Subsistence Wage Employment: Labor Market Dynamics in Urban Ghana

Peter Deffebach

Boston University

This version: October 16, 2024

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 rates of wage work overall. I conduct a panel survey of job-seekers and a survey of firms in urban Ghana to explore the causes of elevated exit rates out of wage work in low-income labor markets. I document entry rates into employment are equal between the US and Ghana, but high exit rates mean Ghanaian job-seekers are only half as successful at finding wage work in the long run. In Ghana, I find exits are dominated by quits, while layoffs play a negligible role, in strong contrast with the USA, where layoffs dominate, and quits are infrequent. I examine, and reject, informational frictions as a key driver of high quit rates and show self-employment at most a moderate role. I show quits are most common among individuals who at Baseline are temporarily without flows of non-wage income. To quantify the contribution of changing non-wage income in driving quitting behavior, I build model of job search in which workers face uncertain non-wage income and accept and quit jobs to cope with temporary losses in income. When calibrated to match experience of job-seekers in both the USA and Ghana, my model attributes 20% of the difference in exit rates to this mechanism. I conclude in poor countries, wage jobs can act as insurance against risk outside the wage sector.

JEL Codes: J63, E24, O17
Keywords: Labor market flows, Self-employment, Ghana

Email: `peterwd@bu.edu`. I thank my committee David Lagakos, Yuhei Miyauchi, and Masao Fukui for guidance in the research process. I also thank James Dzansi and Henry Telli at IGC Ghana for hosting me in Accra and their invaluable introduction to the Ghanaian Labor Market. For survey assistance, I thank Sedzro Kojo Mensah, Martin Agbodzi, along with Twum Abu Bonsra. This project was supported by the IGC and STEG.

1 Introduction

Labor markets in developing countries are characterized by low rates of wage employment, and the cause of such poor labor market performance is a central question of development economics (Lewis, 1954; Harris and Todaro, 1970). Recently Donovan et al. (2020) collected panel data from countries across the development spectrum and showed elevated exit rates out of wage work rather, than low entry rates into wage work, drive differences between countries.

Why, then, are rates of exit out of wage employment so high in poor countries? We have no general evidence on whether exits are due to voluntary quits or involuntary layoffs, nor the causes of either type of exit specifically. Blattman et al. (2019) and Boudreau et al. (2021), show workers in factory jobs frequently quit jobs due to poor working conditions. Yet these jobs may not reflect the average labor market experience in a poor country, where low-skilled service work dominates over factory employment (Bandiera et al., 2021). Rasul (2010) and Mckenzie (2017) show firms are frequently frustrated with the quality of their workers, indicating exits might be driven firm, rather than worker, initiated.

To understand the causes of high exit rates out of wage work, I conduct a new in-depth panel survey of urban job-seekers, along with a survey of firms, in Accra Ghana. My paper documents the importance of exits, rather than entry, in a new setting. More importantly, I document a new fact, that exits are driven by voluntary quits, as opposed to involuntary layoffs, in stark contrast with the USA. I argue highly variable income *outside* the wage sector plays a key role in driving quits, and introduce the notion of "subsistence wage employment", wage work which is taken up only as long as needed to get through hard times. I build a general equilibrium model of unemployment to quantify the importance of this mechanism and show it can explain 20% of the difference in exit rates between the USA and Ghana.

My conclusion that quits, rather than layoffs, drive exits from wage work presents a meaningful break from conventional views of urban labor markets in poor countries. In the classic works of Lewis (1954) and Harris and Todaro (1970), for example, urban job-seekers are confined to an unproductive non-wage sector while queuing for a limited supply of desirable wage jobs. This perspective persists today. Breza et al. (2021) shows workers leave unproductive self-employment as soon as wage jobs are available. To borrow language from Donovan et al. (2020), my work shows workers may not be "falling off" the job-ladder, but voluntarily lowering themselves away from undesirable jobs.

A large literature has emphasized the role of subsistence self-employment in insuring risk against risk in the wage sector (Lagakos and Waugh, 2013; Vollrath, 2009; Falco and Haywood, 2009; Herreño and Ocampo, 2023), I argue the opposite is also true, and wage jobs an insure risk outside the wage sector. 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 in the non-wage sector, as well as Falco and Haywood (2009), which finds the self-employment is often preferred alternative to wage work in urban Ghana, rather than an occupation of last resort.

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 painted a detailed portrait of job-seekers' search strategies, expectations, and outside options, the second assessed labor market outcomes eight months later, documenting wage employment, self-employment, earnings, and more. 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 jobseekers 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 start by documenting three facts about the difference in labor market flows between the USA and Ghana.

First, I show long-run employment rates among job-seekers without wage work are significantly lower in Ghana relative to the USA and this difference is entirely accounted for by exits out of wage work rather than entry into wage work. Beginning populations of job-seekers without wage work in Ghana and the USA, nearly everyone in both groups had found *some* wage employment after eight months. However in Ghana, half of the workers who attained wage work had subsequently left the jobs they found and were again without wage work by eight months. In the USA, by contrast, workers keep their jobs after finding them and long-run employment rates are high. I show this fact is true using my firm survey as well. Firms in Ghana report significantly higher separation rates relative to firms in the USA.

Second, and in a more significant contribution, I document the majority of these flows out of wage work were voluntary quits, while only a small portion of transitions out of wage work were due to involuntary layoffs. To my knowledge my study is the first to measure rates of voluntary and involuntary separations in a developing country, despite these statistics being standard in OECD countries. In the USA, this pattern is reversed.

The majority of flows out of wage work are due to involuntary layoffs, and only a small portion is due to quits. My firm survey also confirms this finding: quits comprise a higher share of separations in Ghana compared to the USA.

Third, I show quits and layoffs are significantly different from one another in Ghana, but in the USA the two forms of exit are similar. Documenting this distinction is important since conventional searching and matching models feature no conceptual distinction between quits and layoffs: Workers and firms jointly choose to separate when joint surplus is low. My evidence suggests this assumption may be reasonable in the USA, but may not hold in my setting. Workers in Ghana face income gains from quits and income losses from layoffs, while in the USA, both quitters and non-quitters experience approximately similar losses in income. In Ghana, jobs ending in a quit pay significantly less than jobs ending in a layoff, while this difference is less stark in the USA.

Having established the role of employment exit, primarily driven by quits, as a cause of low long-run employment rates, I next explore the cause of high quits by examining heterogeneity within my sample. I have three main findings.

First, information frictions do not appear to cause employment exit, voluntary or otherwise. This stands in contrast with a large literature arguing information drives higher labor market churn in poor countries (Donovan et al., 2020; Poschke, 2022; Carranza and McKenzie, 2023), as well as rich ones (Mukoyama, 2014; Menzio et al., 2015; Brugemann and Moscarini, 2010). My rich job-seeker survey gives a detailed portrayal of the information sources available to jobseekers and how much they know about likely future jobs, yet I find no correlation between any measures of information levels with employment entry or exit rates.

Second, I show self-employment plays at most a moderate role in driving quits and layoffs. Existing research on job search emphasizes the role of self-employment in driving low wage-employment rates (Feng et al., 2021; Vollrath, 2009; Herreño and Ocampo, 2023; Bosch and Maloney, 2010). I find that among both quitters and non-quitters, less than half of job-seekers who experienced an employment exit are engaged in self-employment. Transfers from friends and family mediate the difference between quits and layoffs just as much as self-employment.

Third, I document that quits are elevated among job-seekers experiencing a temporary lapse income at baseline. I use this to argue variable income streams outside the wage sector play a key role in driving entry and exit into the wage sector. 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 experience a separation and are more likely to have quit, conditional on separation. I propose wage work in my context operates as an insurance device against bad times, but is often not more valuable than self employment or non-employment. When faced with the loss of an income stream job-seekers take undesirable jobs before quitting them as circumstances improve.

Finally, I build a general equilibrium structural model of unemployment in the spirit of Mortensen and Pissarides (1994) and Diamond (1982) as a tool to quantify how much variation in non-wage income accounts for differences in exit rates between the USA and Ghana. In the model, workers' non-wage income moves across time. Jobs are heterogeneous decide which job offers to accept and reject based on their current level of non-wage income. Workers accept jobs when their earnings are temporarily low, and quit them when their non-wage income opportunities improve. After matching moments related to employment entry and exit, along with differences between quits and layoffs, I conclude 20 percent of difference in exit rates between the USA and Ghana can be attributed to this mechanism.

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 et al. (2020), 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 et al. (2020) says little about labor market flows in Sub-Saharan Africa.[1] In Sub-Saharan Africa, researchers have focused almost exclusively on the margin of entry, testing 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

[1]The data set of Donovan et al. (2020) includes only Rwanda and only in secondary analyses

Blattman et al. (2019) and Abebe et al. (2024), studying factories in Ethiopia, and Boudreau et al. (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 et al. (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 quits and layoffs in Ghana are *more different* than quits and layoffs in the USA. Workhorse models of job-search are silent as to this distinction, with employers and workers mutually agreeing to part ways (McLaughlin, 1991). I show this assumption might be justified in the USA, but needs greater attention in developing countries. In addition, existing work on labor market flows in the USA often treat quits as synonymous with job-to-job flows, and ignore voluntary flows out of employment. My work joins Bagga et al. (2023) and Blanco et al. (2024) which both feature quits to non-employment due to changes in worker's outside option.

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, presenting the first JOLTS-style dis-aggregation from a developing country.

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.[2] In particular, Poschke (2022) builds a structural model of job search and argues noisily observed match quality is the primary driver of higher employment exits in poor countries documented by Donovan et al. (2020).[3] While this mechanism

[2] Abel et al. (2020), and Carranza et al. (2020), Bassi and Nansamba (2020) alleviates information frictions. Franklin (2021) and Banerjee and Sequeira (2021) alleviates transportation frictions. Abebe et al. (2020) addresses both. For more discussion, see Carranza and McKenzie (2023)

[3] Information frictions are also commonly used to explain separations in the USA, beginning with Jo-

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 et al. (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.

2 Data

2.1 Original Survey 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 paints a complete picture of information sources, i.e. how they 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 et al., 2020). The endline survey assessed outcomes 8 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.[4]

vanovic (1979). See Mercan (2017) and Pries and Rogerson (2022), which study the decline in separations across time, as two relevant examples.

[4]Physical amenities are measured in a manner similar to Blattman et al. (2019). I measure dignity in the

How does my sample compare with jobseekers in urban Ghana? To answer this, I compare my sample with job-seekers in Ghana using the 2015 Labor Force Survey. Fortunately, the 2015 Labor Force Survey is unique in that it measures on-the-job search, enabling a precise comparison with my sample. Summary statistics of respondents at Baseline are presented in Table 1. My sample is a highly selected group of urban job-seekers. Respondents are overwhelmingly male (83%), likely due to the nature of recruitment. They are also far more likely to have some higher education relative to the job-seeking population at large (47% vs. 7%). The population is also less likely to be without any work at all (66% vs 81%), yet more likely to be working for someone else (45% vs 13%).

My sample is 30 years old on average and with 100% of the sample has some work experience, with a median of 5 years work experience. Being relatively old and experienced, my sample bears little resemblance to recent work tacking youth low rates of youth employment and first-time job-seekers in Sub-Saharan Africa (Bandiera et al., 2021; Abebe et al., 2020). Overall, jobseekers are overwhelmingly experienced, working, and seeking to move up the job-ladder.

While my sample is highly selected relative to the urban job-seeking population at large, it 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.[5] Additionally, I am not focused on any particular employment sector, such as the high exit out of factory jobs documented in Blattman et al. (2019) and Boudreau et al. (2022).

workplace using questions from Dube et al. (2022)'s work on the working conditions of Walmart workers in the USA.

[5] Carranza et al. (2020) and Bassi and Nansamba (2020) partnered with local non-profits in South Africa and Uganda, respectively. Abel et al. (2020) and Banerjee and Sequeira (2021) partnered with the national unemployment agency of South Africa Notably, Abebe et al. (2020) constructs a representative sample of job-seekers.

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		

2.1.2 Firm survey

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, leading 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.

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	

2.2 Comparing Job-Seekers with the USA

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 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 ever leave the labor force 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 US workers. My methodology to compare firms between Ghana and the USA is discussed in Appendix D.

3 Aggregate Evidence

3.1 Employment Entry and Exit

Aggregate Fact 1: Ghana and the USA feature equally high rates of entry into wage employment. However, Ghana features significantly higher exit rates out of wage employment, such that long-run employment rates are double in the USA compared to Ghana.

How does the experience of my jobseekers compare with those in the USA? I start by exploring entry and exits rates in and out of the wage sector for each country. Starting with job-seekers without wage work in the my Ghanaian sample, I consider three outcomes: (1) whether a job-seeker found any wage employment at all in the subsequent 8 months, (2), whether they are currently working for someone else at the 8-month Endline, and (3) Conditional on *any* entry into wage work in the previous eight months, the proportion of job-seekers who subsequently exited wage work and were once again not working for someone else.

Unfortunately, the CPS does not track employment outcomes over a continuous eight months due to it's 4-months on, 8-months off, 4-months on rotation scheme.[6] As a consequence, to compare with my Ghanaian sample, I measure 12-month equivalents of each variable, then solve for their 8-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 12-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.[7]

Figure 1 documents the trajectories of job-seekers without wage work in the USA and Ghana. Starting in month 0, all job-seekers are, by construction, without wage work. Next, I show the share of workers in Ghana and the USA who took up a wage job at some point between 0 and 8 months, shown in the middle points in Figure 1. Error bars indicate

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

[7] An alternative approach would estimate monthly entry and exit rates directly from the CPS and solve for 8-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.

bootstrapped 95% confidence intervals. In both Ghana and the USA, roughly 75% of job-seekers *some* wage employment between 0 and 8 months. Finally, at the far right points in Figure 1, I show that *at* 8 months, far more workers in the USA are engaged in wage work compared to those in Ghana. In other words, in the USA, 13% of workers who find jobs between between 0 and 8 months had exited and were again without wage work by 8 months. In Ghana, by contrast, 49% of workers who found wage work had exited by the 8 month mark.

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. The the long run, my sample in the USA while spend 76% 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.[8]

Overall Figure 1 demonstrates 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, a result consistent with the findings of Donovan et al. (2020), 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.

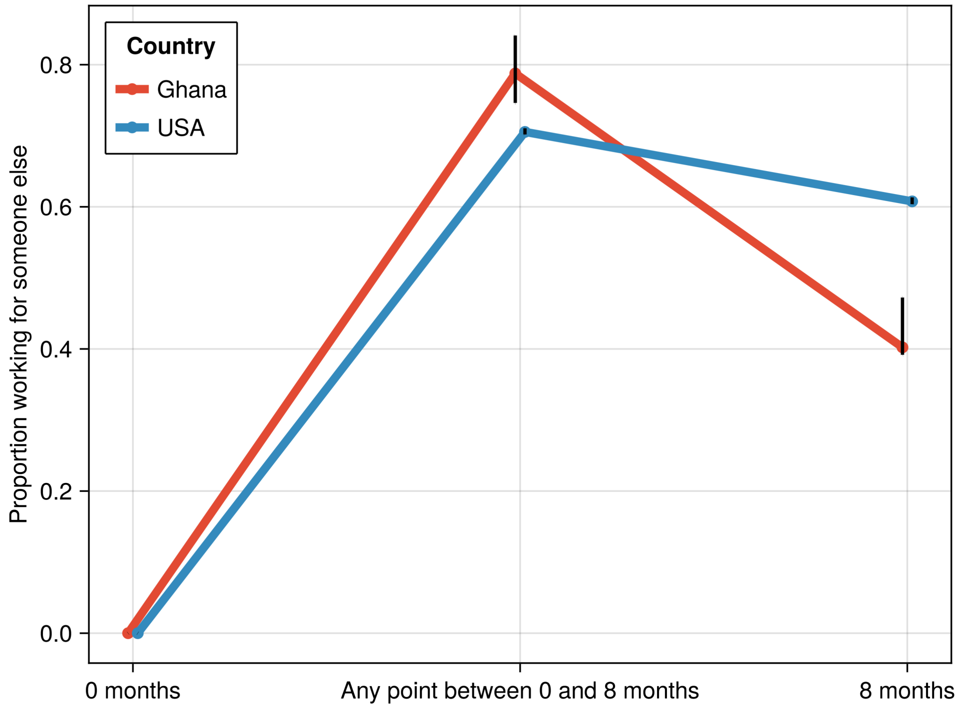
3.2 Quits vs Layoffs as Causes of Employment Exit

Aggregate Fact 2: 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 US, 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.

What are the causes of exit 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 Base-

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

Figure 1: Employment entry and exit over 8 months



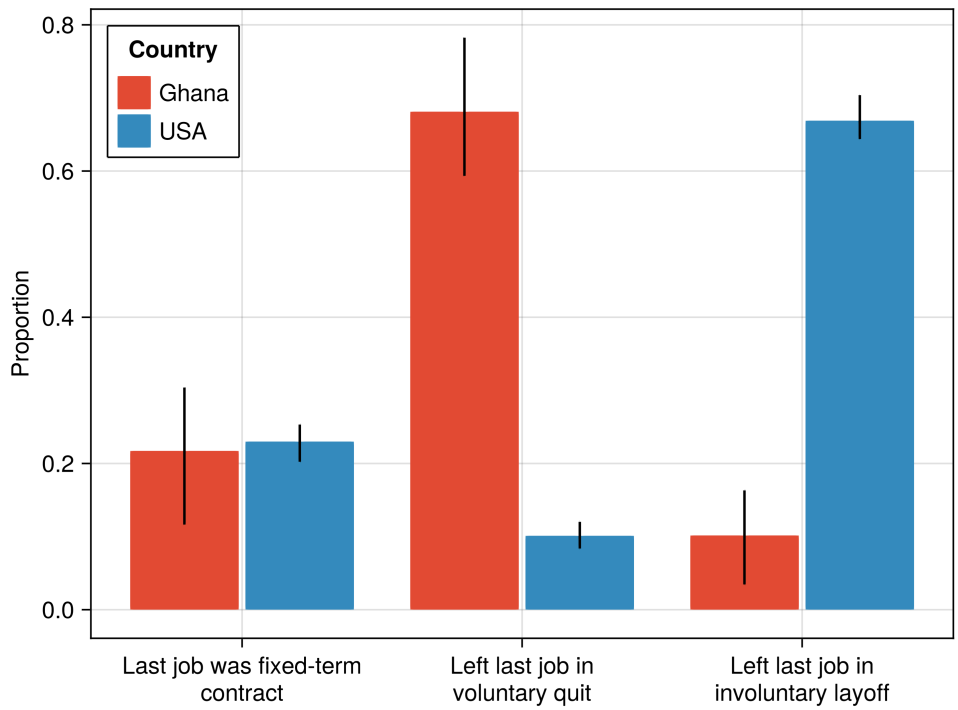
line in Ghana and the weighted sample of job-seekers from the CPS, and then further focuses on jobseekers who find jobs between 0 and 8 months before leaving them and being outside the wage sector at 8 months. For USA equivalent statistics using the CPS, I start with unemployed at month zero then focus on those who are unemployed 12 months later after finding some work in the intervening period. I observe the reason for their unemployment (quit, layoff, or temporary work) at 12 months.

Figure 2 documents Ghana and the USA have strikingly different causes of employment exit. In the 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 22% for both countries. Instead, differences are largely driven by involuntary layoffs. 10% of employment exits are due to involuntary layoffs in Ghana, layoffs account for 67% of exits in the USA.

Appendix Table B.2 compares derived monthly entry and exit rates distinguishing between quits and non-quits (grouping together layoffs and temporary work) in the USA and Ghana. Overall, Appendix Table B.2 emphasizes the importance of quits compared to non-quits. While the layoff rate in Ghana is roughly double that of the USA, in Ghana the quit rate is a remarkable 38 times larger than in the USA.

This finding is new to the literature. To borrow language from Donovan et al. (2020), rather than "falling off" the job-ladder, job-seekers appear to be voluntarily lowering themselves away from unwanted jobs. The high rate of quits contrasts sharply with traditional perspectives on labor markets in poor countries, which treat wage work as both hard to come by and highly desirable relative to other options (Harris and Todaro, 1970; Breza et al., 2021; Bandiera et al., 2021).

Figure 2: Causes of employment exit



3.2.1 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 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 the 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, along with 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.[9] In this way, I can replicate standard statistics reported by the Job Openings and Labor Turnover Survey (JOLTS). Appendix D described the method for comparing firms in the Ghana and the USA.

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, do not in general 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 compared to firms in the USA, firms in Ghana face an order of magnitude higher rates of separation, confirming the findings of Section 3.1.

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.[10] 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.

3.3 Characteristics of Quits and Layoffs

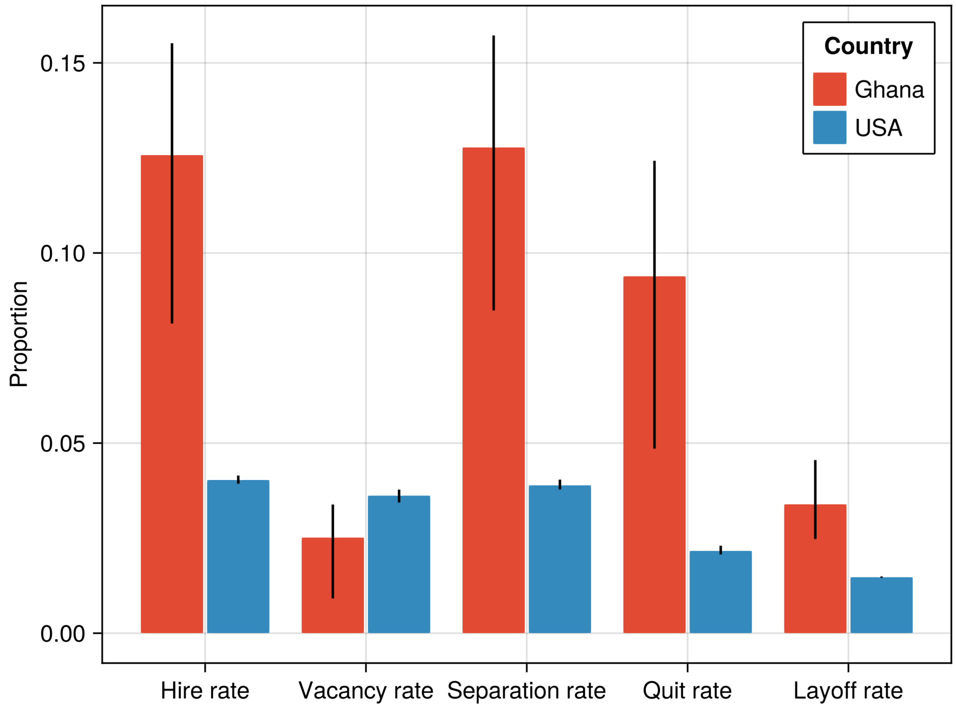
Aggregate Fact 3: Jobs ending in a quit in Ghana have lower incomes than jobs ending in a layoff. This difference is significantly less smaller in the USA. In Ghana, quitters see income gains and non-quitters see income losses. In the USA, both groups experience equally large income losses.

A conventional view in the job search literature is that quits and layoffs are not conceptually different (McLaughlin, 1991). For instance, if workers and firms bargain over the surplus of a match, as in common in searching and matching models in the spirit of

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

[10] 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



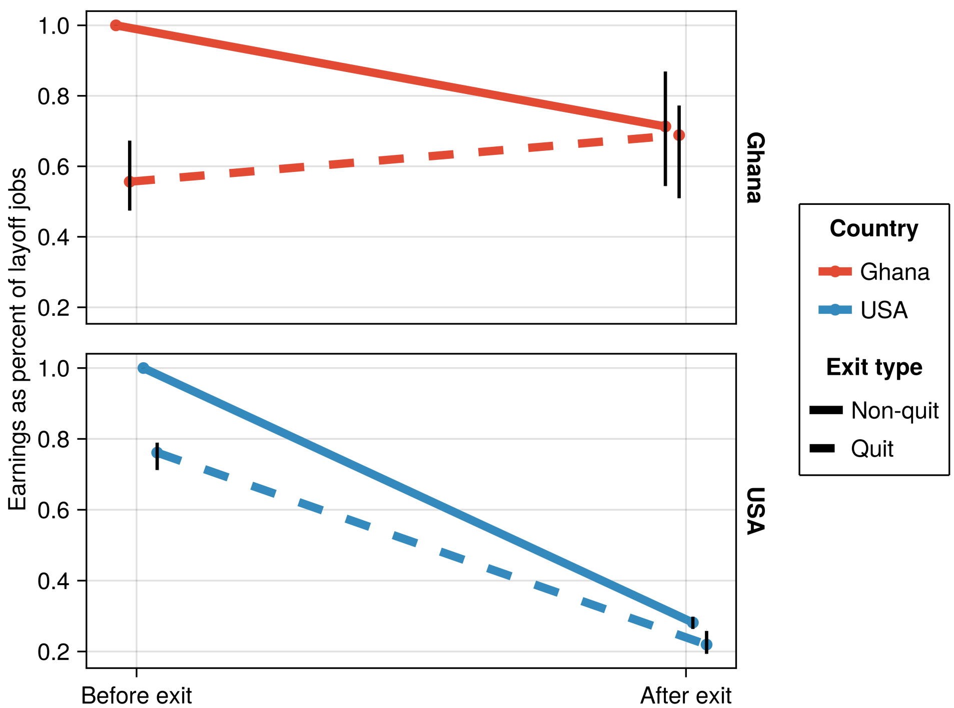
Mortensen and Pissarides (1994), workers separate whenever joint surplus reaches zero. Because this decision is mutual, it is neither worker-initiated (a quit) or firm initiated (a layoff). To argue for the importance of the quit-layoff distinction, I first must show the two really are distinct.

To assess the difference between quits and layoffs, I assess 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 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 4in tabular format.

Figure 4 shows conventional wisdom about the similarity between quits and layoffs holds true in the USA. In Ghana, however, quits and layoffs are highly distinct. Starting with the wages of jobs before an exit, on the left of each graph. In Ghana, jobs ending in a quit pay only 55% of the wages of jobs ending in a layoff. In the USA, by contrast, this difference is less stark, and jobs ending in a quit pay 78% as much as jobs ending in a layoff.

Turning to the right hand side of Figure 4 we see again that quits and layoffs are more different in Ghana relative to the USA. In Ghana, workers who quit their jobs see income gains on the order of 12%, while workers who exit due to a non-quits see income losses of 13%. In the USA, by contrast, both quits and layoffs lead to large changes in total income, with drops due to quits and layoff of 54% and and 72%, respectively.

Figure 4: Income before and after a quits and layoffs



3.4 Discussion of Aggregate 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: This suggests employment exit is likely the cause of low employment rates in Ghana relative to the USA, consistent with the findings of Donovan et al. (2020). Moving beyond the findings of Donovan et al. (2020), I show not only are exits out of wage work elevated 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. Finally, I show the quits and layoffs are meaningfully different in Ghana, as measured by the income gain of quitters vs. non-quitters and the average difference in wages of quit vs. non-quit jobs. In the USA, by contrast, this difference is less stark.

In sum, job-seekers in my sample have been searching for work for an average of two years and profess a strong desire to move into the wage sector. Yet when they secure wage work, a large portion quit their jobs. Why are they quitting at such high rates? More puzzling, workers in Ghana are frequently able to see income gains after a quit. Why, then, take these jobs at all? In the following section I explore the causes of high rates of quits by exploiting heterogeneity within my Ghana sample to answer these questions.

4 Within-Sample Heterogeneity

In this section, I examine heterogeneity across workers to workers so frequently exit wage work voluntarily. First I examine, and reject, information frictions as the leading cause of employment exit in my sample. Next, I examine, and reject, profitable self-employment as the cause of quits, yet show self-employment plays a key role in supporting income after layoffs and quit. Finally, I document a new fact, which is that quits are concentrated among workers who, at baseline, are forced to rely on savings to get by, as opposed to flows of income from family support or self-employment.

A discussion of demographic correlates of exit out of wage work and the characteristics of quit vs. non-quit 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. Consistent with Blattman and Dercon (2018), exits are more concentrated in manual labor jobs, a category which includes wage work, but high exits are primarily driven by layoffs rater than quits.

4.1 Information Frictions

Heterogeneity Fact 1: Information frictions do not correlate with job destruction or quit rates.

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 information frictions are a key driver of high worker exit rates out of employment in developing countries (Abebe et al., 2020; Abel et al., 2020; Carranza et al., 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. For instance, workers may imperfectly observe characteristics of the job relevant to workers but not firms, such as working conditions. 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 observe 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 job 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 3, 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.[11] Table 3 shows job-seekers with higher ex-ante baseline information about jobs are not 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.

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

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

are over-optimistic 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.

Table 3: Job outcomes by baseline information score

Outcome at eight months	Overall Mean	Mean by group		Regression
		Low information	High information	
	(1)	(2)	(3)	(4)
Any employment entry since baseline	0.79	0.82	0.76	-0.059 [0.060]
Any exit conditional on entry	0.49	0.51	0.47	-0.051 [0.088]
Quit conditional on exit	0.68	0.74	0.61	-0.091 [0.123]
Total income at endline	1,255.21	1,258.39	1,251.84	2.149 [174.669]
Wage earnings at endline if employed	1,443.82	1,404.73	1,485.14	-88.396 [236.050]

4.2 Self-Employment and Non-Employment

Heterogeneity Fact 2: Quitters are not more likely to be self-employed after an exit than non-quitters. Self-employment income and transfers from family and friends play roughly equal roles in mediating the differences in income changes after a quit vs. non-quit.

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 et al. (2020) 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 Ocampo, 2023; Boschma et al., 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 4 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 non-quit. Columns (2) and (3) show group means of outcomes, while Column (4) shows a regression difference adjusted for baseline covariates. Table 4 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 options, we would expect a higher share of quitters to be in self-employment than non-quitters. Table 4 shows that among both the quitters and non-quitters, only a minority of jobseekers are engaged in self-employment at Endline. Quitters were 9pp more likely to engage in self-employment than non-quitters, but this difference is only 2pp after adjusting for covariates.

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. In both cases, the overwhelming majority are currently searching for a job. Quitters are more likely to be searching for a job than non-quitters. This finding is consistent with the argument of Donovan et al. (2020), that self-employment is similar to unemployment in poor countries.

Are self-employment among of quitters more profitable than self-employment among quitters? If quits were driven by profitable self-employment opportunities, we might expect quitters to have higher self-employment income than non-quitters. Table 4 shows this is true. The self-employed quitters have higher incomes at endline than the quitters who are not self-employed, after adjusting for covariates, though this difference is only marginally significant.

Figure 4 demonstrates quitters see income gains after exits, while non-quitters see income losses. To what extent are these income gains driven by exits to self-employment? Table 4 shows among the self-employed at endline, both quitters and non-quitters see income gains, while among the non-self-employed, both quitters and non-quitters see income losses. However the difference between quitters and non-quitters in this regard is strongest among the non-self-employed. Non-quitters who are not self-employed at endline face steep income losses, on the order of 985 Cedis, while quitters who are not self-employed face a very small loss, on the order of only 80 Cedis ($5 USD a month). Transfers from friends and family can almost entirely supplement the income losses from an exit in the absence of self-employment opportunities.

In sum, Table 4 provides mixed evidence on the role of self-employment in driving quits.

Workers do not appear to be quitting to particularly profitable opportunities, and even the self-employed are still looking for employment. However quitters appear to be in marginally more profitable self-employment opportunities relative to non-quitters. Table 4 highlights the role of income outside self-employment in driving the differences between quits and layoffs. This heterogeneity is explore in the following section.

Table 4: Outcomes of Quitters and Non-Quitters Conditional on Exit

Outcome at eight months	Overall Mean	Mean by group		Regression
		Non-quit	Quit	
	(1)	(2)	(3)	(4)
Self-employed at endline	0.43	0.36	0.47	0.120
				[0.134]
Searching for a job	0.81	0.73	0.85	0.220
				[0.095]**
Total income at endline	1,227.39	1,256.82	1,213.62	200.736
				[248.076]
Total income if self-employed	1,760.00	1,887.50	1,713.64	558.084
				[497.341]
Total income if not self-employed	817.69	896.43	773.60	-36.742
				[217.333]
Difference in income: Current minus last job	-2.61	-505.91	232.98	713.864
				[287.976]**
Difference if self-employed	520.67	333.75	588.64	145.622
				[494.804]
Difference if not self-employed	-405.13	-985.71	-80.00	581.709
				[365.228]

4.3 Temporary Lapses in Income

Heterogeneity Fact 3: Quits are concentrated among workers facing temporary lapses in income at Baseline.

In this section I document a novel source of heterogeneity driving both employment exit and higher quits. Quits are concentrated among job-seekers who are forced to rely on savings to get by at Baseline, as opposed to income flows from family or self-employment.

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.[12] I divide respondents into two groups, those who with a "flow" of income at Baseline, grouping together those who receive family transfers and self-employment, and those without.

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

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 5 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 5: Baseline differences between savings and non-savings groups

		Mean by group		
Baseline characteristic	Overall Mean	Income flows	Savings	Regression
	(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]**

Table 6 compares outcomes at endline between the two groups. As with Tables F.1 and 4, Column (4) reports a regression difference, controlling for the covariates analyzed in Table 5.

Comparing the two groups, there is little difference in job-finding between the non-savings group and the savings group (78% vs. 85%). Conditional on finding work, however, the savings group is significantly more likely to experience job destruction (76% 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, 55% of the savings group later quit their job, compared with 27% in the non-savings group. Adjusting for covariates, the savings group is 17.5pp more likely to have their job destruction be a quit relative to a non-quit, but this difference is not statistically significant. 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 (46% for non-savings vs 21% for savings).

Finally, Table 6 shows that relying on savings to get by is a temporary state. Of those relying on savings to get by at Baseline, only 30% were still relying on savings to get by at Endline, conditional on non-employment. Of those with income flows at Baseline, 13% of the non-employed were forced to rely on savings at Endline. Additionally, there is suggestive evidence the quitters are less likely to need to rely on savings to get by than non-quitters, at least among the savers at Baseline. Among job-seekers relying on savings at Baseline who then quit their jobs, 18% relied on savings at Endline, among the same group who were laid off from their previous jobs, 57% relied on savings at Endline. I interpret this as slight evidence that the presence of an income stream outside the wage sector may have induced some individuals to quit. However the difference in reliance on savings is not present among quitters and non-quitters at large, without conditioning on baseline reliance on savings.

Table 6: Employment Exit by Reliance on Flow Income

		Mean by group		
Outcome at eight months	Overall Mean	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 non-quit 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]*

4.4 Discussion of Within-Sample Heterogeneity

Why is job destruction, primarily through quits, high among job-seekers in my sample? Evidence from Sections 4.1, 4.2, and 4.3 gives a parsimonious set of facts to discipline a theoretical explanation. First, Section 4.1 presents evidence against information frictions being the cause of job destruction. Section, Section 4.2 demonstrates worker more likely to quit low-wage jobs and they are than able to recuperate lost income after job loss, even in the absence of self-employment. Third, and finally, Section 4.3 shows workers with temporarily lower flows of income at Baseline are more likely quit work conditional on finding employment.

If workers who quit their jobs are able to *increase* their incomes after quitting their previous employment, why accept these jobs in the first place? Similarly, why are job-seekers in a seemingly vulnerable position, without flow income at Baseline, more likely to quit work? I argue these findings are consistent with a model in which quits are driven by movement in a worker's non-wage income across time.

5 Model

In this section, I build a general equilibrium model of job search to formalize this intuition that workers accept and quit jobs to cope with drops in non-wage income. The goal of this model is two-fold. First, I aim to quantify what proportion of quits is due to my proposed mechanism. Second, my model allows for comparison of what underlying features of the labor markets in Ghana and the USA drive differences in entry and exits.

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 ρ. Workers can be in either the wage sector, that is working for a firm and earning a wage, or the non-wage sector. 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 a stream of income outside of the wage sector that changes with time according to a Poisson process. A worker with variable income ψ receives shocks to their non-wage income at rate φ. When a shock arrives, they draw a new value of non-wage income $\psi' \sim F_{\psi}\left(\psi' \mid \psi\right)$. Non-wage income ψ 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 δ 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 ψ 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 ψ. Similarly, employed workers decide whether to stay at or quit a job according to their current potential non-wage income ψ along with the job's productivity z. A job's wages are exogenously determined by match productivity z, which does not change across time, while employed worker's potential non-wage income changes with time even while employed at a job. Consequently, a worker may enjoy a job at one moment and then quit it the next. In addition to wages, workers receive a non-wage amenity of employment which is constant across all matches, ν.

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 λ^w and λ^f, respectively.

When matches are dissolved, firms, 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 ψ has a present discounted value given by $U(\psi)$, while an employed worker with non-wage earning potential ψ in a match with productivity z has a present discounted value given by $W(\psi, z)$. $U(\psi)$ is defined recursively according to

$$\begin{aligned}\rho U(\psi) = &\ \psi \\ &+ q^{w} \int (\max \{W(\psi, z), U(\psi)\} - U(\psi)) f_z(z)\, dz \\ &+ \varphi \int \left(U(\psi') - U(\psi)\right) f_\psi\left(\psi' \mid \psi\right)\, d\psi\end{aligned} \tag{3}$$

While employed present-discounted value is defined recursively according to

$$\begin{aligned}\rho W(\psi, z) = &\ (1-\delta) z + \nu \\ &+ (\lambda^f + \lambda^w)\left(U(\psi) - W(\psi, z)\right) \\ &+ \varphi \int \left(\max\left\{W(\psi', z), U(\psi')\right\} - W(\psi, z)\right) f_\psi(\psi' \mid \psi)\, d\psi\end{aligned} \tag{4}$$

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

$$\begin{aligned}\rho V = &\ -c \\ &+ q^f \int \int J(\psi, z) \times \mathbb{I}(W(\psi, z) > U(\psi)) u(\psi) f_z(z)\, du\, dz\end{aligned} \tag{5}$$

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

$$\begin{aligned}\rho J(\psi, z) = &\ (1-\delta) z \\ &- (\lambda^f + \lambda^w) J(\psi, z) \\ &+ \psi \int J(\psi', z) \times \left(W(\psi', z) > U(\psi') - J(\psi', z)\right) f_\psi(\psi' \mid \psi)\, d\psi'\end{aligned} \tag{6}$$

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, 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 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 ψ can take one of two values, low value ψ_l, and high value ψ_h. Similarly, there are two wages z_l and z_h. Together, ψ_l, ψ_h, z_l, and z_h are such that

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

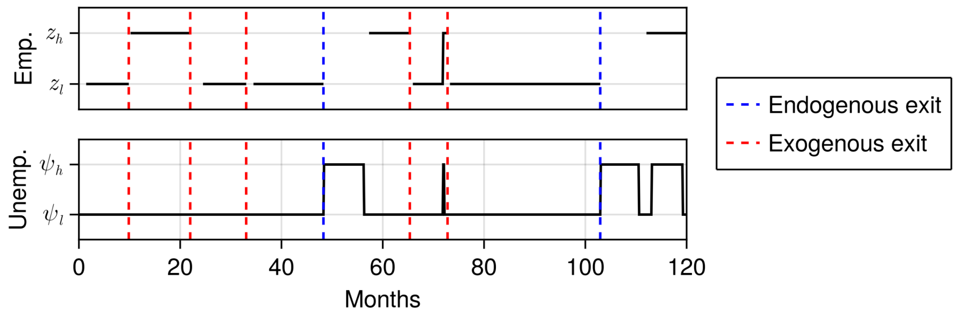
In other words, the worker prefers to work at z_l when their non-wage incomes are ψ_l, but will quit such a job if their non-wage income rise to ψ_h. Job z_h is preferred to the non-wage sector for all values of non-wage income.

In Figure 5, I plot the trajectory of a worker starting in the non-wage sector with non-wage income ψ_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 ψ, which moves between the high state ψ_h and low state ψ_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 φ by a factor of four. When working at job z_l (and by necessity, with unemployment earnings ψ_l), workers are far more likely to experience a jump in earnings from ψ_l to ψ_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

Figure 5: Baseline example economy



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 unemployment 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.

Figure 6: Counterfactual example economies

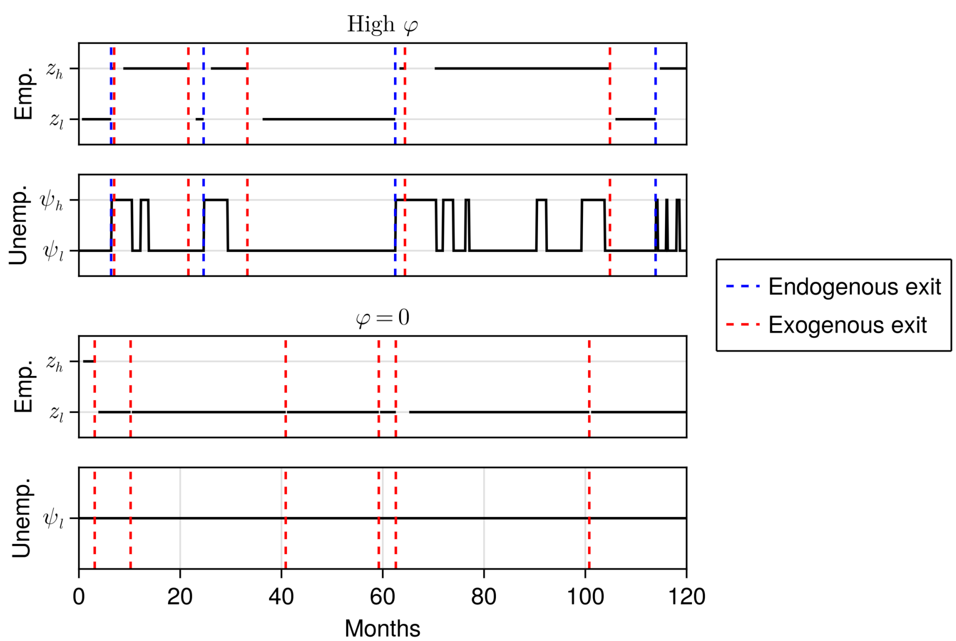


Table 7 shows, in the baseline economy, 24% of exits are caused by endogenous quits. Because endogenous quits are driven by exits from relatively low-productivity jobs, the average earnings gain after a quit is less negative than after a layoff (-0.29 compared to -0.55). In the second economy, with frequent shocks to a worker's non-wage income, not only do endogenous quits constitute a larger share of exits, this is reflected in the average earnings gains after quits and layoffs as well. Quits are *more different* than layoff in the High-φ economy compared to baseline. This difference mirrors the facts observed in Figure 4, which shows quits and layoffs are more different in Ghana relative to the USA. 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. 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 asd layoffs

Model	Outcome		
	Endog. quits / exits	Average earnings gain after a quit	Average earnings gain after a layoff
	(1)	(2)	(3)
Baseline	24	-0.34	-0.57
High φ	41	-0.26	-0.57
$\varphi = 0$	0.0	-0.55	-0.55

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 the Ghana and the USA in order to quantify the role 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 ψ. I assume $F_\psi(\psi' \mid \psi)$ is independent of ψ. In this way, the rate of shocks to re-draw non-wage income, φ, exclusively determines the persistence of non-wage income ψ. I assume ψ is drawn from a log-normal distribution, however I normalize the log-mean of ψ 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 et al. (2021), set the curvature of the matching function γ to 0.7. Finally, I choose the worker's share of of production, δ, to be 0.5.

6.2 Moments

The model features 9 remaining parameters, which I match to 9 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		
ρ	Discount rate	0.0042	0.0042
γ	Matching curvature	0.70	0.70
μ_ψ	Mean of unemployment income	0.0	0.0
δ	Worker share of production	0.50	0.50
	Panel B: Calibrated parameters		
λ^f	Layoff rate	0.12	0.046
λ^q	Quit rate	0.11	0.0046
σ_ψ	Std. dev. of unemployment process	0.58	1.4
φ	Arrival of outside option shocks	0.15	0.0040
μ_z	Mean of productivity	0.0042	-0.080
σ_z	Std. dev. of productivity	0.69	1.3
ν	Amenity value of unemployment	0.51	7.5
χ	Matching efficiency	2.7	3.1
c	Cost of posting vacancy	50	113

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 non-quit, conditional on an exit. Moments in the data for 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 ψ, job offers, and job-seeker's optimal choices. Among job-seekers without wage work, and for each initial state ψ. 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 ψ and the distribution of productivity z.[13] 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.[14]. 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 log the standard deviation of log unemployment earnings and log wage 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 φ, σ_ψ, and σ_z 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 jobseekers at Baseline. I start with the stationary distribution, over non-wage income ψ, 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 two moments are the average earnings gain after a quit and the average earnings gain after a layoff. These moments are derived from Figure 4, and in the USA, they are taken from the SIPP. They

[13]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.

[14]The CPS does not measure unemployment earnings

are emulated in the model by taking the stationary distribution of employed workers, across ψ and z, and examining the non-wage income among the unemployed one month later, separating by whether they left work according to a quit or layoff.

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, we would conclude that quits were all exogenous (driven by λ^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 χ, 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 $\hat{r}$ 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 θ. 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 χ, which is set according to Equation 1 given our knowledge of v and q^w.

Table 9: Model fit

Moment	Ghana		USA	
	Data	Model	Data	Model
	(1)	(2)	(3)	(4)
Any wage employment since Baseline	0.79	0.69	0.71	0.77
Exit conditional on finding work	0.49	0.49	0.13	0.14
Fraction exits from quits	0.68	0.58	0.10	0.099
Correlation of unemployment earnings	0.31	0.30	0.62	0.95
Std. dev. of unemployment earnings	0.50	0.63	1.5	1.4
Std. dev. of employment earnings	0.50	0.44	0.60	0.60
Average earnings gain after a quit	0.13	-0.0022	-0.54	-0.46
Average earnings gain after a layoff	-0.29	-0.29	-0.72	-0.60
Vacancies as a share of employment	0.025	0.026	0.035	0.033

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 the my sample of 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 λ^f and λ^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 φ, 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_ψ, the worker's new non-wage income after a income re-evaluation shock. In the limiting case where I set the variance of F_ψ, my model reduces to a conventional Diamond-Mortensen-Pissaredes model with exogenous wages.

Table 10 analyzes the baseline calibrated models in both 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_{USA} to be the value of outcome y in the baseline calibration in the USA, and y'_{USA} be 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 φ, is reduced to 0, the quit rate reduces in Ghana from 14.6 to 10.2, and the total exit rate reduces from 25.6 to 21.7. 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 19.4% when we shut down variance changes in non-wage income, this indicates my proposed mechanism accounts for a quarter of the difference in exit rates between the two countries. Shutting down the variance of F_ψ 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.

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

Outcome	Value		Difference	% Explained
	USA	Ghana		
	(1)	(2)	(3)	(4)
Baseline				
Endogenous quit rate	0.1	3.6	3.5	-
Quit rate	0.5	13.4	12.9	-
Exit rate	5.1	24.6	19.5	-
Reduce φ 50 percent				
Endogenous quit rate	0.0	2.0	2.0	-
Quit rate	0.4	11.8	11.3	-
Exit rate	5.1	23.0	18.0	8.0
φ is zero				
Endogenous quit rate	0.0	0.0	0.0	-
Quit rate	0.4	9.8	9.4	-
Exit rate	5.0	21.0	16.0	18.0
Reduce variance of F_ψ 50 percent				
Endogenous quit rate	0.1	2.3	2.2	-
Quit rate	0.5	12.1	11.6	-
Exit rate	5.1	23.4	18.2	6.5
Constant ψ				
Endogenous quit rate	0.0	0.0	0.0	-
Quit rate	0.4	9.8	9.4	-
Exit rate	5.0	21.0	16.0	18.0

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 5 exercises. In the first two, I give Ghana USA's non-wage income shock arrival φ and distribution of non-wage incomes F_{ψ}, respectively. In the third, I re-assign both φ and F_{ψ}. 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 differences in exit rates due to changes in non-wage income are over-determined, in that multiple structural differences between the two countries can eliminate these exits. When φ is changed to the level of the USA, endogenous quits fall almost to zero and the overall difference in exits reduces by 20%, consistent with Table 10. However modifying parameters related to the wage sector also reduces the difference in exit rates between 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 11%. When the value of non-wage amenity ν is set to the level of the USA, endogenous quits are eliminated entirely. Table 11 under-scores 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 et al. (2020) may arise from secular improvements in the relative productivity of the wage sector, such as biased structural change discussed in Feng et al. (2021). Appendix Table 11 explores partial equilibrium effect only, and reports similar results.

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				
Endogenous quit rate	0.1	3.6	3.5	-
Quit rate	0.5	13.4	12.9	-
Exit rate	5.1	24.6	19.5	-
Ghana, $\varphi_{\mathbf{USA}}$				
Endogenous quit rate	-	0.1	0.0	-
Quit rate	-	9.9	9.4	-
Exit rate	-	21.1	16.0	18.0
Ghana, $F_{\psi,\mathbf{USA}}$				
Endogenous quit rate	-	5.5	5.4	-
Quit rate	-	15.3	14.8	-
Exit rate	-	26.6	21.4	-9.8
Ghana, $\psi_{\mathbf{USA}}$, $F_{\psi,\mathbf{USA}}$				
Endogenous quit rate	-	0.2	0.1	-
Quit rate	-	9.9	9.4	-
Exit rate	-	21.2	16.1	17.7
Ghana $F_{z,\mathbf{USA}}$				
Endogenous quit rate	-	1.6	1.5	-
Quit rate	-	11.4	10.9	-
Exit rate	-	22.6	17.5	10.2
Ghana $\nu_{\mathbf{USA}}$				
Endogenous quit rate	-	0.0	-0.1	-
Quit rate	-	9.8	9.3	-
Exit rate	-	21.0	15.9	18.6

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 long-run employment half as high in Ghana relative to 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 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 quits away from wage work are driven by profitable opportunities for self employment. I find quits are primarily due to workers leaving low-paying jobs and find 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-quality jobs, and then quit them as outside options improve. I build a partial equilibrium model of job search to benchmark the role variance in non-wage income plays in quitting behavior, and can attribute 20% 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 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 et al. (2020), in which a survey allowing workers to give feedback to managers reduced quits 20%.

Overall, 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 fare higher in Ghana relative to the USA and deserve separate consideration.

References

Abebe, G., Buehren, N. and Goldstein, M. (2024), 'Do Factory Jobs Improve Welfare? experimental Evidence from Ethiopia', *The World Bank Economic Review* .

Abebe, G., Caria, S., Fafchamps, M., Falco, P., Franklin, S. and Quinn, S. (2020), 'Anonymity or Distance? Job Search and Labour Market Exclusion in a Growing African City', *Working paper* .

Abel, M., Burger, R. and Piraino, P. (2020), 'The Value of Reference Letters - Experimental Evidence from South Africa', *American Economic Review: Applied Economics* .

Adhvaryu, A., Molina, T. and Nyshadham, A. (2020), 'Expectations, Wage Hikes, and Worker Voice', *Working paper* .

Attanasio, O., Sánchez-Marcos, V. and Low, H. (2005), 'Female Labor Supply as Insurance Against Idiosyncratic Risk', *Journal of the European Economic Association* **3**(2).

Bagga, S., Mann, L., Şahin, A. and Violante, G. L. (2023), 'Job Amenity Shocks and Labor Reallocation', *Working paper* .

Bandiera, O., Bassi, V., Burgess, R., Rasul, I., Sulaiman, M. and Vitali, A. (2021), 'The Search for Good Jobs: Evidence from a Six-year Field Experiment in Uganda', *Working paper* .

Banerjee, A. and Sequeira, S. (2021), 'Spatial Mismatches and Imperfect Information in the Job Search', *Working paper* .

Bassi, V. and Nansamba, A. (2020), 'Screening and Signaling Non-Cognitive Skills: Experimental Evidence from Uganda', *WOrking Paper* .

Blanco, A., Drenik, A., Moser, C. and Zaratiegui, E. (2024), 'A Theory of Labor Markets with Inefficient Turnover', *Working paper* .

Blattman, C. and Dercon, S. (2018), 'The Impacts of Industrial and Entrepreneurial Work on Income and Health: Experimental Evidence from Ethiopia', *American Economic Journal: Applied Economics* .

Blattman, C., Dercon, S. and Franklin, S. (2019), 'Impacts of Industrial and Entrepreneurial Jobs on Youth: 5-year Experimental Evidence on', *NBER Working Paper* .

Bosch, M. and Maloney, W. F. (2010), 'Comparative analysis of labor market dynamics using Markov processes: An application to informality', *Labour Economics* **17**.

Boschma, R., Eriksson, R. H. and Lindgren, U. (2014), 'Labour Market Externalities and Regional Growth in Sweden: The Importance of Labour Mobility between Skill-Related Industries', *Regional Studies* .

Boudreau, L., Heath, R. and McCormick, T. H. (2021), 'Migrants, Information, and Working Conditions in Bangladeshi Garment Factories', *Working paper* .

Boudreau, L., Heath, R. and McCormick, T. H. (2022), 'Migrants, Experience, and Working Conditions in Bangladeshi Garment Factories', *Journal of Economic Behavior and Organization* .

Breza, E., Kaur, S. and Shamdasani, Y. (2021), 'Labor Rationing', *American Economic Review* .

Brugemann, B. and Moscarini, G. (2010), 'Rent Rigidity, asymmetric information, and volatility bounds in labor markets', *Review of Economic Dynamics* .

Caria, S. and Orkin, K. (2024), 'Barriers to Search and Hiring in Urban Labour Markets', *Vox Dev Literature Review* .

Carranza, E., Garlick, R., Orkin, K. and Rankin, N. (2020), 'Job Search and Hiring with Two-sided Limited Information about Workseekers' Skills', *Working Paper* .

Carranza, E. and McKenzie, D. (2023), 'Job Training and Job Search Assistance Policies in Developing Countries', *Working paper* .

Diamond, P. A. (1982), 'Wage Determination and Efficiency in Search Equilibrium', *The Review of Economic Studies* .

Donovan, K., Lu, W. J. and Schoellman, T. (2020), 'Labor Market Dynamics and Development', *Federal Reserve Bank of Minneapolis Working Paper* .

Dube, A., Naidu, S. and Reich, A. D. (2022), 'Power and Dignity in the Low-Wage Labor Market: Theory and Evidence from Wal-Mart Workers', *Working paper* .

Falco, P. (2014), 'Does risk matter for occupational choices? experimental evidence from an African labour market', *Labour Economics* .

Falco, P. and Haywood, L. (2009), 'Entrepreneurship versus Joblessness: Explaining the Rise in Self-Employment', *Journal of Development Economics* .

Feng, Y., Lagakos, D. and Rauch, J. E. (2021), 'Unemployment and Development', *Working Paper* .

Fields, G. S. (2010), 'Labor Market Analysis for Developing Countries', *Working paper* .

Franklin, S. (2021), 'Enabled to Work: The Impact of Government Housing on Slum Dwellers in South Africa', *Journal of Urban Economics* .

Groh, M., Mckenzie, D., Shammout, N. and Vishwanath, T. (2015), 'Testing the importance of search frictions and matching through a randomized experiment in Jordan', *IZA Journal of Labor Economics* .

Hainmueller, J. (2017), 'Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies', *Political Analysis* **20**(1).

Harris, J. R. and Todaro, M. P. (1970), 'Migration, Unemployment and Development: A Two-Sector Analysis', *The American Economic Review* .

Herreño, J. and Ocampo, S. (2023), 'The macroeconomic consequences of subsistence self-employment', *Journal of Monetary Economics* .

Jovanovic, B. (1979), 'Job matching and the theory of turnover', *Journal of Political Economy* .

Kerr, A. (2018), 'Job Flows, Worker Flows, and Churning in South Africa', *South African Journal of Economics* .

Lagakos, D. and Waugh, M. E. (2013), 'Selection, Agriculture, and Cross-Country Productivity Differences', *American Economic Review* .

Lewis, A. (1954), 'Economic Development with Unlimited Supplies of Labour', *The Manchester School* .

Mckenzie, D. (2017), 'How Effective Are Active Labor Market Policies in Developing Countries? A Critical Review of Recent Evidence', *IZA Dicusccion paper series* .

McLaughlin, K. J. (1991), 'A Theory of Quits and Layoffs with Efficient Turnover', *Journal of Political Economy* .

Menzio, G., Telyukova, I. A. and Visschers, L. (2015), 'Directed search over the life cycle', *Review of Economic Dynamics* .

Mercan, Y. A. (2017), 'Fewer but Better: The Decline in Job Mobility and the Information Channel', *Working paper* .

Mortensen, D. T. and Pissarides, C. A. (1994), 'Job Creation and Job Destruction in the Theory of Unemployment', *The Review of Economic Studies* .

Mueller, A. I., Spinnewijn, J. and Topa, G. (2020), 'Job Seekers' Perceptions and Employment Prospects: Heterogeneity, Duration Dependence and Bias', *Working paper* .

Mukoyama, T. (2014), 'The cyclicality of job-to-job transitions and its implications for aggregate productivity', *Journal of Economic Dynamics and Control* .

Poschke, M. (2022), 'Wage employment, unemployment and self-employment across countries', *Working paper* .

Pries, M. J. and Rogerson, R. (2022), 'Declining Worker Turnover: The Role of Short-Duration Employment Spells', *American Economic Journal: Macroeconomics* **14**(1).

Rasul, I. (2010), 'Firms, Workers, and Labor Markets', *Handbook on Development Economics* .

Shiferaw, A. and Söderbom, M. (2021), 'Worker Turnover and Job Reallocation: Evidence from Matched Employer-Employee Data', *Economic Development and Cultural Change* .

The National Academy of Sciences (2018), 'The 2014 Redesign of the Survey of Income and Program Participation: An Assessment', *The National Academy of Sciences* .

Vollrath, D. (2009), 'The dual economy in long-run development', *Journal of Economic Growth* .

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 3.1. 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 λ

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

I estimate monthly transition rates q and λ by solving

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

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

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

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

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

B Additional Tables Measuring Entry and Exit Rates

Table B.1: Comparison of flows

Outcome	Mean	
	Ghana	USA
	(1)	(2)
Monthly entry rate	0.19	0.15
	[0.16, 0.21]	[0.15, 0.16]
Monthly exit rate	0.28	0.048
	[0.22, 0.34]	[0.047, 0.051]
Stationary rate of wage work	0.41	0.76
	[0.35, 0.45]	[0.76, 0.76]

Table B.2: Comparison of quit and layoff flows

Outcome	Mean	
	Ghana	USA
	(1)	(2)
Monthly entry rate	0.19	0.15
	[0.16, 0.22]	[0.15, 0.16]
Monthly layoff rate	0.088	0.043
	[0.052, 0.13]	[0.040, 0.046]
Monthly quit rate	0.19	0.0049
	[0.095, 0.25]	[0.0039, 0.0056]

C Additional Tables Documenting Results Described in Figures

Table C.1: Comparison of entry and exit

Outcome	Mean: Ghana (1)	Mean: USA (2)
Any wage job at 0 months	0.0	0.0
	[0.0, 0.0]	[0.0, 0.0]
Any entry between 0 and 8 months	0.79	0.71
	[0.75, 0.84]	[0.70, 0.71]
Employed in wage job at 8 months	0.40	0.61
	[0.39, 0.47]	[0.60, 0.61]
Exit conditional on entry	0.49	0.14
	[0.42, 0.51]	[0.13, 0.15]

Table C.2

Outcome	Mean: Ghana (1)	Mean: USA (2)
Last job was fixed-term contract	0.22	0.23
	[0.12, 0.30]	[0.20, 0.25]
Left last job in voluntary quit	0.68	0.10
	[0.59, 0.78]	[0.084, 0.12]
Left last job in involuntary layoff	0.10	0.67
	[0.035, 0.16]	[0.64, 0.70]

Table C.3

Outcome	Mean	
	Ghana	USA
	(1)	(2)
Average income of non-quit jobs	1.0	1.0
	[1.0, 1.0]	[1.0, 1.0]
Average income after a non-quit	0.71	0.28
	[0.54, 0.87]	[0.26, 0.30]
Income difference after a non-quit	-0.29	-0.72
	[-0.46, -0.13]	[-0.74, -0.70]
Average income of quit jobs	0.56	0.76
	[0.47, 0.67]	[0.71, 0.79]
Average income after a quit	0.69	0.22
	[0.51, 0.77]	[0.19, 0.26]
Average difference after a quit	0.13	-0.54
	[-0.037, 0.17]	[-0.55, -0.50]

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_{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_{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_{USA} corresponds to the hiring rate for USA firms reported in Figure 3.

E Additional Tables Showing Baseline Correlates with Exit

Table E.1: Demographic characteristics and exit

Baseline characteristic	Proportion exit conditional on entry			Proportion quit conditional on exit		
	No	Yes	Partial effect	No	Yes	Partial effect
	(1)	(2)	(3)	(4)	(5)	(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	0.484	0.494	0.095	0.645	0.711	0.077
			[0.130]			[0.184]

Table E.2: Job characteristics and exit

Baseline characteristic	Proportion exit conditional on entry			Proportion quit conditional on exit		
	No	Yes	Partial effect	No	Yes	Partial effect
	(1)	(2)	(3)	(4)	(5)	(6)
High-skill services	0.529	0.368	-0.113	0.685	0.643	0.023
			[0.102]			[0.158]
Low-skill services	0.504	0.308	-0.205	0.688	0.500	-0.178
			[0.150]			[0.254]
Manual labor	0.412	0.684	0.272	0.714	0.615	-0.190
			[0.100]			[0.134]***
Retail	0.470	0.525	0.037	0.638	0.762	0.156
			[0.106]			[0.137]
Teaching	0.504	0.273	-0.243	0.662	1.000	0.346
			[0.160]			[0.291]
Earnings greater than median	0.558	0.406	-0.146	0.791	0.500	-0.286
			[0.091]			[0.136]**

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 Non-Quitters 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 (1)	Mean by group: Did not exit (2)	Mean by group: Exited (3)	Regression (4)
High-skill services	0.27	0.33	0.21	-0.082 [0.074]
Low-skill services	0.09	0.12	0.06	-0.068 [0.050]
Manual labor	0.27	0.17	0.38	0.196 [0.072]***
Retail	0.29	0.26	0.31	0.025 [0.072]
Teaching	0.08	0.11	0.04	-0.071 [0.047]
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 Non-Quit Jobs, Conditional on Exit

Characteristic of last or current job	Overall Mean (1)	Mean by group: Did not quit (2)	Mean by group: Quit (3)	Regression (4)
High-skill services	0.27	0.23	0.20	0.015 [0.107]
Low-skill services	0.09	0.09	0.04	-0.047 [0.066]
Manual labor	0.27	0.45	0.35	-0.174 [0.123]
Retail	0.29	0.23	0.35	0.138 [0.121]
Teaching	0.08	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 et al. (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,[15] 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.

[15] 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
Expected dis-amenities minus group average	-0.0268			
	(0.0253)			
Abs. value expected dis-amenities minus group average		-0.0168		
		(0.0316)		
Expected dis-amenities minus group average above median			0.0743	
			(0.103)	
Abs. value expected dis-amenities minus group average above median				0.0836
				(0.0955)
Observations	131	131	131	131

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	-0.0213			
	(0.0490)			
Abs. value expected commute cost minus group average		0.0366		
		(0.0790)		
Expected commute cost minus group average above median			0.0312	
			(0.0922)	
Abs. value expected commute cost minus group average above median				0.0678
				(0.0897)
Observations	131	131	131	131

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 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
Expected dis-amenities minus group average	-0.0118			
	(0.0236)			
Abs. value expected dis-amenities minus group average		-0.00674		
		(0.0293)		
Expected dis-amenities minus group average above median			0.119	
			(0.0952)	
Abs. value expected dis-amenities minus group average above median				0.0219
				(0.0889)
Observations	131	131	131	131

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	-0.0350			
	(0.0454)			
Abs. value expected commute cost minus group average		-0.0293		
		(0.0734)		
Expected commute cost minus group average above median			-0.0728	
			(0.0854)	
Abs. value expected commute cost minus group average above median				0.0323
				(0.0834)
Observations	131	131	131	131

Standard errors in parentheses

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

G Additional Analysis of Flow vs. Non-Flow Income

Table G.1: Employment Exit by Self-employment

Outcome at eight months	Overall Mean	Mean by group: Flows from self-employment	Mean by group: No flows	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 non-quit 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: No flows	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 non-quit 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]

H Additional Counterfactual Experiments

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

Outcome	Value		Difference	% Explained
	USA	Ghana		
	(1)	(2)	(3)	(4)
Baseline				
Endogenous quit rate	0.1	3.7	3.5	-
Quit rate	0.5	13.4	12.9	-
Exit rate	5.1	24.7	19.5	-
Reduce φ 50 percent				
Endogenous quit rate	0.0	2.0	2.0	-
Quit rate	0.4	11.8	11.3	-
Exit rate	5.1	23.0	18.0	8.1
φ is zero				
Endogenous quit rate	0.0	0.0	0.0	-
Quit rate	0.4	9.8	9.4	-
Exit rate	5.0	21.0	16.0	18.1
Reduce variance of F_ψ 50 percent				
Endogenous quit rate	0.1	2.3	2.2	-
Quit rate	0.5	12.1	11.6	-
Exit rate	5.1	23.4	18.2	6.7
Constant ψ				
Endogenous quit rate	0.0	0.0	0.0	-
Quit rate	0.4	9.8	9.4	-
Exit rate	5.0	21.0	16.0	18.1

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

Outcome	Value: USA (1)	Value: Ghana (2)	Difference (3)	% Explained (4)
Baseline				
Endogenous quit rate	0.1	3.7	3.5	-
Quit rate	0.5	13.4	12.9	-
Exit rate	5.1	24.7	19.5	-
Ghana, $\varphi_{\mathbf{USA}}$				
Endogenous quit rate	-	0.1	0.0	-
Quit rate	-	9.9	9.4	-
Exit rate	-	21.1	16.0	18.1
Ghana, $F_{\psi,\mathbf{USA}}$				
Endogenous quit rate	-	5.6	5.5	-
Quit rate	-	15.4	14.9	-
Exit rate	-	26.6	21.5	-9.9
Ghana, $\psi_{\mathbf{USA}}$, $F_{\psi,\mathbf{USA}}$				
Endogenous quit rate	-	0.2	0.1	-
Quit rate	-	9.9	9.4	-
Exit rate	-	21.2	16.1	17.8
Ghana $F_{z,\mathbf{USA}}$				
Endogenous quit rate	-	1.8	1.6	-
Quit rate	-	11.5	11.0	-
Exit rate	-	22.8	17.7	9.7
Ghana $\nu_{\mathbf{USA}}$				
Endogenous quit rate	-	0.0	-0.1	-
Quit rate	-	9.8	9.3	-
Exit rate	-	21.0	15.9	18.7