco (2014), which emphasizes the riskiness of the informal sector in driving labor market choices, but does not address employment exit.

[7] Abel, Burger and Piraino (2020), and Carranza, Garlick, Orkin and Rankin (2020), Bassi and Nansamba (2020) alleviate information frictions. Franklin (2021) and Banerjee and Sequeira (2021) alleviates transportation frictions. Abebe, Caria, Fafchamps, Falco, Franklin and Quinn (2020) addresses both. For more discussion, see Carranza and McKenzie (2023)

[8] Information frictions are also commonly used to explain separations in the USA, beginning with Jovanovic (1979). See Mercan (2017) and Pries and Rogerson (2022), which study the decline in separations across time, as two relevant examples.

# 2 Data

In this section I introduce the job-seeker and firm surveys I conducted in Accra, Ghana. I also introduce the US-based data sources I use to compare job-seekers and firms in my sample with counterparts in the USA. Finally, I document the importance of exit as opposed to entry, in driving low long-run employment rates in Ghana, justifying subsequent focus on the causes of exits out of the wage sector in Ghana.

## 2.1 Original Surveys in Accra, Ghana

### 2.1.1 Job-seeker Survey

In June 2022, I recruited 465 job-seekers for a panel survey through a Facebook, WhatsApp, and flyer campaign. To participate in the survey, respondents must have been actively searching for a job, but could be employed or unemployed, with no other requirements. The survey was conducted by phone and consisted two waves: Baseline, then endline 8 months later.

The baseline survey focused on job search strategies, expectations about future employment, and job-seeker's earnings potential if unable to find wage work. Importantly, the baseline survey painted a complete picture of information sources, i.e. how job-seekers learn about jobs, wages, and working conditions, as well as the full structure of their social network helping them search for jobs. I elicited expectations about future work using questions Survey of Consumer Expectations (Mueller, Spinnewijn and Topa, 2020). The endline survey assessed outcomes eight months later as well as the labor market experience of workers over the intervening period. I measure employment status, wage and non-wage income, as well as workplace amenities.[9]

Table 1 shows summary statistics of job-seekers in my sample compared with job-seekers surveyed in Ghana's 2015 Labor Force Survey.[10] On average, the sample is more male, more educated, and more likely to be searching while on wage employment than job-seekers according to the 2015 Labor Force Survey. As discussed in Section 2.2, I account for the demographic composition of my sample when making comparisons between job-seekers in my sample and counterparts in the USA.

My sample has some benefits relative to existing work. Unlike recent RCTs studying job search, my sampling strategy does not depend on job-seekers' existing relationship with government or non-profit programs.[11] Additionally, I am not focused on any

[9]Physical amenities are measured in a manner similar to Blattman, Dercon and Franklin (2019). I measure dignity in the workplace using questions from Dube, Naidu and Reich (2022)'s work on the working conditions of Walmart workers in the USA.

[10]The 2015 Labor Force Survey in Ghana is unique in asking about

[11]Carranza, Garlick, Orkin and Rankin (2020) and Bassi and Nansamba (2020) partnered with local

Table 1: Characteristics of Job-Seeker Sample

| Variable | Job-seeker Survey | | 2015 Labor Force Survey | |
|---|---|---|---|---|
| | Mean | Median | Mean | Median |
| | (1) | (2) | (3) | (4) |
| Male | 0.83 | - | 0.51 | - |
| Age | 29.2 | 28 | 36.9 | 35 |
| Years of work experience | 6.0 | 5 | - | - |
| Any work experience | 1.00 | - | - | - |
| Currently working | 0.66 | - | 0.81 | - |
| Currently working for someone else | 0.45 | - | 0.13 | - |
| Currently exclusively in self employment | 0.19 | - | 0.68 | - |
| Any work in past year | 0.95 | - | | - |
| High school or less education | 0.40 | - | 0.89 | - |
| University of more education | 0.47 | - | 0.07 | - |
| Vocational training in past year | 0.21 | - | - | - |
| Years living in Accra | 18.14 | 20 | - | - |
| Any dependents | 0.61 | - | - | - |
| Is married | 0.20 | - | 0.62 | - |
| Months so far searching for job | 28.0 | 24 | 12.3 | 9 |
| Average monthly income (2022 USD) | 108.3 | 87 | - | - |
| Average wage income (2022 USD) | 112.2 | 87 | - | - |

***Note**: This table shows the demographic characteristics of job-seekers in my Accra, Ghana survey and compares my sample to job-seekers in Accra as reported in the 2015 Ghana Labor Force Survey. Columns (1) and (2) report mean and median values for characteristics of job-seekers in my survey. Columns (3) and (4) report the same for job-seekers in Ghana from the 2015 Labor Force Survey. Median is omitted for binary variables.*

particular employment sector, such as the high exit out of factory jobs documented in Blattman, Dercon and Franklin (2019) and Boudreau, Heath and McCormick (2022). Finally, my job-seekers are 29 years old on average and all have work experience, such that, in contrast with recent work, my focus is not exclusively on the problem of low youth employment.[12]

#### 2.1.2 Firm survey

Job-seekers represent only one side of the labor market, and evidence on flows in and out of the wage sector produced only from job-seekers is limited in two ways. First, firms and workers may disagree about which separations are quits and which are layoffs, such that distinguishing between the two sources of exit might not capture meaningful economic differences. Second, my sample of job-seekers is selected on a

non-profits in South Africa and Uganda, respectively. Abel, Burger and Piraino (2020) and Banerjee and Sequeira (2021) partnered with the national unemployment agency of South Africa Notably, Abebe, Caria, Fafchamps, Falco, Franklin and Quinn (2020) constructs a representative sample of job-seekers.

[12]Given Africa's current and future age distribution, low rates of youth employment in particular concern policymakers. See Bandiera, Elsayed, Smurra and Zipfel (2022) for a review. Experiments focused on young or first-time job-seekers include Bandiera, Bassi, Burgess, Rasul, Sulaiman and Vitali (2021) and Assy, Ribeiro, Robalino, Rosati, Puerta and Weber (2019).

Table 2: Firm Characteristics

| Variable | Mean (1) | Median (2) |
| --- | --- | --- |
| Wholly domestic | 0.83 | - |
| Wholly foreign | 0.05 | - |
| Joint enterprise | 0.12 | - |
| Employees in firm | 50.51 | 12 |
| Number of employees overseen | 18.29 | 10 |
| Last position was a services position | 0.40 | - |
| Last position required some college or more | 0.15 | - |

***Note:*** *This table shows characteristic of firms interviewed in my firm survey in Accra, Ghana. Columns (1) and (2) report mean and median values. Median is omitted for binary variables.*

few dimensions. Importantly, they are searching for new jobs and thus may have a different attachment to wage work than the long-term employed. Collecting information from firms alleviates both these concerns: I see their perspective on the causes exits and observe patterns of exit from the workforce at large.

Between the baseline and endline surveys, I conducted a separate survey of 111 firms. Rather than draw a random sample of firms, I prioritized firms who employed workers in positions my job-seekers hoped to find. For example, many job-seekers desired jobs as an office assistant, so enumerators searched for firms employing office assistants, which lead to an over-sampling of firms in high-skilled services and phone-based retail. Enumerators requested to speak with the individual in charge of hiring new employees, which in practice was the establishment manager. The firm survey sought to understand the job search strategies of firms and their experience hiring and retaining workers. I collected data on the hires, quits, and layoffs in a manner comparable to the Job Opening and Labor Turnover Survey (JOLTS) in the USA.

Table 2 shows summary statistics of surveyed firms. Firms are overwhelmingly domestic rather than multinational. The average firm has 50 employees, and the average manager oversees 20 employees, with the latter being the relevant denominator when assessing hiring and separation rates. All firms are formally registered. Despite attempting to over-sample services-related firms, for only 40% of firms was the last position open a services-based position, and only 15% required some college or more.

## 2.2 US Data for Comparison

To evaluate the experience of job-seekers in my sample, I benchmark outcomes against a constructed sample in the USA. I use two sources of data from the USA. The first source is years 2014-2019 of the Current Population Survey (CPS), which I use to analyze long-run job-finding rates among job-seekers. The second is the 2014-2018 panel of the Survey of Income and Program Participation (SIPP), which I use to measure wage and non-wage monthly income. While the SIPP is a monthly panel which measures transitions in and out of employment, it is not suitable for the measurement of employment flows. The survey under-estimates employment entry and exit rates by a factor of three (The National Academy of Sciences, 2018).

My sample of job-seekers differs dramatically from the labor force in the USA. To compare job-seekers in the USA with my sample, I conduct the following procedure. First, I restrict the CPS and SIPP samples to only those between the minimum and maximum ages which appear in the Ghana sample (between 18 and 58). Next, I keep only individuals who are unemployed at least some point in the period, since on-the-job search – including of the self-employed – is not measured in SIPP nor CPS. In practice, this means I restrict my Ghanaian analysis of employment entry to the 55% of job-seekers without wage work at baseline when comparing to the USA. As my sample reports almost continuous engagement in both employment and job search, I drop individuals who leave the labor force at any point in the sample period. To address demographic differences such as age, gender, and marital status, I weight individuals in CPS and SIPP according to the entropy balancing method of Hainmueller (2017) such that aggregate means and covariances between demographic variables are the same in both my sample and the samples of USA workers. My methodology to compare firms between Ghana and the USA is discussed in Appendix D.

## 2.3 Documenting high exit rates in Accra, Ghana

Before exploring the causes of exits out of wage work, I first show that exits out of the wage sector are, indeed, the driver of low wage employment rates in my setting. Using my job-seeker survey contrasted with a matched sample from the Current Population Survey, I show entry rates into wage work are similar between the USA and Ghana, but exit rates are far higher in Ghana relative to the USA. As a consequence, job-seekers in Ghana have far lower employment rates in the long run.

Starting with job-seekers without wage work in the my Ghanaian sample, I consider two outcomes: (1) whether a job-seeker found any wage employment at all in the subsequent eight months, (2), whether, at the eight-month mark, jobseekers who had found some employment in the previous eight months were *still* employed in a wage job. The former outcome measures rate of entry into the wage sector, while the latter outcome measures rate of exit out of the wage sector.

Unfortunately, the CPS does not track employment outcomes over a continuous eight months due to it's eight-months on, eight-months off, four-months on rotation scheme.[13] As a consequence, to compare with my Ghanaian sample, I measure twelve-month equivalents of each variable, then solve for their eight-month counterparts according to a procedure described in Appendix A. In brief, I solve for monthly entry and exit rates which are consistent with the twelve-month outcomes from the CPS, construct a monthly transition matrix between wage work and non-wage work states, and predict worker outcomes over the course of 8 months.[14]

Figure 1 documents the employment outcomes of job-seekers without wage work in the USA and Ghana. The sample of Figure 1 is job-seekers without wage work in the USA and Ghana, and error bars report bootstrapped 95% confidence intervals. In the first bar of Figure 1, I show the proportion of such job-seekers who report working for someone else at *any* point in the following eight months. Jobseekers without wage work in the USA and Ghana report roughly equal rates of working for someone else over the next eight months. In Ghana, 78% of job-seekers find wage work in the next eight months. In the USA, this figure is 71%. In other words, the two groups have similar rates of labor entry overall.

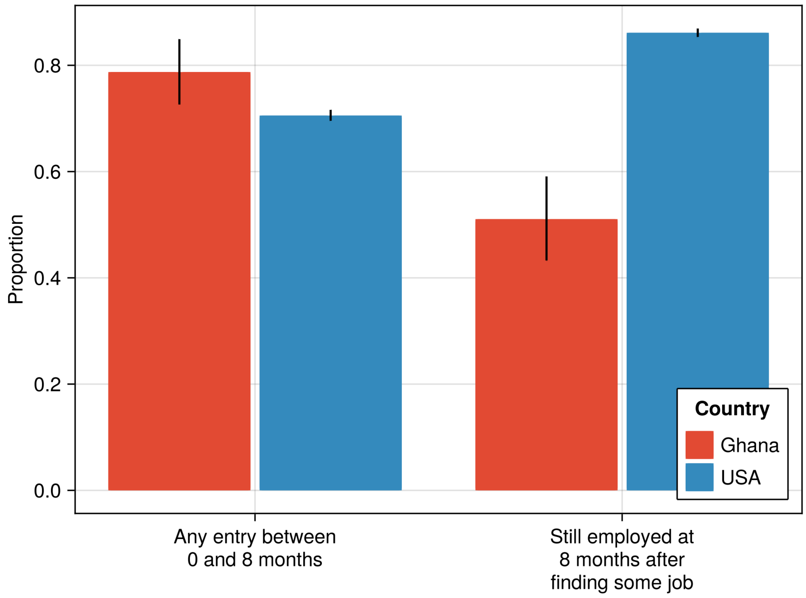
In the next two bars of Figure 1, I show the percentage of job-seekers who are working in a wage job *at* the eight-month mark, conditional on finding some employment before hand. At eight months, 86% of job-seekers who found some work beforehand were still working at a wage job. Few workers exited the wage sector after entry. In Ghana, by contrast, conditional on entering the wage sector at some point in the previous eight months, only 51% of job-seekers are still in the wage sector at the eight-month mark. After entry, almost half of job-seekers experienced an exit out of the wage sector.

Appendix Table B.1 compares derived monthly entry and exit rates using the outcomes presented in Figure 1 and re-affirms the importance of exit relative to entry in long-run employment outcomes. The estimated entry rate is 19% in Ghana and 15% in the USA. This difference is small compared to the estimated monthly exit rates. Which are 5% in the USA compared to 28% in Ghana. While entry rates in Ghana are 1.2 times those of the USA, exit rates are 5.7 times those in the USA. Appendix Table B.1 also documents the derived long-run wage employment rates in both the USA and Ghana among the samples studied. In the long run, my sample in the USA will spend 76%

[13] Respondents are surveyed monthly January-April, then left alone until the following January, and surveyed each month again through April.

[14] An alternative approach would estimate monthly entry and exit rates directly from the CPS and solve for eight-month outcomes. I do not take this approach, as it over-estimates long-run wage employment entry rates. For instance, projecting monthly transition rates forward 12 months predicts 100% of jobseekers find some work in the next 12 months. In practice, I observe 93% of workers find some work. Comparing 12-month transition rates also aligns more closely with my Ghanaian 8-month panel structure.

Figure 1: Entry and Exit over eight months among job-seekers without wage work




***Note:*** *This figure contrasts the trajectories of job-seekers without wage work in the USA and Ghana over the course of eight months. USA data comes from Current Population Survey, re-weighted according to Hainmueller (2017), with eight-month outcomes derived using a method described in Appendix A. Bars represent bootstrapped 95% confidence intervals.*

of their time in wage employment, as opposed to self-employment or unemployment. In Ghana, by contrast, they will spend only 41% of their time in wage work.[15]

Overall Figure 1 demonstrates that differences in exit rates out of wage work are far more important in driving long-run differences in employment rates than differences in entry rates into wage work. This result consistent with the findings of Donovan, Lu and Schoellman (2023), which likewise underscores the relative importance of exit over entry. In the following section, I move beyond aggregate transition rates and explore the causes of high exit rates, something not addressed in existing literature.

# 3 Patterns of Exit

## 3.1 Quits vs Layoffs as Causes of Employment Exit

*Fact 1: In Ghana, employment exit mostly occurs through voluntary quits, and only a small proportion of transitions out of wage work is due to involuntary layoffs. In the USA, by contrast, the majority of transitions out of wage work are due to involuntary layoffs and only a small portion are due to voluntary quits.*

[15] Interestingly, 41% is close to the observed share of job-seekers in wage work overall at baseline, which is 45% as reported in Table 1.

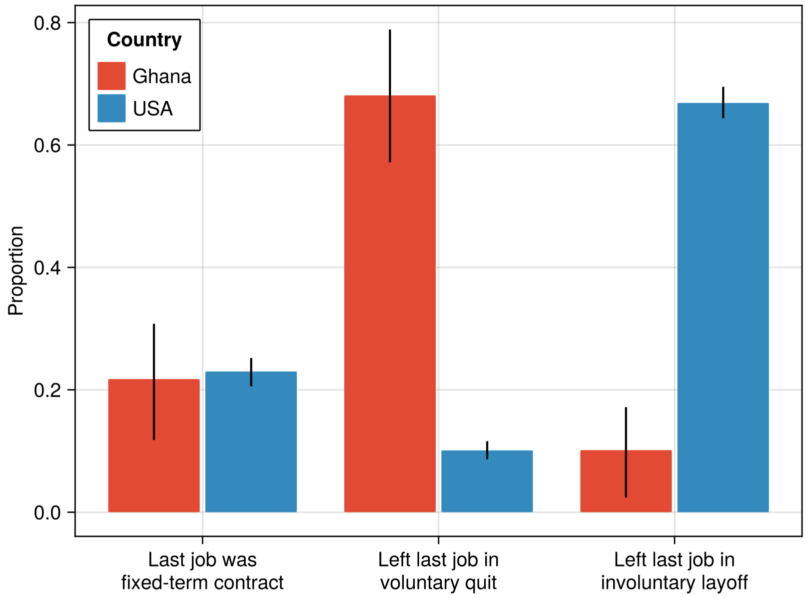
What are the causes of exits out of the wage sector? To start, I distinguish between three types of exits: voluntary quits, involuntary layoffs, and temporary jobs. Figure 2 starts with the same samples of jobseekers as Figure 1, jobseekers without wage work at baseline in Ghana and the weighted sample of job-seekers from the CPS, and then further focuses on jobseekers who find jobs between 0 and 8 months before leaving them and being outside the wage sector at 8 months. For USA equivalent statistics using the CPS, I start with the unemployed at month zero and then focus on those who are unemployed twelve months later after finding some work in the intervening period. I observe the reason for their unemployment (quit, layoff, or temporary work) at twelve months.

Figure 2 documents that Ghana and the USA have strikingly different causes of employment exit. In Ghana, 68% of employment exits are due to voluntary quits, while this figure is only 10% in the USA. Rates of exits due to temporary work are similar in both the USA and Ghana, at roughly 26% for both countries. Instead, differences are largely driven by involuntary layoffs. In Ghana, 10% of employment exits are due to involuntary layoffs, while layoffs account for 67% of exits in the USA.

For simplicity, in what follows I group together exits due to temporary work and exits due to layoffs under the single category of "layoffs" and distinguish between quits and aggregated layoffs broadly. Appendix Table B.2 compares derived monthly entry and exit rates distinguishing between quits and layoffs in the USA and Ghana. Overall, Appendix Table B.2 emphasizes the importance of quits compared to layoffs. While the layoff rate in Ghana is roughly double that of the USA, the quit rate in Ghana is a remarkable 39 times larger than in the USA.

A discussion of demographic correlates of exit out of wage work in my Ghanaian sample of job-seekers, along with the characteristics of quit vs. layoff jobs, is given in Appendix E. Appendix Table E.1 shows, somewhat surprisingly, baseline demographic characteristics do not correlate strongly with exits nor quits. Table E.2 shows exits and quits are high across in all occupations, even ex-ante desirable jobs in high-skill services. This is a new finding, as existing evidence documenting high quit rates in developing countries comes from case-studies in low-amenity factory work (Blattman and Dercon, 2018; Abebe, Buehren and Goldstein, 2024; Boudreau, Heath and McCormick, 2022). Consistent with this literature, exits are more concentrated in manual labor jobs, a category which includes factory work, but high exits are primarily driven by layoffs rather than quits.

Figure 2: Causes of employment exit




***Note:*** *This figure compares the cause of exit among job-seekers without wage work at month zero, then subsequently enter and exit the wage sector. In Ghana, cause of exit is measured among those outside the weight sector at eight-months. In the USA, 12 months. USA data comes from Current Population Survey, re-weighted according to Hainmueller (2017). Bars represent bootstrapped 95% confidence intervals.*

### 3.1.1 Evidence from Firms

So far I have shown, using my survey of job-seekers, that exit rates out of wage work are far higher in Ghana relative to the USA, while entry rates are similar. Furthermore, I have shown that exits are driven by quits rather than layoffs, also in strong contrast with the USA. However the selected nature of my sample limits my ability to generalize about the labor market at large in Ghana. In this section I leverage my firm survey, conducted independently of my job-seeker survey, to show that the differences between the USA and Ghana discussed thus far are present from the firm's perspective as well.

In my firm survey, I asked hiring managers at firms about the number of employees overseen, hires and separations in the previous month —distinguishing between quits and layoffs—as well as the number of workers they were currently seeking to hire.[16] In this way, I can replicate standard statistics reported by the Job Openings and Labor Turnover Survey (JOLTS). Appendix D describes the method for comparing firms in the Ghana and the USA. In short, I construct aggregate entry and exit rates, summing across all firms in my sample. To compare with the USA, I constructed simulated aggregate entry and exit rates, by examining what would happen if firms in Ghana

[16] I did not ask about job destruction due to temporary contracts in order to best compare with JOLTS estimates.

behaved as if firms in the USA behaved.

One notable difference between the firm and job-seeker analysis is the definition of quits. Figure 2 analyzes only transitions out of wage work, and does not address job-to-job flows. Firms, by contrast, generally do not know whether an employee leaving a firm exits to unemployment or to a new job, so "quits" reported by firms in Table 3 encompasses both exits out of wage work as well as movements between jobs.

Figure 3 compares aggregate entry and exit flows between Ghana and the USA, with bootstrapped 95% confidence intervals from both the Ghana sample and simulated sample reported with error bars. Table 3 shows that compared to firms in the USA, firms in Ghana rates of separation an order of magnitude higher, confirming the findings of Section 2.3.

Table 3 also confirms my second job-seeker finding: Quits play a larger role that layoffs in driving job destruction. The rate of layoffs in Ghana is 2.3-times that of the USA, while the rate of layoffs is 4.3-times that of the USA. Quits as a fraction of total separations is 30% higher in Ghana relative to the USA.[17] Interestingly, despite high rates of hiring and separation, firms in Ghana report *lower* vacancy rates compared to firms in the USA. This is further evidence that the rate of matching between firms and workers is not a binding constraint on the size of the wage sector.

## 3.2 Characteristics of Quits and Layoffs

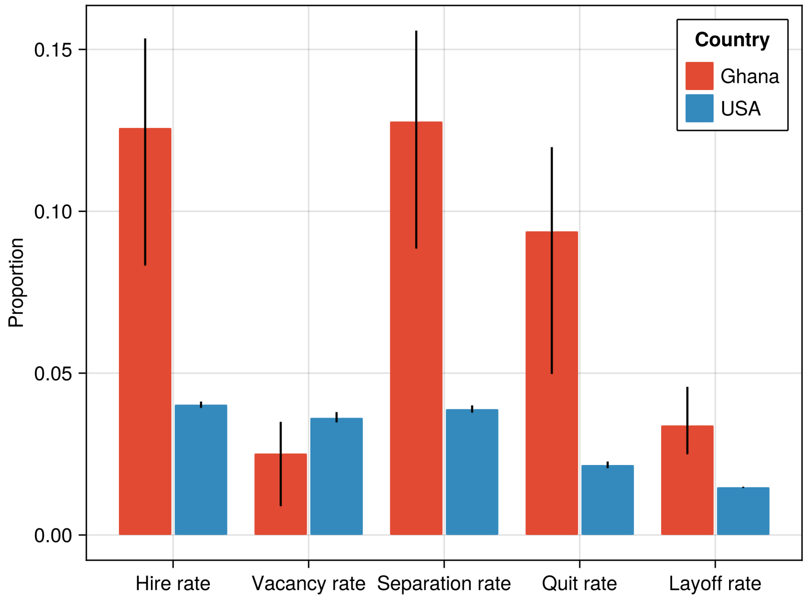
*Fact 2: Jobs ending in a quit in Ghana have significantly lower wages than jobs ending in a layoff, in contrast with the USA. In Ghana, quitters see income gains from quitting work and leaving the wage sector. In the USA, quitters see large income losses when leaving the wage sector.*

The previous section established that the majority of exits out of the wage sector are due to voluntary quits, as opposed to involuntary layoffs. In this section, I document a new fact about quits in Ghana relative to the USA by contrasting the dynamics of quits and layoffs in the two countries. This indicates workers in Ghana quit for very different reasons compared to worker in the USA.

I measure the earnings, both wage and non-wage, of workers before and after an exit out of wage work, distinguishing between quits and layoffs. I consider four outcomes (1) the wage of a worker at a job that will soon end in a layoff; (2) the wage of a worker at a job that will soon end in a quit; (3) the non-wage income of a worker without wage

[17] Additional evidence from my firm survey also highlights the elevated role of quits relative to layoffs: Of the *last* person to leave the firm, 65% did so voluntarily, 19% were fired, and 19% left because their temporary contract finished. This is very close to what is reported by job-seekers. No equivalent statistic is tracked in the USA.

Figure 3: Entry and exits reported by firms



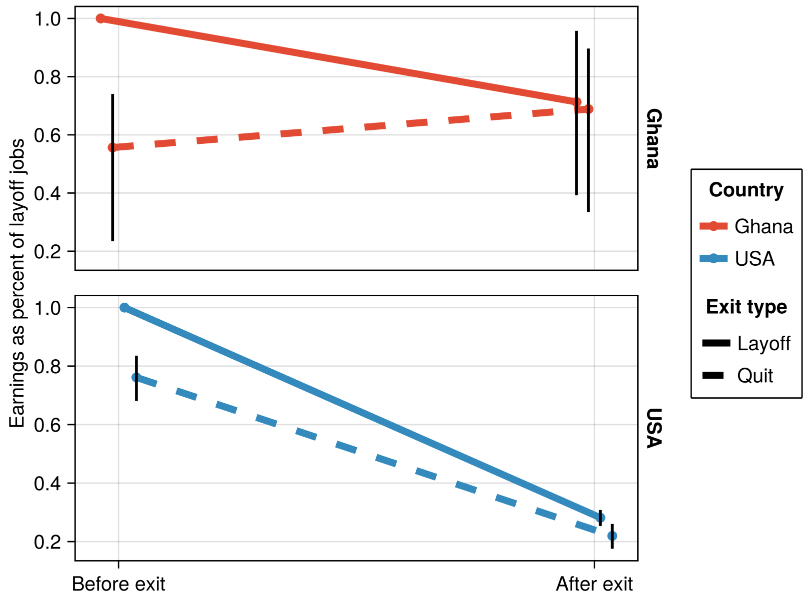

***Note:*** *This figure compares the flows in and out of the workforce as reported by firms. Rates represent aggregate flows across full sample. USA rates come from the Job Openings and Labor Turnover Survey and represent simulated aggregate flows among Ghanaian firms. See Appendix D for a full methodology. Bars represent bootstrapped 95% confidence intervals.*

work after a quit; and (4) the non-wage income of a worker without wage work after layoff. Figure 4 demonstrates these outcomes separately for the USA and Ghana. For ease of exposition, I normalize all outcomes relative to the wages of jobs that will soon end in a layoff. Table C.3 presents the same outcomes as Figure 4 in tabular format.

The left side of Figure 4, which shows the difference in wages between jobs which end in a quit and jobs which end in a layoff, shows that in Ghana, jobs ending in a quit pay only 56% as much as jobs ending in a layoff. In the USA, by contrast, jobs ending in a quit pay 76% as much as jobs ending in a layoff. That is, quit jobs appear to be more negatively selected in Ghana relative to the USA.

Turning to the right side of Figure 4, we again see that characteristics of quits and layoffs are highly distinct in Ghana, while in the USA, quits and layoffs are more similar. In Ghana, workers who quit and leave the wage sector encounter non-wage income sources such that they actually see income gains after leaving the wage sector, with gains averaging 13% the income of jobs ending in a layoff. In the USA, by contrast, quitters are not able to recuperate lost income after quitting the wage sector. Quitters experiencing sharp income losses, on the order of 54%.

Figure 4: Income before and after a quits and layoffs




***Note:*** *This figure shows the wage income of workers before they leave a job and exit the wage sector, compared with their non-wage income after exit. Ghana Sample represents job-seekers without wage work at month zero, who later find work, but later leave the wage sector. USA data comes from the SIPP. Error bars represent 95% confidence intervals.*

## 3.3 Volatility in Non-Wage Income

*Fact 3: Quits are concentrated among workers facing temporary lapses in non-wage at baseline, but who by endline have re-encountered a source of non-wage income*

The previous section documented that jobs ending in a quit pay far less than jobs ending in a layoff. Additionally, quitters appear to be able to supplement their income outside the wage sector, such that quitters see their incomes rise even after leaving the wage sector. This is consistent with the notion that opportunities outside the wage sector might drive quits.

In this section, I present additional evidence in favor of this channel. I focus exclusively on my job-seeker panel survey (leaving behind comparisons with the USA) and explore heterogeneity within my sample. I show workers who are temporarily without a non-wage income source at baseline are more likely to quit work later on. However such individuals, those without income flows at baseline, only quit if they are have re-gained a non-wage income source by endline.

At baseline, I asked respondents without wage work about how they pay for daily necessities in their life: self-employment earnings, transfers from friends and family, or drawing down savings.[18] I divide respondents into two groups, those who with

[18]No respondents mentioned unemployment insurance or other government transfers.

Table 3: Baseline differences between savings and non-savings groups

| Baseline characteristic | Overall Mean | Mean by group | | Regression |
|---|---|---|---|---|
| | | Income flows | Savings | |
| | (1) | (2) | (3) | (4) |
| Age | 29.73 | 29.37 | 31.23 | 1.861 |
| | | | | [1.211] |
| Male | 0.77 | 0.76 | 0.83 | 0.072 |
| | | | | [0.079] |
| University of more education | 0.50 | 0.47 | 0.60 | 0.128 |
| | | | | [0.094] |
| Years of work experience | 6.15 | 5.95 | 6.97 | 1.025 |
| | | | | [0.845] |
| Any dependents | 0.55 | 0.53 | 0.66 | 0.129 |
| | | | | [0.094] |
| Assets index at baseline | 4.12 | 4.14 | 4.06 | -0.082 |
| | | | | [0.313] |
| Total income from all sources past month | 714.36 | 777.36 | 455.14 | -322.218 |
| | | | | [136.791]** |

***Note:*** *This table compares the baseline characteristics of job-seekers without wage work at baseline, distinguishing between job-seekers primarily relying on income flows, such as self-employment income or transfers from friends and family, or savings, to get by. Column (1) shows the mean of the baseline characteristic across the full sample. Column (2) and (3) compare means between the two groups. Column (4) reports the coefficient associated with relying on savings on the baseline characteristic. Standard errors in brackets.* * $p < 0.10$, ** $p < 0.05$, ***$p < .01$

a "flow" of income at baseline, grouping together those who receive family transfers and self-employment, and those without.

First, I demonstrate that relying on savings at baseline, as opposed to other sources of income flows, likely represents the temporary absence of income at baseline, rather than higher savings in general or other differences in underlying characteristics. Table 3 reports baseline differences between the two groups, using the same sample as Figure 1, those without work at baseline. Overall, the two groups are broadly similar across demographic characteristics. Importantly, the savings and non-savings groups have similar levels of durable assets. The only statistically significant difference between the two groups is income levels: The savings group has significantly lower income at baseline.

Table 4 compares outcomes at endline between the two groups. As with Tables F.1 and 6, Column (4) reports a regression difference, controlling for the covariates analyzed in Table 3.

Comparing the two groups, there is little difference in job-finding between the non-savings group and the savings group (77% vs. 86%). Conditional on employment entry, however, the savings group is significantly more likely to exit their job later on (73% in savings group vs. 42% in non-savings group). This difference in job destruction is almost entirely explained by higher quits. Conditional on finding a job, 53% of the savings group later quit their job, compared with 28% in the non-savings group. Due to similar job-finding rates yet different job destruction rates, the non-savings group is significantly more likely to be employed at endline relative to the savings group (44% for non-savings vs 23% for savings).

Table 4 shows individuals without non-wage income flows at baseline are more likely to quit later on. However it also presents evidence consistent with the view that changes in the presence of non-wage income drives such high quit rates. First, Table 4 shows that relying on savings, as opposed to income flows, to get by is a temporary state. Among individuals relying on savings at baseline, only 30% are *still* relying on savings at endline.

Second, changes in the presence or absence of income flows appears to mediate quit behavior. Examining workers without income flows at baseline, but who later quit their jobs, only 19% of this sample, at endline, still lacks flow income. On the other hand, among individuals relying on savings to get by at baseline but who were laid off from their jobs, only 67% do not have access to a source of non-wage income. These results are consistent with a view that workers may be quitting because they have gained access to a stream of non-wage income. Laid off workers, by contrast, may have been laid off before they encountered non-wage income opportunities, and thus were staying at their current employment due to a lack of other options.

Appendix 3.3 shows that the high relative exit rate and quit rate of the savings group is driven both by a contrast with job-seekers self-employed at baseline as well as a contrast with job-seekers relying on social transfers at baseline. In Table G.1 I present the same outcomes as in Table 4, but I omit job-seekers reliant on social transfers at baseline, such that I only compare job-seekers relying on savings at baseline with job-seekers reliant on self-employment income at baseline. The savings group has higher rates of exit (75% vs 41%) and higher rates of quits (53% vs 24%).

In Table G.1, I perform the opposite exercise, by omitting the self-employment group and comparing only the savings group with job-seekers reliant on social transfers at baseline. When compared only to the social transfer group, the savings group also experiences higher exits (73% vs 43%) and quits (53% vs 32%). Consistent with discussion on self-employment, in Table 6 above, Table G.1 shows transfers from friends and family might be just as important in driving quitting behavior as self-employment. The stability of outside income, not its source, appears to drive heterogeneity in exit out of wage work.

Table 4: Employment Exit by Reliance on Flow Income

| Outcome at eight months | Overall Mean | Mean by group: Income flows | Savings | Regression |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Any employment entry since baseline | 0.79 | 0.77 | 0.86 | 0.056 [0.077] |
| Any exit conditional on entry | 0.49 | 0.42 | 0.73 | 0.306 [0.103]*** |
| Any quit conditional on finding work | 0.33 | 0.28 | 0.53 | 0.257 [0.098]*** |
| Any layoff conditional on entry | 0.16 | 0.14 | 0.20 | 0.048 [0.077] |
| Employed at endline | 0.40 | 0.44 | 0.23 | -0.230 [0.093]** |
| Relies on savings at endline if not in a wage job | 0.17 | 0.12 | 0.30 | 0.142 [0.082]* |
| Quit | 0.15 | 0.13 | 0.19 | -0.012 [0.117] |
| Layoff | 0.27 | 0.12 | 0.67 | 0.507 [0.190]** |
| Never-entered | 0.13 | 0.12 | 0.20 | 0.070 [0.154] |

***Note:*** *This table compares the eight-month outcomes of job-seekers without wage work at baseline, distinguishing between job-seekers primarily relying on income flows, such as self-employment income or transfers from friends and family, or savings, to get by. Column (1) shows the mean of the outcome across the full sample. Column (2) and (3) compare means between the two groups. Column (4) reports the coefficient associated with relying on savings on the outcome, controlling for the demographic characteristics listed in Table 3, with the exception of baseline income. Standard errors in brackets.* * $p < 0.10$, ** $p < 0.05$, ***$p < .01$

## 3.4 Discussion of Empirical Evidence

Job-seekers in Ghana and the USA have drastically different trajectories. Both countries see similar entry rates into wage employment, however in Ghana, elevated employment exit rates mean 8-month wage employment rates are only half of those in the US. I show that not only are exits out of wage work higher in Ghana relative to the USA, the composition of these exits are drastically different as well: Quits dominate in Ghana, while layoffs dominate in the USA. Additionally, quitters in Ghana see income gains after leaving the wage sector, in sharp contrast with the USA, where workers who quit work and exit the wage sector see large income losses. Finally, I show evidence that quits are concentrated among workers who lack a flow of non-wage income at baseline, but who later on gain a flow of non-wage income.

This evidence is consistent with a model in which workers face uncertain streams of non-wage income. When faced with a bad shock to their non-wage income job-seekers accept undesirable jobs to get through hard times. Later on, workers quit these jobs when non-wage income opportunities improve. In this way volatility outside the wage sector drives differences in exit rates between the USA and Ghana. In Section

5, I formalize this intuition through a general equilibrium model of job search. Before then, in Section 4, I explore heterogeneity in my job-seeker sample to further motivate a focus on volatility of the non-wage earnings sector. First, in Section F, I examine, and reject, an existing hypothesis on the cause of high exit rates in developing countries, that exits are driven by information frictions. In other words, I ask whether my observed quits are driven by workers having imperfect information about the non-wage characteristics of jobs before they begin work, and I conclude this mechanism does not drive exits or quits in my context. Second, in Section 4.2 I assess whether non-wage income opportunities outside the wage sector are synonymous with self-employment. In other words, I ask if workers are quitting the wage sector to engage in productive self-employment. Surprisingly, and in contrast with existing literature, I show transfer income from friends and family plays a larger role in driving the income gains of quitters relative to workers who were laid off.

# 4 Additional Evidence

## 4.1 Information Frictions

Beginning with Jovanovic (1979), a large literature has argued information frictions—the inability for workers and firms to learn about the quality of their match before agreeing to an employment contract—drives employment exit (Mercan, 2017; Brugemann and Moscarini, 2010). If characteristics related to the job are experience goods, a worker and firm may agree to employment initially and then later separate as they observe the true, low, quality of the match later on. Recent research has argued that information frictions are a key driver of high worker exit rates out of employment in developing countries (Abebe, Caria, Fafchamps, Falco, Franklin and Quinn, 2020; Abel, Burger and Piraino, 2020; Carranza, Garlick, Orkin and Rankin, 2020; Bassi and Nansamba, 2020; Poschke, 2022).

Structural models featuring information frictions do not normally distinguish between quits and layoffs. However, it is easy to informally adapt the logic of Jovanovic (1979) in such a way that information frictions lead to both higher employment exit as well as a higher rate of quits vs. layoffs. I hypothesize workers may imperfectly observe non-wage characteristics of the job. Upon entering a job, they learn the true (low) quality of non-wage characteristics and quit. In this section I test the plausibility of this story, and I conclude it carries little explanatory power.

My survey provides a uniquely comprehensive view into the level of information job-seekers have about potential jobs and the labor market at large. At baseline, I asked workers about expected wages and whether they learn about jobs and wages from social connections, online, or other sources. In addition, I observed whether workers are in contact with employees at firms in which they would like to work.

I assess whether workers who appear to be well informed about potential jobs are more likely to exit employment conditional on finding work. To measure a job-seekers level of information about the labor market in general, I aggregate eight baseline measures into a single "information" index. For example, a job-seeker has higher baseline information if a friend helps the job-seeker find a job at a place where the friend works, or if friend helps a job-seeker learn what jobs they would be best at. Table F.3 describes these variables in detail.

Table 5, shown in the previous section, analyzes the job market outcomes of the "low" and "high" information groups. Each row analyzes a different outcome at endline. Column (4) runs a regression with "High information" as a binary variable, controlling for baseline characteristics.[19] Table 5 shows job-seekers with higher ex-ante baseline information about jobs are not more likely to find jobs, not more likely to experience job destruction, and conditional on job destruction, no more likely to have quit their job. Overall, endline employment outcomes are virtually identical between the two groups. High-information workers are not more likely to exit conditional on taking up a job, and not more likely to quit conditional on exit.

In Appendix F, I assess the effect of information frictions on employment exit through a secondary specification. Instead of measuring a job-seeker's general level of information about the labor market, I examine the accuracy of job-seeker's baseline beliefs about particular non-wage characteristics of jobs. In Appendix Table F.1, I show workers who are over-optimistic about the level of physical comfort at future jobs and workers who are over-optimistic about the cost of commuting are no more likely to exit, conditional on any labor market entry. Appendix Table F.2 shows neither group is more likely to quit, conditional on entry, as well.

## 4.2 Self-Employment and Non-Employment

Having assessed, and rejected, one standard view for the cause of higher employment exit in low-income settings, I next assess another standard view: That workers' exits from wage employment are driven by profitable self-employment opportunities. Donovan, Lu and Schoellman (2023) finds a large share of employment flows can be attributed to movements between wage work and self-employment. Models of job search tailored to developing countries feature self-employment opportunities as the sole driver of voluntary exit out of the wage sector (Poschke, 2022; Herreño and

[19]The baseline controls are Age, Gender, University or more education, Years of work experience, if the job-seeker has dependents, a normalized assets index, and Baseline income.

Table 5: Job outcomes by baseline information score

| Outcome at eight months | Overall Mean | Mean by group: Low information | High information | Regression |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Any employment entry since baseline | 0.79 | 0.78 | 0.81 | 0.044 |
| | | | | [0.064] |
| Any exit conditional on entry | 0.49 | 0.45 | 0.56 | 0.116 |
| | | | | [0.092] |
| Quit conditional on exit | 0.68 | 0.71 | 0.63 | -0.057 |
| | | | | [0.126] |
| Total income at endline | 1,255.21 | 1,193.10 | 1,381.53 | 182.008 |
| | | | | [185.102] |
| Wage earnings at endline if employed | 1,443.82 | 1,428.92 | 1,480.00 | -45.145 |
| | | | | [256.026] |

***Note:*** *This table compares the eight-month outcomes of job-seekers without wage work at baseline, distinguishing between job-seekers with above or below median information about the labor market, using an index comprised of baseline measures listed in Table F.3. Column (1) shows the mean of the outcome across the full sample. Column (2) and (3) compare means between the two groups. Column (4) reports the coefficient associated with being "high information", controlling for the demographic characteristics listed in Table 3. Standard errors in brackets.* * $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Ocampo, 2023; Boschma, Eriksson and Lindgren, 2014). Finally, Falco and Haywood (2009) finds evidence from Ghana that self-employment is not an occupation of last resort, but is often profitable relative to wage work. Self-employment is common among job-seekers in my sample: at both baseline and endline, roughly 20% of my sample is engaged in some form of self-employment. Could it be the case that workers quit frequently to pursue profitable self-employment opportunities?

Table 6 analyzes the endline outcomes of workers who exited out of wage work between baseline and endline, distinguished by whether this exit was due to a quit or a layoff. Columns (2) and (3) show group means of outcomes, while Column (4) shows a regression difference adjusted for baseline covariates. Table 6 uses the same sample as Figure 2: job-seekers without wage work at baseline, who found some job between zero and eight months, but who were exit that job and were again without wage work at eight months.

Are quitters more likely to end up in self-employment? If quits are driven by self-employment, we would expect a higher share of quitters to be in self-employment than laid-off workers. Table 6 shows that among both the quitters and laid-off workers, only a minority of jobseekers are engaged in self-employment at endline. After adjusting for covariates, quitters are 12pp more likely to be engaged in self-employment at Endline, but this difference is not statistically significant.

Are quitters less likely to be searching for a job? If quitting were driven by profitable self-employment opportunities, we would expect to observe quitters as less likely to be currently searching for jobs at endline. I do not observe this. Among both quitters and on-quitters the overwhelming majority are currently searching for a job, and self-employed quitters are more likely to be searching than self-employed laid-off workers. This finding is consistent with arguments, notably Donovan, Lu and Schoellman (2023), that self-employment is similar to unemployment in poor countries.

Is self-employment among of quitters more profitable than self-employment among laid-off workers? If quits were driven by profitable self-employment opportunities, we might expect quitters to have higher self-employment income than laid-off workers. Table 6 does not indicate this is the case. The self-employment income of laid-off workers and of workers who quit their last employment are not statistically different.

Figure 4 demonstrates quitters see income gains after exits, while laid-off workers see income losses. To what extent are these income gains driven self-employment income? Table 6 shows differences income after exit where I exclude transfers from friends and family in the first case, and exclude self-employment in the second case. Both self-employment income and transfers from friends and family play significant roles in mediating the change in income after an exit, in the sense that neither income source explains the recovery in income experienced by workers after an quit. If transfer income from friends and family were excluded, quitters would appear to see an income drop of 454 Cedis per month ($27 USD). On the other hand, if self-employment income were excluded, quitters would appear to see an income drop of 293 Cedis per month ($17 USD). I interpret this evidence to mean transfer income from friends and family plays at least as large a role in supplementing incomes after employment exit, and driving the income gains of quitters after an exit in particular, as self-employment income.

In sum, Table 6 provides mixed evidence on the role of self-employment in driving quits. Quitters are slightly more likely to be engaged in self-employment as laid-off workers, however they are more likely to be searching for a job, indicating self-employment is not the preferred economic activity of workers. Table 6 also shows that non-self-employment income, that is transfers from friends and family, mediate the observed difference between quits and layoffs just as much, if not more than self-employment.

# 5 Model

This section presents a simple model of job search in the presence of a volatile non-wage sector. The model's goal is two-fold. First, it formalizes the intuition that in Ghana, workers frequently take up undesirable wage work when faced with temporarily low non-wage income, then later quit this work when non-wage income op-

Table 6: Outcomes of Quitters and Laid-off Workers Conditional on Exit

| Outcome at eight months | Overall Mean (1) | Mean by group: Layoff (2) | Mean by group: Quit (3) | Regression (4) |
|---|---|---|---|---|
| Self-employed at endline | 0.43 | 0.36 | 0.47 | 0.120<br>[0.134] |
| Searching for a job | 0.81 | 0.73 | 0.85 | 0.220<br>[0.095]** |
| Searching if self-employed | 0.70 | 0.38 | 0.82 | 0.305<br>[0.173]* |
| Searching if not self-employed | 0.90 | 0.93 | 0.88 | 0.100<br>[0.112] |
| Total income at endline | 1,227.39 | 1,256.82 | 1,213.62 | 200.736<br>[248.076] |
| Only self-employment income | 551.88 | 606.82 | 526.17 | 34.551<br>[293.504] |
| Income excluding self-employment income | 675.51 | 650.00 | 687.45 | 166.185<br>[224.208] |
| Difference in income: Current minus last job | -2.61 | -505.91 | 232.98 | 713.864<br>[287.976]** |
| Difference only self-employment income | -678.12 | -1,155.91 | -454.47 | 547.680<br>[360.646] |
| Difference excluding self-employment income | -554.49 | -1,112.73 | -293.19 | 679.313<br>[302.974]** |

***Note:*** *This table compares the eight-month outcomes of job-seekers without wage work at baseline, who found work between baseline and endline, but who were once again without wage work at endline, distinguishing between if the exit was due to a quit or a layoff. Column (1) shows the mean of the outcome across the full sample. Column (2) and (3) compare means between the two groups. Column (4) reports the coefficient associated with quitting, controlling for the demographic characteristics listed in Table 3. Standard errors in brackets.* * $p < 0.10$, ** $p < 0.05$, ***$p < .01$

portunities improve, and that this intuition is consistent with the facts about entry, exit, quits, and layoffs described in Section 3. Second, it allows me to quantify the strength of my proposed mechanism, volatility in non-wage income, in driving differences in exit rates between the USA and Ghana.

The model makes two key simplifications. First, it omits information frictions, which have been put forth as a leading driver behind high exit rates between the developed and less-developed countries (Poschke, 2022; Donovan et al., 2023). This simplification is justified by the findings of Section 4.1, which finds no evidence that workers with better information about jobs are more likely to exit or quit. Second, my model does not distinguish between non-wage income stemming from self-employment and transfers from friends and family. This choice contrasts with existing models of labor market dynamics, which center explicitly model the self-employment sector (Herreño and Ocampo, 2023; Bosch and Maloney, 2010; Feng, Lagakos and Rauch, 2021). This simplification is justified by Section 4.2, which shows similar shares of workers are engaged in self-employment, whether they left the wage sector in a quit or a layoff, and transfer income from friends and family drives the difference in income changes after a quit vs. a layoff just as much as self-employment income.

**Agents and States** Time is continuous and continues forever. There are two agents in the economy, workers and firms. Both parties are risk-neutral and discount the future at rate $\rho$. Workers can be in either the wage sector, that is working for a firm and earning a wage, or the non-wage sector. As discussed above, the non-wage sector represents both unemployment and self-employment while searching for work, but the model abstracts from the distinction between self-employment and unemployment. There is no on-the-job search. Similarly, positions posted by firms can either be vacant or filled with a worker.

**Non-wage income flows** When not in wage work, job-seekers face a stream of income outside of the wage sector that changes with time according to a Poisson process. A worker with variable income $\psi$ receives shocks to their non-wage income at rate $\varphi$. When a shock arrives, they draw a new value of non-wage income $\psi' \sim F_{\psi}(\psi' \mid \psi)$. Non-wage income $\psi$ represents any source of non-wage income, such as transfers from family and friends as well as earnings from self-employment. I do not explicitly model the distinction between self-employment and social transfers.

**Matching and production** Firms and workers meet according to a continuous returns to scale matching function.

$$\mathcal{M}(u, v) \equiv \chi u^{\gamma} v^{1-\gamma} \tag{1}$$

Where $u$ is the mass of workers in the non-wage sector, $v$ is the mass of vacancies. This matching function induces job-finding for workers $q^{w}$ and worker-finding rate for firms $q^{f}$ as a function of market tightness $\theta \equiv \frac{v}{u}$

$$q^{w} \equiv \chi\theta^{1-\gamma} \qquad q^{f} \equiv \chi\theta^{-\gamma} \tag{2}$$

When firm and worker meet, they jointly draw a productivity $z$ unconditionally from distribution $F_z(z)$ and produce according to a linear production function. Wages are exogenously determined, such that workers are assigned a proportion $\delta$ of flow-output. Firms must pay flow cost $c$ while posting a vacancy.

**Wage work entry and exit** Employed workers do not earn non-wage income $\psi$ while employed at a job, yet they always reserve the right to leave their current employment and take advantage of their non-wage income opportunities. Workers in the non-wage sector decide whether to accept or reject jobs based on the job's productivity $z$ and their current non-wage income $\psi$. Similarly, employed workers decide whether to stay at or quit a job according to their current potential non-wage income $\psi$ along with the job's productivity $z$.

My model features exogenous and rigid wages, an important distinction other structural models in the spirit of Mortensen and Pissarides (1994). While wage rigidity for incumbent workers is a common feature among search models, particular those with endogenous quits[20] in general wages at the match stage are influenced by the worker's outside option through a bargaining process. In contrast, here workers are given some share $\delta$ of output $z$, such that wage $w = \delta z$, and this wage is fixed over the course of the match. This assumption might be justified on the grounds that, in a market where job-seekers have differing non-wage income and search is random, firms cannot not observe a worker's true outside option. Because wages are fixed, a worker may enjoy a job at one moment and then quit it the next when their non-wage income $\psi$ improves. In addition to wages, workers receive a non-wage amenity of employment which is constant across all matches, $\nu$.

I refer to quits caused by changes in a worker's outside option as "endogenous" quits, because these choices are a consequence of a worker's optimal quit-stay decisions. Contrasted with endogenous quits are "exogenous" exits. Exogenous quits—exits which are driven by forces not modeled by the researcher—and exogenous layoffs happen at rate $\lambda^w$ and $\lambda^f$, respectively.

When matches are dissolved, firms exit the labor market entirely, such that the continuation value to the firm of a dissolved match is zero. Firms always prefer employment to non-employment.

**Worker value functions** A worker in the non-wage sector with non-wage income $\psi$ has a present discounted value given by $U(\psi)$, while an employed worker with non-wage earning potential $\psi$ in a match with productivity $z$ has a present discounted value given by $W(\psi, z)$. $U(\psi)$ is defined recursively according to

$$\begin{aligned} \rho U(\psi) = & \underbrace{\psi}_{\text{Non-wage income flow}} \\ & \underbrace{+ q^w \int \left(\max\left\{W(\psi, z), U(\psi)\right\} - U(\psi)\right) f_z(z)\, dz}_{\text{Job-finding, accept-reject decision}} \\ & \underbrace{+ \varphi \int \left(U(\psi') - U(\psi)\right) f_\psi\left(\psi' \mid \psi\right)\, d\psi'}_{\text{Changes in non-wage income}} \end{aligned} \tag{3}$$

[20]For example, Blanco, Drenik, Moser and Zaratiegui (2024) features rigid wages, and quits from worker's changing outside option

While employed present-discounted value is defined recursively according to

$$
\begin{aligned}
\rho W(\psi,z) = & \underbrace{(1-\delta)z+\nu}_{\text{Wage and amenity value of work}} \\
& + \underbrace{(\lambda^f+\lambda^w)\left(U(\psi)-W(\psi,z)\right)}_{\text{Exogenous exit}} \\
& + \underbrace{\varphi \int \left(\max\left\{W(\psi',z),U(\psi')\right\} - W(\psi,z)\right) f_\psi(\psi' \mid \psi)\, d\psi'}_{\text{Changes in non-wage income, endogenous quits}}
\end{aligned}
\tag{4}
$$

**Firm value functions** Denote $u(\psi)$ the mass of workers in the non-wage sector with current non-wage income less than $\psi$. The value of a vacancy is given by

$$
\begin{aligned}
\rho V = & \underbrace{-c}_{\text{Vacancy posting cost}} \\
& + \underbrace{q^f \int\int J(\psi,z) \times \mathbb{I}(W(\psi,z) > U(\psi)) u(\psi) f_z(z)\, du\, dz}_{\text{Worker-finding, worker accept-quit decision}}
\end{aligned}
\tag{5}
$$

while the present-discounted value of a firm employing a worker with outside option $\psi$ and productivity $z$ is

$$
\begin{aligned}
\rho J(\psi,z) = & \underbrace{(1-\delta)z}_{\text{Profits}} \\
& - \underbrace{(\lambda^f+\lambda^w) J(\psi,z)}_{\text{Exogenous exit}} \\
& + \underbrace{\varphi \int J(\psi',z) \times \mathbb{I}\left(W(\psi',z) > U(\psi') - J(\psi',z)\right) f_\psi(\psi' \mid \psi)\, d\psi'}_{\text{Changes in worker non-wage income, endogenous quits}}
\end{aligned}
\tag{6}
$$

**Equilibrium** I consider a steady state equilibrium, defined as masses of non-wage workers $u(\psi)$ and employed workers $e(\psi,z)$, along with value function $W(\psi,z)$, $U(\psi,z)$, $J(\psi,z)$, such that workers optimally choose to accept and reject jobs according (Equations 3 and 4), the free entry condition holds, such that the value of a vacancy (Equation 5) is equal to zero, ($\rho V = 0$) and net flows in and out of all states are zero.

## 5.1 Mechanisms and Predictions

The key mechanism of my model is as follows: Because of variable non-wage income, workers frequently find themselves with temporarily low non-wage income and take low-wage jobs. When their non-wage incomes improve, workers quit such low-wage jobs to take advantage of improved non-wage opportunities and search for different, better employment. In this section I illustrate how a stylized parametrization of my model emulates this core logic.

**Baseline stylized model** Consider a simple economy in which $\psi$ can take one of two values, low value $\psi_l$, and high value $\psi_h$. Similarly, there are two wages $z_l$ and $z_h$. Together, $\psi_l$, $\psi_h$, $z_l$, and $z_h$ are such that

$$U(\psi_l) < W(\psi_l, z_l) < U(\psi_h) < W(\psi_h, z_h)$$

In other words, the worker prefers to work at $z_l$ when their non-wage incomes are $\psi_l$, but will quit such a job if their non-wage income rise to $\psi_h$. Job $z_h$ is preferred to the non-wage sector for all values of non-wage income.

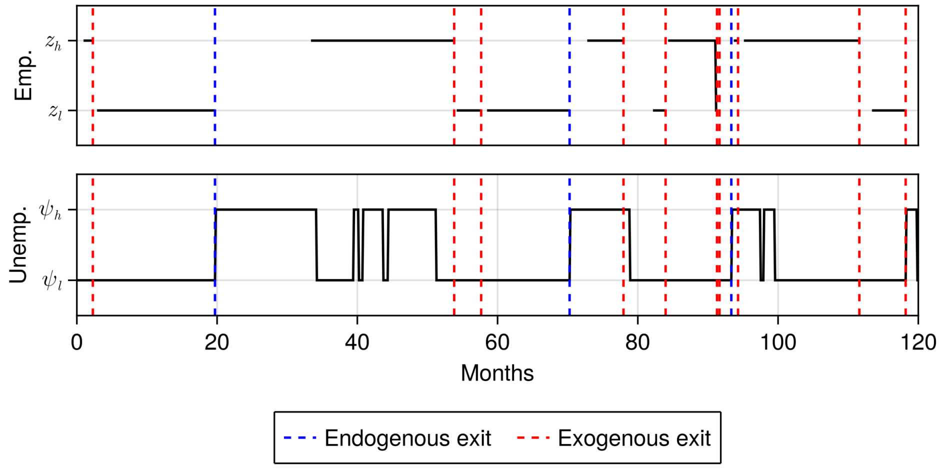
In Figure 5, I plot the trajectory of a worker starting in the non-wage sector with non-wage income $\psi_l$ over the course of 10 years while they accept and leave jobs, and their non-wage income fluctuate across time, show in the x-axis. On the y-axis of the bottom panel of Figure 5 is a worker's non-wage income state $\psi$, which moves between the high state $\psi_h$ and low state $\psi_l$. On the y-axis of the top panel is the worker's employment state, which likewise fluctuates across time (and is blank when the worker is unemployed). Red dashed lines indicate an exogenous exit out of wage work, while blue dashed lines indicate an endogenous exit.

As shown in the bottom panel of Figure 5, the worker faces large fluctuations in their non-wage income. When their non-wage income is in the low state, the worker accepts low-wage jobs. However if they are in a low-wage job and their outside option improves, the worker then quits their current position and chooses to re-enter unemployment, illustrated by the blue-dashed lines, representing exogenous quits, which appear when a worker's outside option spikes and the worker is employed at a low-wage job. High-wage jobs, by contrast, never end with an endogenous quit, instead only ending through an exogenous exit, represented with red dashed lines.

**Volatility of wage earnings** In the top panel of Figure 6, I increase the rate of shocks to a worker's non-wage income $\varphi$ by a factor of four. When working at job $z_l$ (and by necessity, with unemployment earnings $\psi_l$), workers are far more likely to experience a jump in earnings from $\psi_l$ to $\psi_h$ in this new economy relative to the baseline case presented in Figure 5. As a consequence, endogenous quits occur more frequently, as illustrated by the increased density of blue dashed lines. The overall increase in exits is driven exclusively by endogenous quits from the low-wage job.

In the lower panel of Figure 6, I conduct the opposite exercise, reducing the arrival rate of non-wage income shocks to zero. This counterfactual might correspond to an un-

Figure 5: Baseline example economy




employment insurance program, such that workers have guaranteed stable earnings throughout their unemployment spell. As expected, workers in this counterfactual economy never voluntarily exit wage employment, if a worker prefers a job when entering wage employment, their valuation of this job relative unemployment never changes.

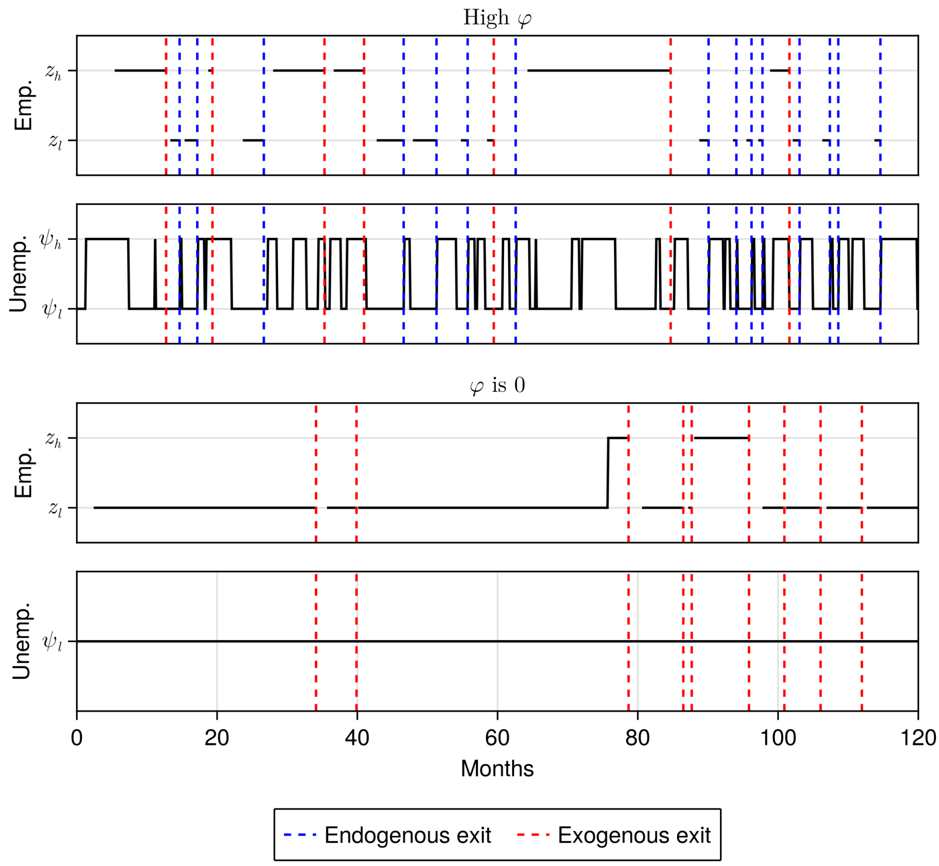
## 5.2 Identification

Table 7 illustrates how moments observed in the data, and presented in Section 3.2, can help identify the share of exits due to changes in worker's non-wage income. Table 7 presents each stylized model presented above: the baseline case along with its high volatility and zero volatility counterparts. For each model, it shows the share of exits which are attributable to changes in a worker's outside option, which cannot be observed in the data, along with three outcomes which can: The average earnings gain after a quit, the average earnings gain after a layoff, and the wage of quit jobs. In all cases, I normalize the outcome to be relative to jobs which end in a layoff.[21] These are the same moments presented in Figure 4 (Table C.3 directly reports the levels of each moment of interest in the USA and Ghana).

Examining Table 7, the baseline stylized model reports approximately 37% of exits can be attributed to changes in a worker's non-wage income. Due to the high number of exits from this force, worker incomes are about equal before and after a quit. On the other hand, the workers in the baseline model experience a loss of income equal to 44%.

[21] Because layoffs are unrelated to match characteristics, in my model the average wage of layoffs jobs is identical to the average wage of all jobs.

Figure 6: Counterfactual example economies




In the second economy, with frequent shocks to a worker's non-wage income, not only do endogenous quits constitute a larger share of exits (62%), this is reflected in the average earnings gains after quits and layoffs as well. Quitters in the high-$\varphi$ economy experience small income gains after a quit, while the loss of income after a layoff stays large. Also as a consequence of the large share of exits due to workers' changing non-wage incomes, the average wage of quit jobs relative to layoff is lower in the high-$\varphi$ economy relative to the baseline case (72% compared to 84%). That is, higher volatility means quit jobs are more negatively selected compared to layoff jobs.

In the final counterfactual, which does feature any endogenous quits, changes in income after a quit and layoff are identical, since exogenous quits and exogenous layoffs function identically in the model ($\lambda^w$ and $\lambda^f$). In this case, the wages of quit jobs are identical to the wages of layoff jobs. In sum, Table 7 shows differences in the changes in income after a quit and layoff inform the prevalence of endogenous exits.

Table 7: Endogenous exits and gains and losses from quits and layoffs

| Model | Outcome | | | |
|---|---|---|---|---|
| | Endog. quits as share of exits (1) | Average earnings gain after a quit (2) | Average earnings gain after a layoff (3) | Ratio of wages in quit vs layoff jobs (4) |
| Baseline | 37 | 0.00019 | -0.44 | 0.84 |
| High $\varphi$ | 62 | 0.13 | -0.42 | 0.72 |
| $\varphi$ is 0 | 0.0 | -0.84 | -0.84 | 1.0 |

# 6 Quantitative Analysis

I have described a model of unemployment and shown, through a stylized parametrization, it has the potential to match key patterns described in the data. In this section I calibrate my model to the experiences of both Ghana and the USA in order to quantify the role that variation in non-wage income plays in driving employment exit differences between the two countries.

## 6.1 Parametrization

I begin by parametrizing the distribution of non-wage income $\psi$. I assume $F_\psi(\psi' \mid \psi)$ is independent of $\psi$. In this way, the rate of shocks to re-draw non-wage income, $\varphi$, exclusively determines the persistence of non-wage income $\psi$. I assume $\psi$ is drawn from a log-normal distribution, however I normalize the log-mean of $\psi$ to zero.

$$\psi' \sim \log \mathcal{N}\left(0, \sigma_\psi\right) \tag{7}$$

I parametrize the distribution of match-specific productivity $z$ be log-normal as well

$$z \sim \log \mathcal{N}\left(\mu_z, \sigma_\psi\right) \tag{8}$$

I choose the unit of time to be a week, and consequently set the monthly discount rate of workers and firms to the value $\rho = \frac{0.05}{12} \approx 0.004$. Following Feng, Lagakos and Rauch (2021), set the curvature of the matching function $\gamma$ to 0.7. Finally, I choose the worker's share of of production, $\delta$, to be 0.5.

## 6.2 Moments

The model features nine remaining parameters, which I match to ten moments, calibrating values separately for the USA and Ghana. Chosen parameters are given in Table 8, and model fit is given in Table 9.

Table 8: Parameter choices

| Parameter | Description | Value | |
|---|---|---|---|
| | | Ghana | USA |
| | | (1) | (2) |
| **Panel A: Pre-assigned parameters** | | | |
| $\rho$ | Discount rate | 0.0042 | 0.0042 |
| $\gamma$ | Matching curvature | 0.70 | 0.70 |
| $\mu_\psi$ | Mean of unemployment income | 0.0 | 0.0 |
| $\delta$ | Worker share of production | 0.50 | 0.50 |
| **Panel B: Calibrated parameters** | | | |
| $\lambda^f$ | Layoff rate | 0.082 | 0.047 |
| $\lambda^q$ | Quit rate | 0.053 | 0.0045 |
| $\sigma_\psi$ | Std. dev. of unemployment process | 0.57 | 1.3 |
| $\varphi$ | Arrival of outside option shocks | 0.14 | 0.0046 |
| $\mu_z$ | Mean of productivity | 0.0079 | -0.28 |
| $\sigma_z$ | Std. dev. of productivity | 0.74 | 1.4 |
| $\nu$ | Amenity value of unemployment | 0.76 | 9.3 |
| $\chi$ | Matching efficiency | 1.5 | 3.4 |
| $c$ | Cost of posting vacancy | 50 | 160 |

**Moments related to entry and exit** The first three moments in Table 9 concern the endline outcomes of job-seekers without work at baseline: whether they are employed, experienced job destruction conditional on entry into employment at some point, whether employment exit was due to a quit or layoff, conditional on an exit. Moments in the data for the USA and Ghana correspond exactly to the values presented in Figure 1 (entry and exit at large) and Figure 2 (quits as a share of exits). In the USA, all three moments are taken from the CPS. I simulate these moments in my model by estimating the aggregate continuous Markov transition matrix, accounting movement in $\psi$, job offers, and job-seeker's optimal choices. Among job-seekers without wage work, and for each initial state $\psi$ I start with the stationary distribution of job-seekers not in wage work and project their outcomes over the following eight months.

**Moments related to earnings processes** The next three movements bound the distribution of non-wage income $\psi$ and the distribution of productivity $z$.[22] First, I estimate the correlation of log unemployment earnings across the span of eight months using both data from my Ghanaian jobseekers as well as the SIPP.[23]. To account for persistent differences in unemployment income due to demographic characteristics, I residualize log earnings on age, gender, years of education, and marital status.

Next, I estimate the standard deviation of log unemployment earnings and log wage

[22] Unlike other moments, these three moments are presented only for the purposes of calibration, and do not appear in other tables or figures in this paper.

[23] The CPS does not measure unemployment earnings

earnings. To accomplish this, I exploit the panel nature of my data in both my Ghana survey as well as the SIPP. I run the following panel regression containing jobseekers at zero and eight months

$$\log \text{Income}_{it} = \beta_0 + \beta_1 \text{Employee}_{it} + \gamma_j + \lambda_i + \epsilon_{it} \tag{9}$$

where $i$ indexes workers and $t$ represents time (zero month baseline and eight month endline). I produce residuals $\hat{\epsilon}_{it}$ and report the standard deviation of $\hat{\epsilon}_{it}$ among the employed and unemployed.

While $\varphi$, the frequency of non-wage income shocks, $\sigma_\psi$ the standard deviation of non-wage income, and $\sigma_z$, the standard distribution of productivity, naturally correspond to these three moments, they cannot be estimated from the data directly because the distribution of observed earnings among those with and without wage employment is conditional on selection into each outcome. I account for this selection process by, again, simulating the eight-month outcomes of job-seekers at baseline. I start with the stationary distribution, over non-wage income $\psi$, of job-seekers without wage work and assess the distribution of wage and non-wage income after eight months later.

**Moments related to the difference between quits and layoffs** The next moment is the wage of jobs which end in quits relative to the wage of jobs which end in layoffs, a moment derived from Figure 4. Following this are the average earnings gain after a quit and the average earnings gain after a layoff, also derived from Figure 4. These three moments are emulated in the model by taking the stationary distribution of employed workers, across $\psi$ and $z$, and examining the non-wage income among those outside the wage sector one month later, separating by whether they left work according to a quit or layoff.

As discussed in Section 5.2, these three moments are the most important in quantifying the role changes in non-wage income play in driving employment exits. If, the income change from a quit and a layoff were identical, and the wages of quit and layoff jobs were identical, we would conclude that quits were all exogenous (driven by $\lambda^w$) and changes in non-wage income played no role in driving exits.

**Vacancies as a share of employment** All the moments described above are estimated from the worker data alone and can be calibrated without appealing to the general equilibrium nature of the model. To calibrate firm-side parameters $c$, as well as back out the matching efficiency $\chi$, I leverage my firm survey and the JOLTS data, presented in Figure 3, in the following way. Calibrating the model to the experience of job-seekers only gives an estimate of job-finding $q^w$ and the unemployment rate $u$. Let $\hat{r}$

Table 9: Model fit

| Moment | Ghana | | USA | |
|---|---|---|---|---|
| | Data | Model | Data | Model |
| | (1) | (2) | (3) | (4) |
| Any wage employment since Baseline | 0.79 | 0.65 | 0.71 | 0.64 |
| Exit conditional on finding work | 0.49 | 0.37 | 0.13 | 0.15 |
| Fraction exits from quits | 0.68 | 0.52 | 0.10 | 0.098 |
| Correlation of unemployment earnings | 0.36 | 0.31 | 0.62 | 0.73 |
| Std. dev. of unemployment earnings | 0.50 | 0.58 | 1.5 | 1.5 |
| Std. dev. of employment earnings | 0.50 | 0.46 | 0.60 | 0.60 |
| Ratio of wages in quit vs layoff jobs | 0.56 | 0.86 | 0.76 | 0.95 |
| Average earnings gain after a quit | 0.13 | 0.17 | -0.54 | -0.55 |
| Average earnings gain after a layoff | -0.29 | -0.23 | -0.72 | -0.73 |
| Vacancies as a share of employment | 0.025 | 0.023 | 0.035 | 0.040 |

represent the ratio of vacancies to employed workers in the economy such that

$$\hat{r} = \frac{v}{1-u} \tag{10}$$

Given we observe $\hat{r}$ in Ghana and the USA, we can solve for $v$ and consequently $\theta$. Given that $q^f = \theta q^w$, we can back out $q^f$ and leverage the free-entry condition to estimate vacancy cost $c$. Knowing vacancies as a share of employment also allows us to measure $\chi$, which is set according to Equation 1 given our knowledge of $v$ and $q^w$.

## 6.3 Quantifying the importance of non-wage income flows

The purpose of my model is to quantify the importance of non-wage income flows in driving differences in exit and quit rates between jobseekers in Ghana and the USA. My model is well equipped to perform this task. My model features both quits and layoffs for exogenous reasons, unrelated to income flows (via $\lambda^f$ and $\lambda^w$), such that it is not ex-ante designed to attribute all quits to the mechanism I highlight. Further more, I demonstrate in Section 5.1 how the changes in worker income before and after an exit identify the importance of quits due to changing non-wage income. In this section I take the model to task and assess the contribution of non-wage income flows in driving quits, layoffs, and equilibrium wage employment rates.

**Shutting down changes to non-wage income** To isolate the importance of non-income flows I shut down changes in worker's income across time in two ways. First, by reducing $\varphi$, the frequency of arrival of shocks which change a worker's non-wage income flows. This counterfactual preserves permanent differences in income, and workers are less likely to move between states. Second, I reduce the variance of $F_\psi$, the worker's new non-wage income after an non-wage income re-evaluation shock. In the limiting case where I set the variance of $F_\psi$, my model reduces to a conventional Diamond-Mortensen-Pissaredes model with exogenous wages.

Table 10 analyzes the baseline calibrated models in the USA and then conducts two counterfactuals. Rows represent outcomes, analyzing rate of quits that occur due to changes in worker's non-wage income, the rate of quits at large, and the rate of exits at large. Column (1) shows the value of the outcome in the USA under each counterfactual, Column (2) shows the value for Ghana, Column (3) shows the difference in the outcome in the two counterfactuals, and Column (4) shows the percent reduction in the difference in the outcome between the two countries in the counterfactual relative to the baseline calibration. For simplicity, I only report differences in the total rate of exit between the two economies.

Specifically, denote outcome $y_{\text{USA}}$ to be the value of outcome $y$ in the baseline calibration in the USA, and $y'_{\text{USA}}$ the outcome in the USA in some counterfactual. Define analogous measures for Ghana, then we define the percentage of the difference explained as

$$\%\text{ Explained} = \frac{y'_{\text{USA}} - y'_{\text{Ghana}}}{y_{\text{USA}} - y_{\text{Ghana}}} \tag{11}$$

A value of "% Explained" at 100 represents the entire difference in outcome between the USA and Ghana can be accounted for by the proposed counterfactual. A negative value indicates the gap between the two countries *increases* in the counterfactual.

Table 10 shows that when the arrival rate of non-wage earnings shocks $\varphi$, is reduced to zero, the quit rate reduces in Ghana from 8.4 to 5.3, and the total exit rate reduces from 16.4 to 13.6. In the USA, by contrast, this reduction is small, shutting off the endogenous quits channel reducing entry and exit by only 0.1. Overall, the gap in total exit rates decreases by 25% when we shut down variance changes in non-wage income, this indicates my proposed mechanism accounts for 26% of the difference in exit rates between the two countries. Shutting down the variance of $F_\psi$ has an analogous effect. I analyze partial equilibrium, which hold the job-finding rate of workers $q^w$ fixed, in Appendix Table H.1. Results are virtually identical, indicating a negligible role of firm-side response in driving observed effects.

**Comparing the USA and Ghana** What differences in the underlying structural parameters between the USA and Ghana drive differences in exits? In Table 11 I iteratively set various features of Ghana's economy to the estimated value in the USA. I conduct five exercises. In the first two, I give Ghana USA's non-wage income shock arrival $\varphi$ and distribution of non-wage incomes $F_\psi$, respectively. In the third, I re-assign

Table 10: Effect of reducing non-wage income shock arrival rate $\varphi$ on quits and exits

| Outcome | Value USA (1) | Value Ghana (2) | Difference (3) | % Explained (4) |
|---|---|---|---|---|
| **Baseline** | | | | |
| Quit rate | 0.5 | 8.2 | 7.7 | - |
| Exit rate | 5.2 | 16.4 | 11.2 | - |
| **Reduce $\varphi$ 50 percent** | | | | |
| Quit rate | 0.5 | 7.0 | 6.5 | - |
| Exit rate | 5.2 | 15.2 | 10.1 | 10.3 |
| **$\varphi$ is zero** | | | | |
| Quit rate | 0.4 | 5.3 | 4.9 | - |
| Exit rate | 5.2 | 13.6 | 8.4 | 25.0 |
| **Reduce variance of $F_\psi$ 50 percent** | | | | |
| Quit rate | 0.5 | 7.2 | 6.7 | - |
| Exit rate | 5.2 | 15.5 | 10.3 | 8.4 |
| **Constant $\psi$** | | | | |
| Quit rate | 0.4 | 5.3 | 4.9 | - |
| Exit rate | 5.2 | 13.6 | 8.4 | 25.1 |

both $\varphi$ and $F_\psi$. In the next two, I alter the desirability of employment. I give Ghana the USA's distribution of wages, then assign Ghana the USA's estimated value of the non-wage amenity of employment.

Table 11 shows that multiple structural differences between the two countries can reduce exit rates due to changes in non-wage income. When $\varphi$ is changed to the level of the USA, the overall difference in exits reduces by 24%, consistent with Table 10 ($\varphi$ is far higher in Ghana relative to the USA). Modifying parameters related to the wage sector also reduces the difference in exit rates between the USA and Ghana. The reason for this is simple: As jobs are more valuable, workers are less likely to find the non-wage sector preferable to the wage sector, and thus quit less. When the distribution of wages in the wage sector in Ghana is replaced with that of the USA, the difference in exits between the USA and Ghana reduces by 15.5%. When the value of non-wage amenity $\nu$ is set to the level of the USA, endogenous quits in Ghana are eliminated entirely, and the gap in exit rates between the USA and Ghana shrinks by 17.5%, as if there were no volatility at all. Table 11 underscores the interaction between the wage and non-wage sector in driving exits. Changes in non-wage income only affect employment decisions to the extent the non-wage sector is a desirable option relative to wage employment. Overall, Table 11 supports the idea that decline in exits discussed in Donovan, Lu and Schoellman (2023) may arise from secular improvements in the relative productivity of the wage sector, such as biased structural change discussed in Feng, Lagakos and Rauch (2021). Appendix Table 11 explores partial equilibrium

Table 11: Effect of setting parameter values in Ghana to those of the USA on exits

| Outcome | Value USA (1) | Ghana (2) | Difference (3) | % Explained (4) |
|---|---|---|---|---|
| **Baseline** | | | | |
| Quit rate | 0.5 | 8.2 | 7.7 | - |
| Exit rate | 5.2 | 16.4 | 11.2 | - |
| **Ghana, $\varphi_{\mathbf{USA}}$** | | | | |
| Quit rate | - | 5.4 | 4.9 | - |
| Exit rate | - | 13.7 | 8.5 | 24.4 |
| **Ghana, $F_{\psi,\mathbf{USA}}$** | | | | |
| Quit rate | - | 10.6 | 10.1 | - |
| Exit rate | - | 18.8 | 13.6 | -21.6 |
| **Ghana, $\psi_{\mathbf{USA}}$, $F_{\psi,\mathbf{USA}}$** | | | | |
| Quit rate | - | 5.5 | 5.0 | - |
| Exit rate | - | 13.7 | 8.5 | 23.8 |
| **Ghana $F_{z,\mathbf{USA}}$** | | | | |
| Quit rate | - | 6.4 | 5.9 | - |
| Exit rate | - | 14.7 | 9.5 | 15.5 |
| **Ghana $\nu_{\mathbf{USA}}$** | | | | |
| Quit rate | - | 5.3 | 4.8 | - |
| Exit rate | - | 13.6 | 8.3 | 25.5 |

effect only, and reports similar results.

# 7 Conclusion

To understand why poor countries have such high exit rates out of wage employment, I conducted panel survey of job-seekers and a supplementary survey of firms, in Accra, Ghana. I compare the experiences of jobseekers and firms in my sample using administrative data in the USA. Entry into employment is similar between Ghana and the USA, but high employment exit rates mean the long-run level of wage employment in Ghana is half that of the USA. In the primary contribution of this paper, I show quits, rather than layoffs or temporary employment are the dominant cause of job destruction. I also show quits are more distinguished from layoffs in Ghana relative to the USA.

Exploring within-sample heterogeneity, I examine, and reject, two leading theories for higher job churn in poor countries. I find no evidence to support information frictions as the cause of job destruction, and find only moderate evidence that quits away from wage work are driven by profitable opportunities for self employment. I find that quits are primarily due to workers leaving low-paying jobs and find that quits are more prevalent among those facing temporary lapses in income at baseline.

I argue this is consistent with a model in which time-varying non-wage income causes individuals to accept low-productivity jobs, and then quit them as outside options improve. I build a partial equilibrium model of job search to benchmark the role that changes in non-wage income plays in quitting behavior, and can attribute 26% of the gap in exit rates between the USA and Ghana to this mechanism.

Given quits drive a quantitatively large difference in exits between the USA and Ghana, what can firms and policymakers do to reduce worker exits? My structural model suggests reducing the risk workers face in the non-wage sector has the potential to reduce exits. Reducing worker turnover may be an un-examined benefit of cash transfers and unemployment insurance.

Firms can also reduce exits by improving working conditions. Unfortunately, we have scant evidence on which interventions firms can undertake to reduce quits. In particular, because I find quits are high even outside of uncomfortable factory work, policies to reduce quits may require changes in management, and not simply the physical conditions of the workplace. One promising avenue is the "worker voice" intervention studied in Adhvaryu, Molina and Nyshadham (2020), in which a survey allowing workers to give feedback to managers reduced quits by 20%.

Overall, over 80% of the difference in exits between the USA and Ghana remains unexplained even after accounting for differences in the movement of non-wage incomes between the two countries. While this paper focuses on quits, layoffs are also far higher in Ghana relative to the USA. There remains considerable scope for research describing additional sources of worker exit.

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# Appendix

## A Estimating Flows From 8 and 12-month Transitions

In this section I describe my procedure for recovering 8-month employment outcomes from the 12-month outcome reported by the CPS as reported in Section 2.3. In the process, I also describe how I recover estimated monthly entry and exit rates from long-run transitions in and out of wage work.

In the January CPS survey, I start with an unemployed worker. To assess if that worker has taken *any* job over the next 12 months (regardless if they stay in the wage sector or leave) first I check if they employed in February, March, or April, which I observe directly. Next, I use the retrospective question asked the following January if the worker was employed in the previous 12 months. If they answer "Yes", then they are considered to have worked in the previous year, even if I don't observe any employment during the first round of surveys. To assess if a worker is in the wage sector after 12 months, I simply check their employment state in the following January.

I observe 93% of job-seekers find *some* work between 0 and 12 months, yet after 12 months, only 78% of these jobseekers are currently employed. To estimate 8-month outcomes from 12-month outcomes, consider the Markov process where one moves between wage work, according to entry rate $q$ and exit rate $\lambda$

$$\Pi \equiv \begin{array}{c c} & \begin{array}{cc} \text{Not wage sector} & \text{Wage sector} \end{array} \\ \begin{array}{c} \text{Not wage sector} \\ \text{Wage sector} \end{array} & \begin{pmatrix} \quad q \quad & \quad 1-q \quad \\ 1-\lambda & \lambda \end{pmatrix} \end{array}$$

I estimate monthly transition rates $q$ and $\lambda$ by solving

$$\begin{bmatrix} 1 & 0 \end{bmatrix} e^{\Pi \times 12} = \begin{bmatrix} 0.93 \\ 0.78 \end{bmatrix}$$

And then evaluate 8-month rates according to the following expression:

$$\begin{bmatrix} \text{Not employed in wage work at endline} \\ \text{Employed in wage work at endline} \end{bmatrix} = \begin{bmatrix} 1 & 0 \end{bmatrix} e^{\Pi \times 8}$$

The outcome "Found any wage work at all in previous 8 months" is constructed through the same procedure, where $\Pi$ is modified such that employment is an absorbing state. Let $\Pi'$ be this modified transition matrix, such that the second row of $\Pi'$ is $\begin{bmatrix} 0 & 1 \end{bmatrix}$, allowing us to generate the following outcomes

$$\begin{bmatrix} \text{Never found any wage work at all in previous 8 months} \\ \text{Found any wage work at all in previous 8 months} \end{bmatrix} = \begin{bmatrix} 1 & 0 \end{bmatrix} e^{\Pi' \times 8}$$

Table B.1: Comparison of flows

| Outcome | Mean Ghana (1) | Mean USA (2) | Difference (3) | Ratio (4) |
|---|---|---|---|---|
| Monthly entry rate | 0.19 | 0.15 | 0.041 | 1.3 |
| | [0.15, 0.23] | [0.15, 0.16] | [0.0093, 0.083] | [1.1, 1.5] |
| Monthly exit rate | 0.28 | 0.048 | 0.23 | 5.7 |
| | [0.18, 0.35] | [0.045, 0.052] | [0.16, 0.33] | [4.2, 7.8] |
| Stationary rate of wage work | 0.41 | 0.76 | -0.35 | 0.54 |
| | [0.34, 0.49] | [0.75, 0.77] | [-0.42, -0.27] | [0.44, 0.64] |

Table B.2: Comparison of quit and layoff flows

| Outcome | Mean Ghana (1) | Mean USA (2) | Difference (3) | Ratio (4) |
|---|---|---|---|---|
| Monthly entry rate | 0.19 | 0.15 | 0.041 | 1.3 |
| | [0.15, 0.23] | [0.15, 0.16] | [0.0099, 0.082] | [1.1, 1.5] |
| Monthly layoff rate | 0.088 | 0.043 | 0.045 | 2.0 |
| | [0.040, 0.13] | [0.041, 0.046] | [0.0063, 0.092] | [1.1, 3.1] |
| Monthly quit rate | 0.19 | 0.0049 | 0.18 | 39 |
| | [0.11, 0.24] | [0.0040, 0.0057] | [0.13, 0.26] | [27, 58] |

# B Additional Tables Measuring Entry and Exit Rates

Table C.1: Comparison of entry and exit

| Outcome | Mean Ghana (1) | Mean USA (2) | Difference (3) | Ratio (4) |
|---|---|---|---|---|
| Any wage job at 0 months | 0.0 | 0.0 | - | - |
| | - | - | - | - |
| Any entry between 0 and 8 months | 0.79 | 0.71 | 0.082 | 1.1 |
| | [0.73, 0.85] | [0.70, 0.72] | [0.019, 0.14] | [1.0, 1.2] |
| Employed in wage job at 8 months | 0.40 | 0.61 | -0.21 | 0.66 |
| | [0.34, 0.47] | [0.60, 0.62] | [-0.27, -0.14] | [0.55, 0.77] |
| Exit conditional on entry | 0.49 | 0.14 | 0.35 | 3.5 |
| | [0.41, 0.57] | [0.13, 0.15] | [0.27, 0.43] | [2.9, 4.2] |
| Still employed at 8 months after finding some job | 0.51 | 0.86 | -0.35 | 0.59 |
| | [0.43, 0.59] | [0.85, 0.87] | [-0.43, -0.27] | [0.50, 0.68] |

Table C.2: Comparison of quits and layoffs

| Outcome | Mean Ghana (1) | Mean USA (2) | Difference (3) | Ratio (4) |
|---|---|---|---|---|
| Last job was fixed-term contract | 0.22 | 0.23 | -0.013 | 0.95 |
| | [0.12, 0.31] | [0.21, 0.25] | [-0.11, 0.089] | [0.54, 1.4] |
| Left last job in voluntary quit | 0.68 | 0.10 | 0.58 | 6.7 |
| | [0.57, 0.79] | [0.087, 0.12] | [0.47, 0.69] | [5.4, 8.4] |
| Left last job in involuntary layoff | 0.10 | 0.67 | -0.57 | 0.15 |
| | [0.024, 0.17] | [0.64, 0.70] | [-0.64, -0.49] | [0.048, 0.27] |

# C Additional Tables Documenting Results Described in Figures

Table C.3: Comparison of income changes after quits and layoffs

| Outcome | Mean | | Difference | Ratio |
|---|---|---|---|---|
| | Ghana | USA | | |
| | (1) | (2) | (3) | (4) |
| Average income of layoff jobs | 1.0 | 1.0 | - | - |
| | - | - | - | - |
| Average income after a layoff | 0.71 | 0.28 | 0.43 | 2.5 |
| | [0.39, 0.96] | [0.25, 0.31] | [0.18, 0.75] | [1.7, 3.7] |
| Income difference after a layoff | -0.29 | -0.72 | 0.43 | 0.40 |
| | [-0.61, -0.043] | [-0.75, -0.69] | [0.18, 0.75] | [-0.046, 0.74] |
| Average income of quit jobs | 0.56 | 0.76 | -0.20 | 0.73 |
| | [0.23, 0.74] | [0.68, 0.84] | [-0.41, 0.12] | [0.48, 1.2] |
| Average income after a quit | 0.69 | 0.22 | 0.47 | 3.1 |
| | [0.34, 0.90] | [0.18, 0.26] | [0.26, 0.83] | [2.2, 4.9] |
| Average difference after a quit | 0.13 | -0.54 | 0.67 | -0.24 |
| | [-0.048, 0.29] | [-0.61, -0.47] | [0.50, 0.88] | [-0.59, 0.039] |

# D Additional Details on Firm Survey Comparison

Here I describe the methodology I use to compare firms between the USA and Ghana.

My goal is to compare standard measures of aggregate hiring, separation, quit, and layoff rates between the USA and Ghana. My firm survey consists of firm-level outcomes — for each firm, the number of employees overseen, the number of hires in past month, etc. Comparison with the USA is complicated on two dimensions. First, I do not have access to firm-level data from the USA, and cannot match USA and Ghanaian firms using the weighting method of Hainmueller (2017), as I did with jobseekers. Second, JOLTS statistics are aggregates, not averages. That is, the hiring rate does not correspond to the average of firm-level hiring rates, but rather the number of hires across all firms divided by the total employment across all firms.

I construct comparable statistics in the following way. First, I assign USA hiring rates to my Ghanaian firms by matching on establishment size. Next, I generate simulated USA aggregate flows by assuming firms in Ghana experienced hires and separations "as if" they were USA firm. In other words, I ask "what would the aggregate hiring rate of firms in my Ghanaian sample be if they behaved similar firms in their same size bracket behaved?".

Let $H^s_{i,\text{Ghana}}$ be the number of hires for a firm $i$ of establishment size $s$ in Ghana. Similarly let $E^s_{i,\text{Ghana}}$ be the equivalent number of employees overseen by such a firm. Let $h^s_{\text{USA}}$ be the hiring rate for firms in the USA of size $s$. Define the observed aggregate hiring rate in Ghana as

$$h_{\text{Ghana}} = \frac{\sum_s \sum_i H^s_{i,\text{Ghana}}}{\sum_i E^s_{i,\text{Ghana}}}$$

$h_{\text{Ghana}}$ corresponds to the hiring rate for Ghanaian firms reported in Figure 3. Now define the aggregate hiring rate among my sample if they behaved *as if* matched firms in the US did.

$$h_{\text{USA}} = \frac{\sum_s \sum_i h^s_{\text{USA}} E^s_{i,\text{Ghana}}}{\sum_i E^s_{i,\text{Ghana}}}$$

$h_{\text{USA}}$ corresponds to the hiring rate for USA firms reported in Figure 3.

Table E.1: Demographic characteristics and exit

| Baseline characteristic | Proportion exit conditional on entry No (1) | Yes (2) | Partial effect (3) | Proportion quit conditional on exit No (4) | Yes (5) | Partial effect (6) |
|---|---|---|---|---|---|---|
| Greater than 30 years old | 0.466 | 0.528 | -0.070 | 0.732 | 0.607 | -0.194 |
| | | | [0.154] | | | [0.224] |
| Male | 0.444 | 0.500 | 0.083 | 0.583 | 0.702 | 0.167 |
| | | | [0.109] | | | [0.155] |
| University of more education | 0.522 | 0.459 | -0.083 | 0.686 | 0.676 | 0.087 |
| | | | [0.098] | | | [0.131] |
| Married | 0.491 | 0.486 | -0.093 | 0.750 | 0.471 | -0.300 |
| | | | [0.128] | | | [0.161]* |
| Any dependents | 0.439 | 0.524 | 0.087 | 0.720 | 0.659 | -0.026 |
| | | | [0.102] | | | [0.138] |
| Above median assets index | 0.526 | 0.444 | 0.091 | 0.732 | 0.607 | 0.080 |
| | | | [0.148] | | | [0.215] |
| Higher than median income | 0.480 | 0.500 | 0.159 | 0.694 | 0.667 | -0.143 |
| | | | [0.138] | | | [0.200] |

Table E.2: Job characteristics and exit

| Baseline characteristic | Proportion exit conditional on entry No (1) | Yes (2) | Partial effect (3) | Proportion quit conditional on exit No (4) | Yes (5) | Partial effect (6) |
|---|---|---|---|---|---|---|
| High-skill services | 0.519 | 0.389 | -0.103 | 0.685 | 0.643 | 0.023 |
| | | | [0.103] | | | [0.158] |
| Low-skill services | 0.500 | 0.333 | -0.163 | 0.688 | 0.500 | -0.178 |
| | | | [0.156] | | | [0.254] |
| Manual labor | 0.416 | 0.667 | 0.251 | 0.714 | 0.615 | -0.190 |
| | | | [0.099] | | | [0.134]** |
| Retail | 0.485 | 0.488 | -0.014 | 0.638 | 0.762 | 0.156 |
| | | | [0.101] | | | [0.137] |
| Teaching | 0.500 | 0.300 | -0.199 | 0.662 | 1.000 | 0.346 |
| | | | [0.169] | | | [0.291] |
| Earnings greater than median | 0.558 | 0.406 | -0.146 | 0.791 | 0.500 | -0.286 |
| | | | [0.091] | | | [0.136]** |

# E Additional Tables Showing Baseline Correlates with Exit

Table E.3: Demographic Differences between Job-Exiters and Job-Stayers

| Baseline characteristic | Overall Mean | Mean by group: Did not exit | Mean by group: Exited | Regression |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Age | 29.73 | 29.29 | 30.43 | 1.144 |
| | | | | [0.990] |
| Male | 0.77 | 0.74 | 0.83 | 0.090 |
| | | | | [0.065] |
| University of more education | 0.50 | 0.50 | 0.49 | -0.007 |
| | | | | [0.077] |
| Years of work experience | 6.15 | 5.99 | 6.39 | 0.404 |
| | | | | [0.690] |
| Any dependents | 0.55 | 0.50 | 0.64 | 0.138 |
| | | | | [0.076]* |
| Assets index at baseline | 4.12 | 4.15 | 4.07 | -0.082 |
| | | | | [0.255] |
| Total income from all sources past month | 714.36 | 701.09 | 735.51 | 34.416 |
| | | | | [113.172] |

Table E.4: Demographic Differences among Quitters and Laid-off Workers Conditional on Exit

| Baseline characteristic | Overall Mean | Mean by group: Did not quit | Mean by group: Quit | Regression |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Age | 29.73 | 31.36 | 30.00 | -1.364 |
| | | | | [1.676] |
| Male | 0.77 | 0.77 | 0.85 | 0.078 |
| | | | | [0.099] |
| University of more education | 0.50 | 0.50 | 0.49 | -0.011 |
| | | | | [0.131] |
| Years of work experience | 6.15 | 7.05 | 6.09 | -0.955 |
| | | | | [1.081] |
| Any dependents | 0.55 | 0.68 | 0.62 | -0.065 |
| | | | | [0.126] |
| Assets index at baseline | 4.12 | 4.50 | 3.87 | -0.628 |
| | | | | [0.355]* |
| Total income from all sources past month | 714.36 | 693.18 | 755.32 | 62.137 |
| | | | | [192.035] |

Table E.5: Differences between Exited Jobs and Non-Exited Jobs

| Characteristic of last or current job | Overall Mean | Mean by group | | Regression |
|---|---|---|---|---|
| | | Did not exit | Exited | |
| | (1) | (2) | (3) | (4) |
| High-skill services | 0.26 | 0.31 | 0.21 | -0.074 |
| | | | | [0.073] |
| Low-skill services | 0.09 | 0.11 | 0.06 | -0.051 |
| | | | | [0.049] |
| Manual labor | 0.28 | 0.18 | 0.38 | 0.187 |
| | | | | [0.074]** |
| Retail | 0.31 | 0.31 | 0.31 | -0.010 |
| | | | | [0.075] |
| Teaching | 0.07 | 0.10 | 0.04 | -0.053 |
| | | | | [0.045] |
| Earnings at last or current job | 1,339.18 | 1,443.82 | 1,230.00 | -180.635 |
| | | | | [173.160] |

Table E.6: Differences between Quit Jobs and Layoff Jobs, Conditional on Exit

| Characteristic of last or current job | Overall Mean | Mean by group | | Regression |
|---|---|---|---|---|
| | | Did not quit | Quit | |
| | (1) | (2) | (3) | (4) |
| High-skill services | 0.26 | 0.23 | 0.20 | 0.015 |
| | | | | [0.107] |
| Low-skill services | 0.09 | 0.09 | 0.04 | -0.047 |
| | | | | [0.066] |
| Manual labor | 0.28 | 0.45 | 0.35 | -0.174 |
| | | | | [0.123] |
| Retail | 0.31 | 0.23 | 0.35 | 0.138 |
| | | | | [0.121] |
| Teaching | 0.07 | 0.00 | 0.07 | 0.068 |
| | | | | [0.057] |
| Earnings at last or current job | 1,339.18 | 1,762.73 | 980.64 | -513.128 |
| | | | | [253.094]** |

# F Additional Analysis of Information Frictions

Having assessed in Section 4.1 whether job-seekers with more information sources about potential jobs *in general* have lower rates of employment exit, here I assess whether job-seekers with more accurate beliefs about *particular* aspects of the labor market have lower rates of employment exit.

At baseline, I asked job-seekers about non-wage amenities they were likely to experience at jobs they eventually find. I focus on two such aspects: physical comfort and the cost of commuting. At the 8-month endline, I asked employed individuals about these characteristics. In this way, I can compare job-seekers with accurate beliefs at baseline with in-accurate beliefs at baseline and assess whether quits and exits are driven by job-seekers with unrealistic expectations about future employment.

Physical comfort at jobs are measured using Blattman, Dercon and Franklin (2019)'s assessment of working conditions in Ethiopia. At baseline I asked respondents "At the job you are most likely to find, will you have enough time for short breaks?". Then, 8-months later I asked employed respondents if they felt they had time for short breaks at their current job.

To measure belief accuracy, I partitioned the my sample into baseline groupings according to expected future occupation, I constructed groups by partitioning the sample into occupation,[24] above or below median age, and university or more education. At endline, I calculated average earnings among each group (For example, the average earnings of all drivers below median age and without university education), then I compared this value with expected earnings for each individual (Expected earnings among all job-seekers expecting to find a job as a driver, without university education, and below the median age.) I perform the same exercise for beliefs about non-wage amenities.

Table F.1 asks how beliefs correlate with exit, conditional on finding work. Panel (a) addresses beliefs about physical comfort at work, while Panel (b) addresses beliefs about commuting costs. For each measure, I assess 2 version of the independent variable, (1) whether job-seekers are over-optimistic, the expected measure minus the group average, and (2) whether job-seekers have accurate beliefs overall. I consider both continuous and binary versions of the each measure. Table F.1 shows job-seeker predictions do not influence exits, whether through a quit or a non-quit. Analogously, Table F.2 shows job-seeker predictions do not influence quits specifically.

[24]Occupational groups are Construction, Driving, Factory Work, High Skilled Services (e.g. secretary work), Low-Skilled Services (e.g. security guard), Retail (which includes the food services industry), and Teaching

Table F.1: Prediction accuracy of non-wage amenities and commute cost on exit

(a) Accuracy of beliefs about workplace dis-amenities

| | (1) Exit | (2) Exit | (3) Exit | (4) Exit |
|---|---|---|---|---|
| Optimism about physical amenities | 0.0113 | | | |
| | (0.0170) | | | |
| In-accuracy about physical amenities | | -0.0140 | | |
| | | (0.0221) | | |
| Above median optimism about physical amenities | | | 0.00905 | |
| | | | (0.0602) | |
| Above median in-accuracy about physical amenities | | | | -0.0212 |
| | | | | (0.0601) |
| Observations | 285 | 285 | 285 | 285 |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < .01$

(b) Accuracy of beliefs about the cost of commuting

| | (1) Exit | (2) Exit | (3) Exit | (4) Exit |
|---|---|---|---|---|
| Expected commute cost minus group average | -0.0265 | | | |
| | (0.0302) | | | |
| Abs. value expected commute cost minus group average | | -0.0213 | | |
| | | (0.0503) | | |
| Expected commute cost minus group average above median | | | -0.0454 | |
| | | | (0.0589) | |
| Abs. value expected commute cost minus group average above median | | | | -0.0500 |
| | | | | (0.0586) |
| Observations | 285 | 285 | 285 | 285 |

Standard errors in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < .01$

Table F.2: Prediction accuracy of non-wage amenities and commute cost on quits

(a) Accuracy of beliefs about workplace dis-amenities

| | (1) Quit | (2) Quit | (3) Quit | (4) Quit |
|---|---|---|---|---|
| cond_expect_diff | -0.0238* | | | |
| | (0.0128) | | | |
| In-accuracy about physical amenities | | -0.0231 | | |
| | | (0.0168) | | |
| cond_expect_diff_g_med | | | -0.0942** | |
| | | | (0.0454) | |
| Above median in-accuracy about physical amenities | | | | -0.112** |
| | | | | (0.0452) |
| Observations | 285 | 285 | 285 | 285 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

(b) Accuracy of beliefs about the cost of commuting

| | (1) Quit | (2) Quit | (3) Quit | (4) Quit |
|---|---|---|---|---|
| Expected commute cost minus group average | -0.0310 | | | |
| | (0.0229) | | | |
| Abs. value expected commute cost minus group average | | -0.0655* | | |
| | | (0.0380) | | |
| Expected commute cost minus group average above median | | | -0.0774* | |
| | | | (0.0446) | |
| Abs. value expected commute cost minus group average above median | | | | -0.0250 |
| | | | | (0.0446) |
| Observations | 285 | 285 | 285 | 285 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table F.3: Summary of information index components

| Variable | Mean (1) | Median (2) | N (3) |
|---|---|---|---|
| Social connections help me get a job at the place they work | 0.27 | | 179 |
| Greater than median number of social connections helping them find work | 0.34 | | 179 |
| Social connections helping me find jobs are well-connected | 0.34 | | 179 |
| Any experience at job I think I am most likely to get | 0.85 | | 179 |
| Social connections tell me about job openings | 0.84 | | 179 |
| Social connections tell me the wages jobs pay | 0.25 | | 179 |
| Social connections help me travel to look for work | 0.12 | | 179 |
| Social connections tell me which jobs I would be best at | 0.18 | | 179 |
| Social connections refer me to people they know | 0.45 | | 179 |

Table G.1: Employment Exit by Self-employment

| Outcome at eight months | Overall Mean | Mean by group: Flows from self-employment | Mean by group: Savings | Regression |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Any employment entry since baseline | 0.81 | 0.79 | 0.86 | 0.138 |
| | | | | [0.091] |
| Any exit conditional on entry | 0.52 | 0.41 | 0.73 | 0.266 |
| | | | | [0.121]** |
| Any quit conditional on finding work | 0.34 | 0.24 | 0.53 | 0.308 |
| | | | | [0.116]*** |
| Any layoff conditional on entry | 0.18 | 0.17 | 0.20 | -0.042 |
| | | | | [0.102] |
| Employed at endline | 0.39 | 0.47 | 0.23 | -0.174 |
| | | | | [0.110] |
| Relies on savings at endline if not in a wage job | 0.20 | 0.13 | 0.30 | 0.142 |
| | | | | [0.103] |

Table G.2: Employment Exit by Social Transfers

| Outcome at eight months | Overall Mean | Mean by group: Flows from social transfers | Mean by group: Savings | Regression |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Any employment entry since baseline | 0.78 | 0.75 | 0.86 | 0.022 |
| | | | | [0.087] |
| Any exit conditional on entry | 0.54 | 0.43 | 0.73 | 0.300 |
| | | | | [0.126]** |
| Any quit conditional on finding work | 0.40 | 0.32 | 0.53 | 0.243 |
| | | | | [0.126]* |
| Any layoff conditional on entry | 0.14 | 0.11 | 0.20 | 0.057 |
| | | | | [0.090] |
| Employed at endline | 0.36 | 0.42 | 0.23 | -0.228 |
| | | | | [0.107]** |
| Relies on savings at endline if not in a wage job | 0.19 | 0.12 | 0.30 | 0.053 |
| | | | | [0.104] |

# G Additional Analysis of Flow vs. Non-Flow Income

Table H.1: Effect of reducing non-wage income shock arrival rate $\varphi$ on quits and exits, partial equilibrium

| Outcome | Value | | Difference | % Explained |
|---|---|---|---|---|
| | USA | Ghana | | |
| | (1) | (2) | (3) | (4) |
| **Baseline** | | | | |
| Quit rate | 0.5 | 8.2 | 7.7 | - |
| Exit rate | 5.2 | 16.4 | 11.2 | - |
| **Reduce $\varphi$ 50 percent** | | | | |
| Quit rate | 0.5 | 7.0 | 6.6 | - |
| Exit rate | 5.2 | 15.3 | 10.1 | 10.0 |
| **$\varphi$ is zero** | | | | |
| Quit rate | 0.4 | 5.3 | 4.9 | - |
| Exit rate | 5.2 | 13.6 | 8.4 | 25.1 |
| **Reduce variance of $F_\psi$ 50 percent** | | | | |
| Quit rate | 0.5 | 7.2 | 6.7 | - |
| Exit rate | 5.2 | 15.5 | 10.3 | 8.4 |
| **Constant $\psi$** | | | | |
| Quit rate | 0.4 | 5.3 | 4.9 | - |
| Exit rate | 5.2 | 13.6 | 8.4 | 25.1 |

# H Additional Counterfactual Experiments

Table H.2: Effect of setting parameter values in Ghana to those of the USA on exits, partial equilibrium

| Outcome | Value USA (1) | Ghana (2) | Difference (3) | % Explained (4) |
|---|---|---|---|---|
| **Baseline** | | | | |
| Quit rate | 0.5 | 8.2 | 7.7 | - |
| Exit rate | 5.2 | 16.4 | 11.2 | - |
| **Ghana, $\varphi_{\mathbf{USA}}$** | | | | |
| Quit rate | - | 5.4 | 4.9 | - |
| Exit rate | - | 13.7 | 8.5 | 24.4 |
| **Ghana, $F_{\psi,\mathbf{USA}}$** | | | | |
| Quit rate | - | 10.8 | 10.3 | - |
| Exit rate | - | 19.0 | 13.8 | -23.4 |
| **Ghana, $\psi_{\mathbf{USA}}$, $F_{\psi,\mathbf{USA}}$** | | | | |
| Quit rate | - | 5.5 | 5.0 | - |
| Exit rate | - | 13.7 | 8.5 | 23.8 |
| **Ghana $F_{z,\mathbf{USA}}$** | | | | |
| Quit rate | - | 6.6 | 6.1 | - |
| Exit rate | - | 14.9 | 9.7 | 13.7 |
| **Ghana $\nu_{\mathbf{USA}}$** | | | | |
| Quit rate | - | 5.3 | 4.8 | - |
| Exit rate | - | 13.6 | 8.3 | 25.6 |