Untangling Informality: Wages, Preferences, and Sectoral Sorting in Bangladesh's Garment Industry*

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Abstract

In many low income countries, a regulated formal sector and an unregulated informal sector coexist within the same industry and occupation. Understanding why workers choose to work at informal rather than formal jobs is critical to crafting effective labor market policy. This paper studies the importance of two determinants of worker sorting between sectors: (1) search frictions and (2) worker preferences for nonwage amenities. Focusing on the garment industry in urban Bangladesh, I collect data on workers' job histories and elicit their preferences for specific job amenities in a choice experiment. I use the data to estimate a partial equilibrium model of job search that incorporates (1) a dual-sector labor market with sector-specific search frictions and (2) heterogeneous preferences for amenities. I find that search frictions differ by sector—workers searching for a job from unemployment are 22pp more likely to receive offers from the informal sector than the formal sector over the course of a year. Additionally, preferences for nonwage amenities are strong, with some workers willing to pay nearly 30% of their wages for amenities like good supervisors and factory formality. Finally, I use the model to understand the impact of various unemployment benefit policies, from universal cash transfers to targeted unemployment insurance. I show that targeted policies, which are hard to implement in a high-informality setting, can push workers who are more salary-motivated into the informal sector.

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1 Introduction

Understanding why workers choose to work in the informal sector is a key policy priority since these jobs are often hidden from the reach of government regulators. Global estimates suggest that around 61.2% of workers are in the informal sector, with even higher shares in low- and middle-income countries (LICs) (ILO, 2018; Elgin et al., 2021). Informal workers are generally subject to lower wages and more unregulated working conditions (Dell'Anno, 2022; Ulyssea, 2020). As a result, policymakers concerned with improving worker welfare often prioritize eliminating or reducing the informal sector[1]. Whether formalization benefits workers and whether it is the best approach to improving worker welfare are both open questions. Answering these questions requires a characterization of how workers choose between jobs and sectors.

While there are several plausible mechanisms of worker sorting, the role of worker preferences for nonwage amenities is important and understudied. Skills-based sorting, where high-skill workers match with high-productivity formal firms, does not explain the empirical pattern that similarly skilled workers are often observed in both formal and informal jobs (Pratap and Quintin, 2006). So why do observably similar workers choose to work in different sectors? One explanation is that search frictions trap workers who are unable to find jobs in their sector of choice (Meghir et al., 2015). A second explanation is heterogeneity in preferences for nonwage job amenities, which is an important determinant of labor supply choices in South Asia (Sharma, 2023; Mahmud et al., 2021; Jalota and Ho, 2024). Sorting based on underlying preferences could explain why workers' observed characteristics are not sufficient to predict sector choice. To my knowledge, there is no work to date that has combined these explanations and quantified their importance in shaping employment outcomes in a dual-sector labor market. Determining whether workers are sorted by their circumstances or choose to sort based on their heterogeneous preferences is important for characterizing the distributional effects of policies.

In this paper, I investigate the importance of (1) search frictions and (2) preferences for nonwage amenities in sectoral sorting among garment workers in Bangladesh. I first define the formal sector as the set of garment factories that are both registered by the government and regularly inspected to ensure compliance with regulation. Next, I show that workers move between sectors, but that there are patterns of within-sector persistence that suggest

[1] Bangladesh's Industrial Policy for 2023, for example, listed formalization as a key focus area. (Dallakoti, 2024)

search frictions. I also present evidence on the strength of heterogeneous worker preferences for job amenities. Then I build a partial equilibrium model of labor supply that weighs the relative roles of each explanation.

There are three main challenges to identifying the importance of each proposed channel of worker sorting. First, there is scarce data on job mobility and informal firm amenities in the South Asian context. I address this by surveying 622 garment workers about their past jobs and constructing a retrospective panel of jobs and amenities across the formal and informal sector. Second, correlations between offered wages and amenities make it hard to separate workers' willingness-to-pay (WTP) for specific amenities from firm decisions to offer certain wage-amenity bundles in the observed market equilibrium (Wiswall and Zafar, 2017). I capture workers' heterogeneous preferences for four amenities—supervisor quality, flexible leave, overtime rates, and factory formality—through a choice experiment varying levels of wages and amenities. Third, identifying worker preferences for amenities is difficult without specifying the structure of the job search environment (Bonhomme and Jolivet, 2009; Gronberg and Reed, 1994; Hwang et al., 1998). Accordingly, I build a partial equilibrium model of job search that involves three key features: (1) a dual-sector market with formal and informal jobs as well as an unemployed state, (2) off- and on-the-job search with sector-specific search frictions, and (3) heterogeneous preferences for nonwage job amenities.

Bangladesh's ready-made garments (RMG) industry provides an ideal setting to study informality. There is an abundance of both formal and informal factories and job tasks are similar in both sectors. The RMG industry has driven urban economic growth in the country, accounting for over 10% of the country's GDP in 2023 and employing millions of workers. Formal factories, which are registered with the government and regularly inspected by one of three independent organizations to ensure they meet regulatory standards, coexist with informal factories that are uninspected or irregularly inspected. All firms in this industry produce ready-to-wear garments. Job tasks for entry-level workers, such as sewing machine operators, are well-defined and relatively similar in both formal and informal jobs, allowing for a high degree of worker mobility between sectors.

Studying worker mobility in this context requires data that accurately reflects patterns of job moves and working conditions among a representative set of workers. For this reason, I collect survey data in a single neighborhood in the capital city of Dhaka containing both formal and informal factories. Importantly, the study area comprises one effective labor market—the vast majority of moves between jobs happen between firms located within the bounds of the neighborhood. I target younger workers (aged 18-35) and also include unemployed individuals with previous garment-sector experience, ensuring that the sample captures more complete job histories and accurate unemployment patterns. Finally, to obtain truthful reporting of working conditions, I chose to interview workers at their homes rather than their workplaces, which tends to be the norm in similar studies (Boudreau et al., 2024). I develop a novel geographic sampling technique to randomly sample respondents from 46 residential clusters where garment workers tend to live. I show that the resulting sample is similar in demographics to the national Labor Force Survey (LFS) and is likely representative of labor market dynamics among urban garment workers in the country.

Constructing a job history panel from workers' responses, I establish empirical facts that motivate my modelling approach and deemphasize the role of skills-based sorting. For one, transition rates between sectors show some state-dependence—conditional on making a move, formal workers are more likely to end up in formal jobs. Additionally, even among voluntary moves, not all moves are wage improving, which suggests that nonwage amenities play a role. Finally, I provide two pieces of evidence to rule out skills-based positive assortative matching. First, workers with observably similar skills work at jobs in both sectors. This result holds across a wide set of skill measures, including education, numeracy, and noncognitive skills. Second, controlling for worker fixed effects that capture individual ability does not significantly change estimates of the wage gap between formal and informal sector. This suggests that the wage premium of the formal sector is not simply reflecting the skill premium of high skill workers. Taken together, the evidence does not support a story of high skill workers moving into the formal sector and instead points to the role of search frictions and amenity preferences.

I supplement the job mobility data with evidence from the choice experiment showing that workers have preferences for specific amenities and that these preferences are heterogeneous. The results show that workers care about salaries, formality, and supervisor quality. I verify that the results from the choice experiment are consistent with job mobility choices in the sample. To explore unobserved heterogeneity in preferences, I use a correlated random effects model to classify workers into latent classes. Setting the number of classes equal to three, I recover groups with distinct prefrences— 11% of the sample is "salary-seeking", 53% are "formality-seeking", and 36% are "supervisor-seeking". These results suggest that there is significant heterogeneity in which amenities workers look for in a job.

Next, I build and estimate a partial equilibrium model of labor search that rationalizes empirical mobility patterns and preferences for amenities. Workers in the model can be in one of three states — working at a formal job, working at an informal job, or unemployed. They gain utility from both wages and amenities, as in the models of Hwang et al. (1998) and Bonhomme and Jolivet (2009). I allow for unobserved heterogeneity in preferences for amenities, identifying heterogeneous groups based on the analysis of the previous section. I classify individuals based on predicted posterior probabilities of latent class membership from the choice experiment. After this classification, I can identify transition parameters, offer distributions, and preferences. I estimate the model using a two-part maximum likelihood—the first part uses conditional choice probabilities of moves to estimate job search and preference parameters, while the second uses the likelihood of observed responses on the choice experiment to understand preference parameters.

The estimated model parameters show that search frictions differ by sector when exiting unemployment and strong preferences drive worker mobility decisions. First, search frictions are low when searching from unemployment, with yearly arrival rates of 71% for formal jobs and 93% for informal jobs. Search frictions are much higher in on-the-job search but are not significantly different between sectors—yearly job arrival rates vary between 5-18%. I also find that the wage and amenity offer distributions differ by sector. While jobs with flexible leave policies and good supervisors are similarly offered in both sectors, formal jobs are more likely to have high overtime rates. Additionally, formal jobs tend to offer higher wages, though the distributions overlap. There are non-neglibile correlations between wages and certain amenities in the offer distributions that differ by sector. For example, jobs with good supervisors are positively correlated with wages in the informal sector but not in the formal sector. Finally, the latent class preferences align qualitatively with the findings from the choice experiment. Salary-seekers exhibit no significant preferences for amenities, formality-seekers are willing to pay 37.4% of monthly wages for formality, and supervisor-seekers are willing to pay 28.6% of monthly wages for a good supervisor.

To understand how each hypothesized channel contributes to worker sorting, I simulate data from model parameters and vary the intensity of four channels. First, I lower on-the-job search frictions significantly. Second, I remove dynamics so that workers are making myopic decisions over the flow utilities of jobs. Third, I equalize offer distributions so that informal jobs offer the same wages and amenities as formal jobs. Fourth, I shut down workers' preferences for amenities. I find that lowering search frictions does not change the sorting of workers. Removing dynamics, equalizing offer distributions, and shutting down preferences decrease the size of the formal sector. Jointly, this implies that preferences play an important role in keeping people employed in formal jobs even in the presence of high-paying informal jobs.

Finally, to connect the findings of the model with labor market policy, I conduct several counterfactuals. I first examine the impact of two extreme methods of eliminating informality — removing all informal firms from the economy and transitioning all of them to formal firms. These provide a lower (-11.4%) and upper bound (1.73%) on the welfare impacts of more realistic policies that try to reduce informality by increasing enforcement. I then use these numbers to benchmark the effect of social safety net policies that increase support for unemployed workers. Implementing these policies in a labor market with high informality can be a challenge due to the hidden nature of informality and the potential for moral hazard (Ndiaye et al., 2023). Targeted programs aimed at the unemployed are hard to implement without worker registration databases, which can allow informal workers to claim unemployment benefits. I estimate the size of the formal sector and worker outcomes under three policy scenarios—1) a universal basic income-style cash transfer to all workers, 2) a targeted cash transfer for unemployed workers, and 3) an unemployment insurance policy. The two targeted policies have the most effect in changing worker sorting patterns, especially driving salary-seeking workers into the informal sector. The untargeted cash transfer has the biggest effect on improving welfare, realizing roughly 84% of the welfare gains from the upper bound of eliminating informality by transitioning all informal jobs to formal.

This paper's results contribute to a fuller understanding of informal jobs by emphasizing the importance of nonwage job amenities. Literature studying sorting from a macroeconomic perspective demonstrates the counter-cyclicality of the size of the informal sector, but this empirical pattern does not reveal workers' motivations in moving between jobs in each sector (Bosch and Esteban-Pretel, 2012). Honing in on an individual worker's labor supply decision, another strand of the literature posits models of skills-based sorting and positive assortative matching. In this paper I present evidence that the skills channel is not a driving force in the Bangladeshi garment industry (Albrecht et al., 2009; Boeri et al., 2005; Haanwinckel and Soares, 2021). Additionally, there is evidence that observably identical workers seem to work in both formal and informal jobs, which Meghir et al. (2015) rationalize using a model with labor market search frictions. In this paper, I rationalize a similar pattern with both search frictions and unobserved heterogeneous preferences for amenities that vary across groups of workers.[2]

[2] Another strand of literature examines firm formalization decisions (Ulyssea, 2018; Almeida and Carneiro, 2012; de Andrade et al., 2014; De Mel et al., 2013). However, these studies usually do not investigate the type of worker-side mechanisms that are the focus of the present paper. Additionally, firm-side interventions

My approach to studying workers' preferences for amenities aligns closely with recent work using choice experiments to recover willingness-to-pay for specific job amenities such as job flexibility (Maestas et al., 2023; Wiswall and Zafar, 2017; Mas and Pallais, 2017). There is evidence that similar amenities matter for labor supply decisions in the South Asian context especially for women (Jalota and Ho, 2024; Sharma, 2023). My analysis adds to this evidence base and uses a choice experiment to elicit preferences, building on the work of Gutierrez et al. (2019) who conduct a similar choice experiment across a sample of urban workers in Bangladesh. Focusing on the garment industry in this study, I can sidestep concerns about the heterogeneity of worker and job types across industries. Additionally, I elicit worker preferences for a job at a formal factory, which places a valuation on the bundle of amenities offered at formal firms separately from wage concerns.

The partial equilibrium model of labor search in this paper draws on insights from a long tradition of hedonic search models in labor economics (Hwang et al., 1998; Sorkin, 2018; Bonhomme and Jolivet, 2009; Sullivan and To, 2014; Gronberg and Reed, 1994). The modeling approach for incorporating amenities is closest to Bonhomme and Jolivet (2009), but innovates by accounting for dual-sector nature of the labor market in line with Meghir et al. (2015). Part of the estimation approach uses the logic of valuing job amenities based on the flows of workers moving to and from each job, as in Sorkin (2018). Incorporating the choice experiment is an innovation on this approach, allowing me to better identify heterogeneous preferences in a limited sample and link workers' stated preferences to their realized job mobility decisions.

Finally, the results presented in this paper add to a small but growing literature about job mobility in South Asia. In Bangladesh, Mahmud et al. (2021) are the first to provide some evidence on mobility between formal and informal jobs, though they do not elicit full information on the duration of jobs and unemployment. This paper also differs from theirs by defining formality by the inspection and registration status of factories, which I am able to verify due to the unique data and documentation available on the RMG industry. Menzel and Woodruff (2021) provide some evidence on job duration in the RMG industry. However, since they use administrative data, they are limited to formal workers. Finally, work by Boudreau et al. (2024) provides evidence on the existence of search frictions and the fact that workers move towards better jobs over time. This paper verifies the empirical facts reported in previous work and builds a model that rationalizes them to understand how labor policies affect workers in this market.

aimed at reducing the cost of formalization have had limited success at curbing informality (Ulyssea, 2020).

The rest of the paper proceeds as follows. Section 2 provides background on the Bangladeshi garment industry. Section 3 presents detail on the data collection and reports descriptive statistics about the sample. Section 4 describes the patterns of job mobility in the sample and Section 5 describes the design and results of the choice experiment over job amenities. Section 6 outlines a model of hedonic job search and 7 includes the procedure I use to estimate the model from collected data. Section 8 discusses the main parameter estimates and model fit. Section 9 contains counterfactual exercises considering various unemployment benefit policies. Section 10 concludes.

2 Context: Garment Industry Jobs in Dhaka

Bangladesh's ready-made garments (RMG) industry has risen to prominence over the past three decades and now supplies buyers across the globe including H&M, Walmart, and Adidas. RMG exports totaled $46 billion USD in 2023, amounting to 80% of total exports and 10.35% of the country's GDP (BGMEA, 2024; Elgin et al., 2021). The rapid growth of the industry attracts many workers, especially recent migrants to urban areas. The nature of the work has allowed women to join the workforce at much higher rates than in other industries. The industry employs over 4 million workers who largely live in the dense urban clusters where garment factories tend to agglomerate. Between 60-70% of the workforce is female.

As with any rapidly expanding industry, the RMG industry was not without its growing pains—firms sought to meet burgeoning international demand while also addressing calls for increased inspection and regulation within their factories. For the first few decades of its growth, the industry was relatively unregulated and under pressure to meet tight production deadlines set by international buyers. These conditions led to the 2013 Rana Plaza tragedy, in which a poorly maintained building housing five garment factories collapsed and killed thousands. In the wake of this disaster, local policymakers, trade unions, and worker groups teamed up with international buyers to create a set of safety standards. Regulations for building, occupational, and worker safety standards were enforced through implementing bodies—The Bangladesh Accord on Fire and Building Safety (Accord) and the Alliance for Bangladesh Workers Safety was formed by North American buyers (Alliance).[3] Since 2018, the responsibility for standards enforcement has transitioned from these international

[3]The Accord was formed by a consortium of European buyers and the Alliance was formed by North American buyers. Both required inspections of electrical, structural, and fire safety as well as general worker rights protections

coalitions to the Bangladeshi government's National Initiative (NI) program.

In this paper, I define a formal job as a job at a factory inspected by the Accord, Alliance, or National Initiative. Factories that work with one of these programs have to be officially registered with the government, which meaning they are subject to all formal labor laws. Additionally, they have to be regularly inspected by one of the programs to ensure up-to-date compliance with standards and regulations.[4] The proposed definition captures the dimensions along which worker-facing policies are enforced, connecting it with economic theories of formal and informal labor (Ulyssea, 2020; Dell'Anno, 2022).

The worker safety movements of the past decade have resulted in a complex ecosystem of formal and informal factories in Bangladesh. An independent data source mapping factories in Dhaka shows at least 265 formal factories and at least 770 informal ones, though the latter is an underestimate due to difficulties in finding and cataloguing smaller informal factories (MIB, 2023). Formal factories tend to be large, employing 500-1000 workers and focus on export-oriented production. Informal factories tend to be smaller, usually employing fewer than 500 workers, and often produce clothes for domestic consumption. Smaller informal factories may not be registered with the Bangladesh Garments Manufacturers Export Association (BGMEA) and cannot directly export goods, but often supplement their revenues by taking subcontracted jobs from export-oriented factories on tight production deadlines.

From the worker's perspective, the job tasks at formal and informal factories are similar. Helpers and sewing machine operators make up the majority of entry-level jobs. Workers in these occupations use similar machinery and techniques to construct garments regardless of factory formality. Both types of factories have production lines with workers conducting specific tasks (e.g. sewing on a pocket), though the degree of specialization is higher at formal jobs.

While job tasks are similar, working conditions vary both between and within sector. Due to regular inspections, formal jobs have better building and structural safety as well as compliance with labor laws such as minimum wages. Worker and women's empowerment initiatives championed by the regulatory bodies have also pushed for formal factories to offer amenities like child care facilities, health facilities, and maternity leave. Though not all inspected factories have these amenities, they are much more likely to have them than informal factories. Beyond these sector-specific formal amenities, even jobs within the same

[4] While VAT and Trade Licenses are also ways to register a business with the government, being part of the Accord, Alliance, or NI programs requires both of these licenses as well as a host of other inspections, which makes it a more stringent definition in addition to a more policy-relevant one.

sector may vary in their working conditions in ways that matter to workers. For example, in focus groups, garment workers highlighted their desire for jobs with good supervisors, overtime work, and flexible leave policies, which are less sector-specific and instead vary by job.

3 Data and Descriptives

Estimating a job search model of informality is challenging in the Bangladeshi context due to the lack of longitudinal work history data. Additionally, there is limited evidence on which job amenities workers prefer. To address these challenges, I survey 622 garment workers in the Mirpur neighborhood of Dhaka. I ask questions about their past jobs and recover a panel of retrospective job history data. Additionally, I present them a series of choice experiment questions varying salient amenities of jobs to recover their preferences.

3.1 Sampling Design: A Two-Step Geographic Technique

The two driving motivations behind sampling design were (1) gathering a complete picture of mobility within an effective labor market and (2) eliciting truthful responses from workers about their working conditions and beliefs. To address the former, I focus on workers living in the greater Mirpur area of Dhaka,[5] since workers likely search for jobs within their neighborhoods.[6] As a result I capture a switching between the same set of jobs and factories. Eliciting complete retrospective job histories is also hard given survey time limitations and issues with recall of old jobs. I focus on younger workers between the ages of 18-35 who can better provide information on all their past jobs. Finally, I interview both employed and unemployed workers with at least 6 months of garment industry experience to get an idea of unemployment dynamics and job search methods.

To elicit truthful responses about working conditions, I chose to interview respondents at their residences rather than their workplaces. This ensured that they would not feel pressured by their employer to respond in a certain way. Identifying a set of workers representative of the garment industry labor market as a whole was a challenge due to a lack of an accessible sampling frame for neighborhoods garment workers tend to live in. I addressed this issue

[5]The "greater Mirpur" region I define includes the Dhaka city wards of Adabor, Darus Salam, Kafrul, Mirpur, Pallabi, Shah Ali, and Sher-e-bangla Nagar.

[6]This assumption is borne out in the data. Out of 1,246 reported jobs with data on job location, only 101 were outside the greater Mirpur area.

by developing a two-stage geographic sampling technique to first identify eligible residential clusters and then sample from them according to the number of workers living there.

In the first stage of sampling, I combine data about factory locations from Mapped in Bangladesh (MiB) and predicted residential settlements in the Global Human Settlement Layer (GHSL) to identify clusters where garment workers were likely to live (MIB, 2023; Kemper et al., 2021). Since workers live close to their workplaces and in low-lying makeshift buildings, I restricted the sampling map to areas in greater Mirpur that were within 2km of a garment factory and had low-lying residences that were less than 6m tall (LFS, 2017)[7]. From these identified areas, I randomly selected 100 GPS clusters with 200m radii and had a survey team conduct a count census within each to get estimates of the number of households and population of garment workers.[8]

In the second stage of sampling, I used census estimates to draw a population-weighted number of interviews to conduct in each cluster. Survey teams conducted interviews starting at the centroid of each cluster and walking in a direction to identify all eligible households. In households with multiple eligible garment workers, a single respondent was randomly selected. Enumerators continued interviewing respondents until the total number of assigned interviews in that cluster was finished.[9] Figure 1 displays the final 46 clusters of households as well as the location of mapped factories, highlighting the factories which respondents mentioned working at in the survey.

3.2 Survey Instrument and Sample Description

The administered survey contained questions about demographic information and detailed job histories, as well as a choice experiment (discussed in Section 5). Collected demographic information includes information on gender, education, marital status, household composition, and income. Table 1 presents summary statistics of the sample. The sample is largely made up of married young women living in makeshift housing situations (as indicated by the presence of tin roofs or less durable building materials). The average household has just

[7]The MiB dataset contains the vast majority of formal factories and a limited amount of informal factories. Based on piloting and the on-the-ground knowledge of the survey team, we knew that there were several prominent clusters of informal factories in the chosen study area.

[8]We discarded clusters that were impossible to survey (e.g. due to a centroid being placed in a government compound or restricted area) or that had too few RMG workers. The final sample was surveyed from 46 clusters.

[9]Workers who were not at home during the initial approach were re-visited two more times, including on a weekend day when factories were not operating, in order to prevent any unexpected bias. Respondents who were unable to be reached after two attempts were replaced with the next eligible household. Appendix Table A8 reports response and replacement rates by cluster.

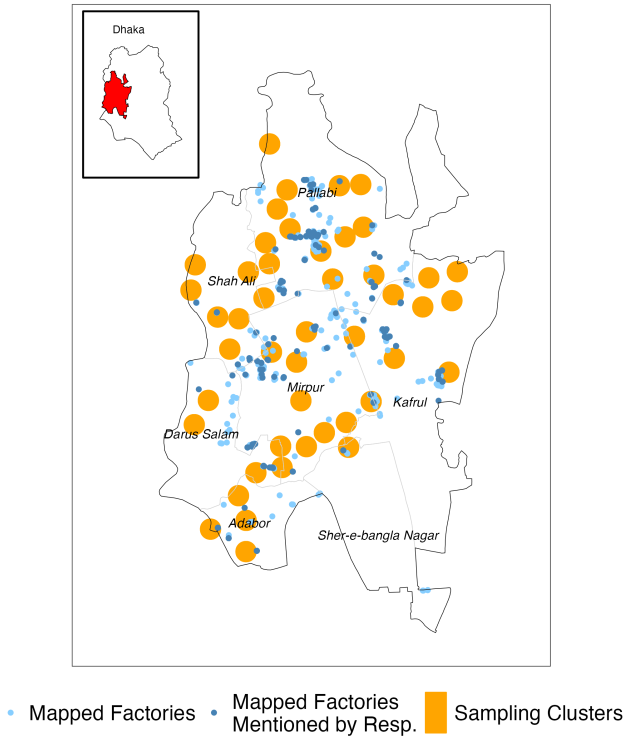

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Figure 1: Sampling Clusters and Factories in Greater Mirpur

under four people and the mean ratio of dependents, including children and elderly adults who cannot work, to total members is 0.26.[10] The median income among households is 25,590 Bangladeshi taka (BDT) or about 233 USD. This number is roughly equivalent to the salary of two minimum-wage garment workers. Comparing to data from the 2016-17 Bangladesh Labor Force Survey (LFS), my sample has more women but otherwise matches the characteristics of the broader sample of garment workers living in Dhaka.

To get a better measure of job-relevant skills, I included numeracy and non-cognitive skills modules.[11] In the numeracy module, respondents were asked about math questions related to work in the garment industry—for example, reading and interpreting a ruler measuring a piece of fabric. The framing of these questions captures skills that are more salient to respondents' work than educational achievement metrics. Additionally, non-cognitive skills can shape labor market outcomes (Heckman et al., 2006; Alderotti et al., 2023). To measure these skills, I include a culturally-adapted version of the Big 5 Inventory, also known as the OCEAN scale (Islam, 2019).[12] Evidence from around the world shows that non-cognitive

[10]Crucially, dependents do not include housewives who may contribute to household production even if they do not work in the market.

[11]See which are Appendix C.3 for the specific questions asked.

[12]The inventory asks questions to determine openness, conscientiousness, agreeableness, extraversion and

traits like conscientiousness are strongly associated with wages (Alderotti et al., 2023; Allemand et al., 2023).

Table 1: Demographic Summary Statistics

	Worker Survey		LFS 2016-17		Test Diff.
Demographic Variable	**Mean**	**SD**	**Mean**	**SD**	**p-value**
Age	24.73	5.03	27.50	7.90	0.298
Female (%)	85.53	35.21	65.09	47.69	0.002
Married (%)	72.51	44.68	75.30	43.14	0.673
Some Primary Education (%)	52.73	49.97	59.29	49.15	0.351
Some Secondary Education (%)	40.03	49.04	39.72	48.95	0.965
Single Bedroom Household (%)	85.05	35.69	85.51	35.21	0.938
Dwelling has Tin Roof (%)	70.90	45.46	79.18	40.61	0.202
Dwelling has Tin Walls (%)	27.01	44.44	20.82	40.61	0.338
Household Size	3.72	1.58	3.44	1.43	0.818
Household Number of Dependents	1.16	1.13			
Ratio of Dependents to Workers	0.26	0.22			
Monthly HH Income (Thousands of Taka)	25.70	10.24			
	N = 622*		N = 1518		

Note: The first panel of this table presents descriptive statistics on individual and household level information from the survey conducted in this paper. The second panel presents similar demographics from the 2016-17 Bangladesh Labor Force Survey conducted by the government. The LFS sample is restricted to garment workers in non-managerial positions living in Dhaka. The third panel reports p-values from a two-sided t-test of the difference in means between this paper's survey and the LFS. Source: LFS (2017)
* Sample size for the monthly household income variable is 621 due to a missing response.

In the job history module of the survey, respondents were asked about their three most recent jobs as well as their first garment industry job in reverse chronological order.[13] For each job, respondents reported information about factory names, self-reported formality status, pay, and amenities offered. Factory names were matched to the MiB database to verify the formality status of jobs where possible.[14] I also asked about job start and end dates, probing respondents for information about job moves with relation to months of the Bangladeshi calendar and milestone yearly events such as Eid-ul-Adha and Eid-ul-Fitr to triangulate job move periods with precision. Using this information, I narrow move dates to

neuroticism/emotional control.

[13]Work by Assaad et al. (2018) suggests that asking for job histories in chronological order starting with the first job after schooling can minimize recall bias. This was difficult since we were not always eliciting complete job histories and rather only asking about the three most recent jobs. However, we did ask enumerators to verify reported job histories with respondents in chronological order before starting to fill in information on each job.

[14]Respondents were able to name the factory for 80% of jobs. For the other 20%, I use self-reports of the formality status of the factory.

four-month periods of each year.[15]

Information on respondents' current or most recent job is in Table 2, split by formality status of the job. Overall, 62% of respondents work at formal jobs, earning higher wages and having worked at fewer total jobs. Most of the surveyed respondents are working full time.[16] Job amenities vary, with only holiday bonuses and overtime pay being near-universal characteristics of garment jobs. Certain reported amenities are strongly associated with formality including the presence of high overtime pay rates, maternity leave, childcare, and health facilities. Meanwhile amenities such as good supervisors and flexible leave policies are less clearly associated with a specific sector and instead seem to vary by job.

Table 2: Descriptive Statistics on Current or Most Recent Job

	Formal Mean	**Informal Mean**	**Difference**	**N**
Monthly Earnings (Thousands of BDT)	13.60	11.01	2.592***	617
Fulltime Work (%)	71.35	66.09	5.260	617
Number of Jobs	2.41	2.87	-0.461***	618
Maternity Leave (%)	77.40	32.19	45.214***	618
Child Care Facilities (%)	43.90	9.44	34.454***	618
Health Care Facilities (%)	75.32	39.48	35.840***	618
Holiday Bonuses (%)	98.70	90.13	8.573***	618
Overtime Pay (%)	96.88	94.42	2.463	618
Overtime Rate (BDT)	60.90	44.22	16.678***	584
Good Supervisor (%)	44.42	47.41	-2.998	617
Flexible Leave (%)	41.50	48.15	-6.650	536

Note: The total sample size of eligible respondents in this table is 618 since four respondents reported working at freelancing/contract jobs that cannot be classified by formality status. Overall, 62% of workers were currently or recently working in a formal factory. Appendix D.4 explains the missing values for the flexible leave and overtime rates and outlines the empirical strategy to handle these values.
Significance levels: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

4 Empirical Patterns of Job Mobility

Using the reconstructed job history of respondents, I document empirical facts about mobility that motivate my modeling choices. The final panel has a total of 611 unique individuals with 1,352 unique job spells.[17] Table 3 reports durations of job and unemployment spells

[15] Appendix D.2 has the full details on how responses on these questions were used to pinpoint job move periods in the final data used for model estimation.

[16] Full time work in this sector is a 6 day workweek with 9 hour workdays with overtime common in both formal and informal sectors.

[17] The 11 individuals without reliable start or end dates for at least their current job could not be assigned into this panel.

in the panel, showing that formal jobs tend to last longer. The median job duration of 2.42 years in the formal sector is only slightly higher than the median stint length of 2.07 years reported in administrative data from formal garment factory hiring rolls collected by Menzel and Woodruff (2021). Additionally, the median length of unemployment is about 6 months.

Table 3: Job and Unemployment Duration by Sector

Duration in years	**Median**	**Mean**	**SD**
Formal Job	1.75	2.42	2.37
Informal Job	1	1.41	1.43
Unemployment	0.25	0.57	0.83

4.1 Degree and Direction of Mobility

To motivate choices about how to model search frictions, I first examine empirical patterns about the degree of mobility in the sample. The unconditional period-to-period rate of transition in Panel A of Table 4 shows there is a large within-sector persistence in jobs. Panel B provides better insight into how workers move between sectors conditional on a job-to-job move. Workers in the formal sector tend to stay in formal sector jobs. This pattern of persistence is less pronounced in informal jobs. In the model, I allow for the possibility of sector-specific search frictions, which may account for this persistence. Additionally, there are moves between sectors in all directions, which does not support a story of workers sorting based on comparative advantage.[18]

Importantly, even among workers who willingly change jobs, not all moves are wage-improving in real terms. Panel C of Table 4 shows that nearly 30% of voluntary formal-to-formal job moves result in salary decreases.[19] This result points to the role of nonwage amenities in driving sorting.

4.2 A Minimal Role for Skills in Sorting

Sorting on observable skills does not seem to be a large factor in this market for three reasons. First, workers do not exhibit different mobility patterns based on their educational attainment or numeracy levels. Second, observably similar workers are found in both sectors.

[18] Appendix Figure A1 shows that for workers with more than 2 jobs, there is switching back and forth between sectors and that flows are not just unidirectional.

[19] The numbers in this panel are higher than the 57-64% that Bonhomme and Jolivet (2009) report for European markets.

Table 4: Sectoral Transition Parameters

A: Uncond'l Transitions

	Form	Inf	N
Form	0.993	0.006	7285
Inf	0.041	0.959	1976

Rows sum to one

B: Cond'l on Move

	Form	Inf	N
Form	0.794	0.206	223
Inf	0.547	0.453	150

Rows sum to one

C: % Wage ↑ & Voluntary

	Form	Inf	N
Form	71.9	77.1	181
Inf	83.3	75.0	123

Note: Panel A reports the unconditional period-to-period transition matrix between sectors, which includes people who may stay at their job. Panel B reports the same matrix conditional on a move. Panel C reports the % of wage improving *voluntary* moves. A wage improving move $\equiv \Delta$ real wage $> -3\%$ (in case of reporting errors)

Third, unobserved worker skills do not seem to explain the wage gap between the formal and informal sectors.

Worker transitions between sectors in the data are similar by education and numeracy level. Tables A1 - A4 reproduce the transition parameters from Table 4 by low and high skill levels and the results are similar. In fact, in these tables low skill workers are more likely to transition from informal to formal jobs, though small sample sizes caveat these results.

Table 5: Characteristics of Respondents by Sector of Current or Most Recent Job

	Formal Mean	**Informal Mean**	**Difference**	**N**
Age	25.19	23.98	1.208***	618
Female (%)	87.01	83.26	3.751	618
Married (%)	72.99	71.67	1.313	618
Some Primary Education (%)	50.65	56.65	-6.003	618
Some Secondary Education (%)	41.56	37.34	4.219	618
Numeracy Score	1.79	1.89	-0.098	614
Noncognitive skill: Extraversion	5.15	5.18	-0.029	618
Noncognitive skill: Agreeableness	6.17	6.11	0.059	618
Noncognitive skill: Conscientiousness	5.59	5.44	0.152	618
Noncognitive skill: Emotional Control	4.65	4.65	0.001	618
Noncognitive skill: Openness	5.35	5.23	0.129	618
Years of RMG Sector Experience	5.13	3.97	1.163***	618

Note: This table displays differences between the demographics of those who worked in the formal vs. informal sectors in their current or most recent job.

Formal and informal workers are similar on a host of demographic and skill characteristics. Table 5 presents evidence that workers who were employed in the formal sector at their current or most recent job are not different on educational attainment, numeracy, or noncognitive skill measures. Workers are similar across sectors except for one aspect: formal workers are about 1 year older on average than informal workers. The extra year of age also translates to an extra year of work experience in the garments industry. A natural story here might be that young workers join informal work to develop skills before moving to formal jobs. If we restrict to older workers above the age of 25, the experience difference disappears which means that experienced workers still choose informal jobs (see Table A5).

Finally, I show evidence to rule out sorting on unobserved skills. Though the numeracy measure used was tailored to be job-relevant, it is possible that it is an incomplete measure of the skills required to excel in RMG jobs.[20] To address this, Table 6 shows how the wage premium of the formal sector changes when we account for various factors including unobservable skills as captured through an individual fixed effect. Adding controls for the level of amenities present at the job shrinks the wage gap by around 75%, but adding individual fixed effects between specifications (3) and (4) does not significantly affect the formal wage premium. This suggests that the formal wage premium does not arise from the differential sorting of workers based on their ability.

Table 6: Sector Wage Gap Regressions

	Log Earnings			
	(1)	(2)	(3)	(4)
Formal Job	0.162***	0.0484***	0.0224*	0.0312*
	(0.00808)	(0.00889)	(0.0113)	(0.0131)
Year FE	Yes	Yes	Yes	Yes
Amenity controls		Yes	Yes	Yes
Firm location-size FE			Yes	Yes
Individual FE				Yes
N	6428	5566	5259	5226

Note: To avoid bias from outliers who have been at the same job for a long time, analysis keeps individuals with jobs starting after 2016—resulting in 590 unique individuals.

[20]Menzel and Woodruff (2021) list some industry-specific measures of worker productivity including the number of processes that a worker knows to execute, but these are hard to accurately elicit from workers without testing them in a factory setting or referring to administrative records.

Table 7: Attribute Levels for the Choice Experiment

Attribute	**Levels**	**Units**
Salary	100, 120, 150, 175, 200	% of current monthly salary
Leave policy	As needed, 14 days	-
Overtime	40, 50, 60	taka per hour
Supervisor	Good, Unknown	quality
Formality	Compliant, Non-compliant	factory

5 Evidence on Preferences for Job Amenities

To supplement the empirical evidence on job dynamics, I conduct a choice experiment varying salary and four amenities—good supervisor, flexible leave policies, overtime rates, and factory formality. In this section I describe the strength of worker preferences along these dimensions as well as the heterogeneity in the sample over these preferences.

The four amenities and their levels in the choice experiment were chosen based on piloting and focus groups asking workers what they looked for when searching for a job. More than 50% of workers mentioned each of these attributes. Levels of each amenity were chosen based on data from a pilot survey revealing the types of jobs in which respondents worked. Table 7 lists the levels.

The full combination of each of these amenities would have been impossible to administer in a survey, which is why I designed a more succinct experiment. I used priors of the coefficients from pilot and field testing to run a Bayesian d-efficient design algorithm that gave me four blocks of five questions.[21] This algorithm selects and groups questions in the right way to maximize power to detect coefficients that are different from zero.[22] This is especially useful when working with a limited sample size.

Each respondent was randomized into one of the four blocks and was presented five binary choices between jobs with different levels of wages and amenities. Enumerators were specifically instructed to tell respondents that the only difference between the two jobs presented were those that were listed in the question. We asked a follow-up question to the choice experiment to understand why respondents selected the options they chose.

Table 8 reports the results of the choice experiment. Respondents care about higher

[21]Appendix E has details on the algorithm.
[22]Given this structure, it is not possible to estimate correlations in preferences for wages and amenities.

salaries, good supervisors, and formality. As a validation that stated preferences in the experiment reflect reality, I also look at coefficients by the formality status of respondents' current or most recent job. Though everyone prefers formality, those working in the formal sector value it more.

Table 8: Choice Experiment Results: Overall & By Current Job Formality

	Overall		**Curr. Informal**		**Curr. Formal**	
	Coef.	Ratio	Coef.	Ratio	Coef.	Ratio
Salary	0.0087***	.	0.0117***	.	0.0075***	.
	(0.0011)		(0.0019)		(0.0013)	
Flexible Leave	0.0087	-0.11	-0.0229	-1.94	0.0079	0.89
	(0.0408)		(0.0686)		(0.0515)	
Good Supervisor	1.155***	131.27	1.204***	102.99	1.153***	151.65
	(0.0654)		(0.107)		(0.0830)	
Overtime						
50 taka / hr	-0.0154	-1.75	0.0302	2.58	-0.0282	-3.73
	(0.0562)		(0.0968)		(0.0696)	
60 taka / hr	0.100	11.42	0.0527	4.50	0.122	16.15
	(0.0570)		(0.0990)		(0.0708)	
Formality	1.671***	190.75	1.347***	115.12	1.853***	247.06
	(0.0872)		(0.147)		(0.107)	

Note: Ratio column takes ratio of each coefficient to the coefficient on salary. The split in the right panel of this table looks at worker whose current or most recent job was formal vs. informal. Salary enters as the % increase to present salary. Flexible leave is a binary of whether the respondent chose as needed leave as their preferred option.

Though the choice experiment was not incentivized, I show that it does reflect preferences that are salient to respondents' job choices. The choice experiment did not offer participants actual jobs corresponding to the offered options. A concern is that participants then do not answer in a way that reflects their real world choices. I address this concern in two ways. First, I asked enumerators to include a small appeal to respondents to truthfully report their preferences so that the research could help other garment workers. Second, I compare respondents' preferences in the choice experiment to their realized job mobility decisions in the retrospective sample. Table A6 reports how the probability of quitting a job depends on the amenities present in the job. In the vein of Gronberg and Reed (1994), longer job durations (i.e. lower quit probabilities) imply a higher preference for that bundle of amenities. While magnitudes are different, the qualitative pattern is similar between the panel and the choice experiment.

In addition to estimating preferences for amenities, the choice experiment can be used to uncover preference heterogeneity. Appendix A7 reports results along observable dimensions of heterogeneity, including gender and household composition. However, there are two outstanding issues. First, observable characteristics may not be detailed enough to capture workers' preferences. Second, even with a rich set of observables, the choice experiment only recovers workers' valuations in the aggregate rather than at the individual level. Adding an exhaustive list of covariates would make it impossible to recover estimates.

As a way to incorporate observed heterogeneity and reduce the dimensionality of the problem, I use a logit mixture to model with latent classes to understand the decisions made in the choice experiment (Bhat, 1997; Gupta and Chintagunta, 1994).[23] In the model, individuals make decisions in the choice experiment based on their latent class-specific preferences. Latent classes, in turn are predicted using a set of observed covariates as in a correlated random effects model. Using an expectation-maximization algorithm, this approach jointly recovers: (1) coefficients on the class membership predictors, and (2) estimates of the amenity valuation coefficients by class. In this estimation, I choose to estimate parameters for three separate classes.

The results of the choice experiment accounting for unobserved heterogeneity in preferences are found in Table 10. To interpret these results, we can look at the covariates that predict class membership to understand the types of workers found in each group. Table 9 contains estimated coefficients on class membership, normalized by Class 3's coefficients. Workers in Class 1 come from households that are more likely to owe unexpected loans. Meanwhile those in class 2 have higher numeracy scores as well as more dependents in the household. These features align with the preferences of each group as reported in Panel B — Class 1 (11% of the sample) are salary-seekers, Class 2 (53%) are formality-seekers, and Class 3 (35%) are supervisor seekers.

[23]Appendix F has details on the latent class approach.

Table 9: Class Membership Coefficients

	Class 1	Class 2
Female	-0.863	-0.041
	(0.534)	(0.359)
Married	0.415	0.341
	(0.491)	(0.261)
Some Secondary	-0.321	-0.124
	(0.426)	(0.236)
Numeracy	-0.122	0.299**
	(0.230)	(0.145)
HH # Dependents	-0.316	0.355*
	(0.343)	(0.182)
HH Wealth Index	-0.188	-0.089
	(0.202)	(0.119)
HH Recent Migrant	-0.968**	-0.45
	(0.539)	(0.275)
HH Owe Unexpected	0.865**	0.321
	(0.471)	(0.326)
HH Income Rank	0.001	0.001
	(0.001)	(0.001)
Constant	0.608	0.168
	(1.281)	(0.79)

Note: Coefficients on covariates are reported with relation to Class 3. This normalization is necessary to identify the latent class model

6 A Dual-Sector Search Model

Workers in the model gain utility from the wages and amenities present at a job. For a worker of type x, flow utility in a given period is

$$u(w, a; x) = \ln(w) + \xi(x)'a$$

where w represents wages and a amenities. Note that the vector a also includes a formal-sector-specific amenity that represents the bundle of working conditions available at a formal firm. In the dual-sector setup of the model, this amenity is always present in formal sector jobs. Heterogeneity, observed or unobserved, can enter through preference parameters $\xi(x)$.

Table 10: Coefficient Estimates by Class

	Class 1	Class 2	Class 3
Salary	0.048**	0.013**	-0.003
	(0.024)	(0.003)	(0.007)
Leave	-0.18	0.043	-0.089
	(0.237)	(0.096)	(0.267)
Supervisor	0.323	1.366**	2.346**
	(0.279)	(0.252)	(0.327)
High Overtime	-0.029	0.057	0.597*
	(0.257)	(0.156)	(0.339)
Formality	0.674*	3.486**	0.353
	(0.362)	(0.615)	(0.597)

Note: High overtime is defined as 60 taka per hour or above, which is around the median in the sample for workers' current or most recent job.

Workers maximize their lifetime expected utility discounting at rate $\beta \in [0, 1]$.

In each period, workers have a job in sector $j \in \{0, 1, 2\}$. Sector 0 indexes unemployment, sector 1 is the formal sector, and sector 2 informal. Workers in both sectors search for jobs and receive offers at Poisson rates denoted as λ_{od} with o indexing the origin sector where the person currently works and d indexing the destination sector where the job offer comes from. This produces six job arrival rates: $\lambda_{01}, \lambda_{02}, \lambda_{11}, \lambda_{12}, \lambda_{21}$, and λ_{22}. If a worker does receive an offer, they draw a job from the exogenous offer distribution of the destination sector $F_j(w, a)$ and decide whether to accept the new job. We assume that amenities are constant for the duration of the job, but that wages can change due to salary increments, which are common in both formal and informal jobs. Workers can also be involuntarily terminated from jobs in each sector at rates δ_j. After job offers and separation are realized but before decisions are made, the workers receive taste shocks parametrized as random variables $\varepsilon \overset{iid}{\sim} Gumbel(0, 1)$ that affect the perceived value for each job option.

Combining this information, we can work through the value of a job for formal sector worker. A formal worker receives a flow utility from each job based on her preferences for wages and amenities. In the next period, she loses her job with probability δ_1. If she loses her job, the worker searches as though she is unemployed, receiving a formal job offer with probability λ_{01}, an informal job offer with probability λ_{02}, or no offer with probability

$1-\lambda_{01}-\lambda_{02}$. In the case of no offer, the worker lapses into unemployment. In the case of a formal or informal offer, the worker realizes a one-period preference shock and chooses whether or not to accept the job by comparing it to the value of staying unemployed. The process of on-the-job search is analogous, but with offer arrival rates λ_{11} and λ_{12}, which should reflect a lower search intensity. If a worker does not lose their job and receives no job offers, they stay at their current job.

Denoting $V_x^j(w,a)$ as the value of a job in either sector, I write a Bellman equation for the formal worker below. Note $\mathbb{E}_j$ represents an expectation taken with respect to offer distribution $F_j(w,a)$ and $\mathbb{E}_\varepsilon$ represents the expectation over the error terms.

$$V_x^1(w,a) = \underbrace{u_x(w,a)}_{\text{flow util}} + \beta\Bigg\{\delta_1\Bigg(\underbrace{\lambda_{01}\mathbb{E}_1\left[\mathbb{E}_\varepsilon\left[\max\{V_x^1(w',a')+\varepsilon_{11}, V_x^0+\varepsilon_{12}\}\right]\right]}_{\text{lose job, get formal offer}} + \tag{1}$$

$$\underbrace{\lambda_{02}\mathbb{E}_2\left[\mathbb{E}_\varepsilon\left[\max\{V_x^2(w',a')+\varepsilon_{13}, V_x^0+\varepsilon_{14}\}\right]\right]}_{\text{lose job, get informal offer}} + \underbrace{(1-\lambda_{01}-\lambda_{02})V_x^0}_{\text{lose job, no offers}}\Bigg) \tag{2}$$

$$(1-\delta_1)\Bigg(\underbrace{\lambda_{11}\mathbb{E}_1\left[\mathbb{E}_\varepsilon\left[\max\{V_x^1(w',a')+\varepsilon_{15}, V_x^1(w,a)+\varepsilon_{16}\}\right]\right]}_{\text{get formal offer on the job}} + \tag{3}$$

$$\underbrace{\lambda_{12}\mathbb{E}_2\left[\mathbb{E}_\varepsilon\left[\max\{V_x^2(w',a')+\varepsilon_{17}, V_x^1(w,a)+\varepsilon_{18}\}\right]\right]}_{\text{get informal offer on the job}} + \underbrace{(1-\lambda_{11}-\lambda_{12})V_x^1(w,a)}_{\text{no job loss, no offers}}\Bigg)\Bigg\} \tag{4}$$

The value function for the informal worker is symmetric, but has different offer arrival rates in the case of on-the-job search due to the sector-specific frictions.

$$V_x^2(w,a) = \underbrace{u_x(w,a)}_{\text{flow util}} + \beta\Bigg\{\delta_2\Bigg(\underbrace{\lambda_{01}\mathbb{E}_1\left[\mathbb{E}_\varepsilon\left[\max\{V_x^1(w',a')+\varepsilon_{11}, V_x^0+\varepsilon_{12}\}\right]\right]}_{\text{lose job, get formal offer}} + \tag{5}$$

$$\underbrace{\lambda_{02}\mathbb{E}_2\left[\mathbb{E}_\varepsilon\left[\max\{V_x^2(w',a')+\varepsilon_{13}, V_x^0+\varepsilon_{14}\}\right]\right]}_{\text{lose job, get informal offer}} + \underbrace{(1-\lambda_{01}-\lambda_{02})V_x^0}_{\text{lose job, no offers}}\Bigg) \tag{6}$$

$$(1-\delta_2)\Bigg(\underbrace{\lambda_{21}\mathbb{E}_1\left[\mathbb{E}_\varepsilon\left[\max\{V_x^1(w',a')+\varepsilon_{15}, V_x^2(w,a)+\varepsilon_{16}\}\right]\right]}_{\text{get formal offer on the job}} + \tag{7}$$

$$\underbrace{\lambda_{22}\mathbb{E}_2\left[\mathbb{E}_\varepsilon\left[\max\{V_x^2(w',a')+\varepsilon_{17}, V_x^2(w,a)+\varepsilon_{18}\}\right]\right]}_{\text{get informal offer on the job}} + \underbrace{(1-\lambda_{21}-\lambda_{22})V_x^1(w,a)}_{\text{no job loss, no offers}}\Bigg)\Bigg\} \tag{8}$$

Finally, the value of unemployment is denoted V^0 and the unemployed worker gets flow utility b, which combines both the value of unemployment benefits and the the disamenity of work.

$$V_x^0 = \underbrace{b}_{\text{unemployment benefit}} + \beta\Bigg\{\underbrace{\lambda_{01}\mathbb{E}_1\left[\mathbb{E}_\varepsilon\left[\max\{V_x^1(w,a)+\varepsilon_{01}, V_x^0+\varepsilon_{02}\}\right]\right]}_{\text{formal offer}} + \tag{9}$$

$$\underbrace{\lambda_{02}\mathbb{E}_2\left[\mathbb{E}_\varepsilon\left[\max\{V_x^2(w,a)+\varepsilon_{03}, V_x^0+\varepsilon_{04}\}\right]\right]}_{\text{informal offer}} + \tag{10}$$

$$\underbrace{(1-\lambda_{01}-\lambda_{02})V_x^0}_{\text{no offer}}\Bigg\} \tag{11}$$

I set b to be the same across all workers. This is a slightly restrictive assumption since it rules out heterogeneity in the disamenity of working. However, different groups of workers can still have distinct reservation utilities determining their entry into employment. This is because reservation utility is the value of the wage-amenity bundle that makes a worker indifferent between employment and unemployment. So for a formality-seeking worker, reservation utility will be higher for jobs arriving from the informal sector.

6.1 An Intuitive Sketch of Identification

Understanding sorting through the lens of the model requires estimation of four sets of parameters: unobserved heterogeneity entering through x, search frictions λ_{od} for all origin-desitination pairs, offer distributions $F^{j}(w, a)$ for $\jmath \in 1, 2$, and preference parameters ξ

I first identify unobserved heterogeneity using the latent class analysis from Section 5 to group workers with similar preferences. Repeated measurements of choices for observably similar workers enables identification of the underlying heterogeneity in the sample. One limitation of this approach is that the number of latent classes estimated has to be set by the researcher. In this setting, I specify three latent classes.

Holding latent classes fixed, search frictions and offer distributions are identified through the mechanisms detailed in similar job search models (Sorkin, 2018; Meghir et al., 2015; Bonhomme and Jolivet, 2009). I estimate exogenous separation rates δ_1 and δ_2 separately from the model, using self-reported information on whether a job change was voluntary or not. Respondents who reported being fired or that their factory shut down were counted as involuntary movers. Next, moves from unemployment and after an involuntary job loss provide information about both search frictions and offer distributions in both sectors. Additionally, the probability of transitioning to a new job and the probability of staying at the current job both provide information about these objects.

Two sources of information help identify preferences. The first is the flow of similar individuals to and from jobs, which reveals a ranking of preferred jobs (Sorkin, 2018). If workers at the same job, indexed by the same wage and amenity levels, receive offers from two different jobs A and B, the share of workers accepting each offer reveals the relative rankings of jobs A and B. This logic from Sorkin (2018) relies on the assumption that jobs of all types are available in similar quantity, which may not be true for two reasons in my setting. For one, there may be higher rates of offers from formal or informal sector depending on the job growth in each sector. Additionally, correlation in the wage-amenity offer distributions may result in certain jobs being far more common than others, preventing a purely revealed preference approach from pinning down worker preferences for specific amenities (Wiswall and Zafar, 2017). Thus, the second source of information to help identify preferences is the choices that respondents make in the choice experiment. Though levels of amenities in the choice experiment were chosen based on those reported in the pilot survey, the choice experiment design does not consider the correlation between wages and amenities observed in the sample. As a result, the experimentally varied jobs identifies worker preferences for amenities separately from the firm decision to offer certain bundles of wages and amenities.

7 Estimation

To estimate the model from Section 6, I use a constrained maximum likelihood approach. I use the model above to derive the probability of jointly observing job-to-job transitions as well as the selections made in the choice experiment. I constrain the estimation so that the value functions for each of the three states in the model are satisfied. This procedure follows the mathematical programming with equilibrium constraints (MPEC) approach outlined in Su and Judd (2012). Before specifying the likelihood, I take two preliminary steps. First, I discretize the model for tractability and to allow nonparametric estimation of offer distributions in each sector. Second, I assign individuals to latent classes based on the analysis in Section 5.

7.1 Discretizing the Model

I discretize the the space of wage-amenity offers into K points of support to enable the nonparametric estimation of offer distributions and enforce the value function constraints. For $j \in \{1, 2\}$, the offer distributions $F_j(w, a)$ can now be written as $\{p_{jk}\}_{k=1}^{K}$ where $\sum_{k=1}^{K} p_{jk} = 1$. Value functions $V_x^j(w, a)$ are rewritten as $\left\{V(x)_k^j\right\}_{k=1}^{K}$. Similarly, utility functions are now $\left\{u(x)_k^j\right\}_{k=1}^{K}$. We can rewrite the value function for a formal worker using these discretizations as well as the properties of the Gumbel distribution.[24] For simplicity, I suppress notation describing how heterogeneous groups x enter this equation, but each value function holds for a given value of x.

[24]See Appendix G for the derivation of this value function.

$$V_k^1 = u_k + \beta \Bigg\{ \delta_1 \Bigg(\lambda_{01}\mathbb{E}_1 \left[\gamma + \ln\!\big(\exp\{V_{k'}^1\} + \exp\{V^0\}\big)\right] + \tag{12}$$

$$\lambda_{02}\mathbb{E}_2 \left[\gamma + \ln\!\big(\exp\{V_{k'}^2\} + \exp\{V^0\}\big)\right] + (1-\lambda_{01}-\lambda_{02})V^0 \Bigg) \tag{13}$$

$$(1-\delta_1)\Bigg(\lambda_{11}\mathbb{E}_1 \left[\gamma + \ln\!\big(\exp\{V_{k'}^1\} + \exp\{V_k^1\}\big)\right] + \tag{14}$$

$$\lambda_{12}\mathbb{E}_2 \left[\gamma + \ln\!\big(\exp\{V_{k'}^2\} + \exp\{V_k^1\}\big)\right] + (1-\lambda_{11}-\lambda_{12})V_k^1 \Bigg) \Bigg\} \tag{15}$$

Here k indexes the wage and amenity values at the current job, while k' indexes an offer drawn from one of the offer distributions. Additionally, $\gamma \approx 0.5772$, the Euler-Mascheroni constant. Appendix G similarly derives discretized versions of the informal and unemployed workers' value functions.

Assigning Latent Classes. The latent class approach discretizes unobserved heterogeneity into a fixed number of classes. Taking the results of the logit mixture model from Section 5, I predict posterior probabilities of class membership. I assign each individual to the class for which they have the highest predicted membership probability. These assigned classes are now the variables x that enter the model and create heterogeneity in preferences.

7.2 Conditional Choice Probabilities

Information on mobility between jobs is critical to identifying search friction and offer distribution parameters. I use the model to derive transition probabilities between jobs as well as the probability of staying in the same job for each sector. In the case of a formal worker ($s = 1$) at a job indexed by (w_m, a_m), their probability of moving to another job ($M = 1$) in the formal sector indexed by (w_ℓ, a_ℓ) is as follows.

$$\begin{aligned} P(w_\ell, a_\ell, s=1 | w_m, a_m, s=1, M=1) &= \delta_1\lambda_{01}p_{1\ell} + (1-\delta_1)\lambda_{11}p_{1\ell}\mathbb{P}\left(V_\ell^1 + \varepsilon_{13} > V_m^1 + \varepsilon_{14}\right) \\ &= \delta_1\lambda_{01}p_{1\ell} + (1-\delta_1)\lambda_{11}p_{1\ell}\frac{1}{1+\exp\{V_m^1 - V_\ell^1\}} \end{aligned}$$

The first term is the probability that the worker lost their formal job and received an offer (w_ℓ, a_ℓ) from the formal sector. The second term captures the probability that the worker did not lose their job but received a formal offer through on-the-job search that was better than their current job. The form of the T1EV errors allows simplification of this latter probability into a more tractable form.

I similarly derive conditional probabilities for cross-sector moves, moves to and from unemployment, and the probability of a person staying at a given job. For formal workers who stay at the same job, the period-to-period probability is:

$$P(w_m, a_m, |w_m, a_m, s = 1, M = 0) = (1 - \delta_1)\Bigg\{(1 - \lambda_{11} - \lambda 12) \\ + \lambda_{11} \sum_{k=1}^{K} p_{1k} \frac{1}{1 + \exp\{V_k^1 - V_m^1\}} + \lambda_{12} \sum_{k=1}^{K} p_{2k} \frac{1}{1 + \exp\{V_k^2 - V_m^1\}}\Bigg\}$$

Workers only stay at their job if they do not get fired. Within the large brackets, the first term is the probability that workers do not receive any job offers from other sectors. The second term captures the probability that they receive a formal job offer but that the offer is not better than the current job. Similarly, the third term captures the probability of recieving an informal job offer that is not better than the current job. Appendix H contains the derivation of the remaining conditional transition probabilities.

Finally, we can also write the model-derived probability of making choices in the choice experiment. One innovation here is that I assume that workers are making forward looking decisions in the choice experiment—they are comparing not just the flow utilities but also the future value of the jobs. This approach is only made possible by jointly estimating the model and the choice experiment. Based on the model, choices in the choice experiment are made as follows. Let us say participants are offered job A in sector s with wage-amenity indexed by k. The other option is job B in sector s' with wage-amenity k'. Then the probability of observing a choice A is:

$$\mathbb{P}(\text{choose } A) = \frac{1}{1 + \exp\{V_{k'}^{s'} - V_k^s\}}. \tag{16}$$

7.3 Joint Likelihood

The joint likelihood multiplies conditional transition and choice probabilities from the retrospective panel and the choice experiment. I define 11 different move types (MT) from the data, including transitions to and from each sector as well as the probability of workers staying in the same job or staying in unemployment. Each of these corresponds to a model-derived transition probability, which are listed in Appendix H. For each of the five questions on the choice experiment, I specify the probability that workers choose alternatives a or b. Further, the estimation will require two constraints: that the value functions hold and that the discrete offer distributions sum to one. A notationally simplified likelihood can be written as:

$$L_{jt} = \prod_{m=1}^{11} \mathbb{P}(\text{MT } = m)^{1\{\text{MT } = m\}} \prod_{q=1}^{5} \mathbb{P}(V_{a,q} > V_{b,q})^{1\{\text{choose } a_q\}} \mathbb{P}(V_{b,q} > V_{a,q})^{1\{\text{choose } b_q\}}$$
$$\text{s.t. Equations (12), (A.1), and (A.2) hold}$$
$$\sum_{k=1}^{K} p_{1k} = 1 \qquad \sum_{k=1}^{K} p_{2k} = 1$$

This method follows the mathematical programming with equilibrium constraints (MPEC) approach outlined in Su and Judd (2012). I verify that the estimated value function parameters are a fixed point. Getting analytical standard errors from this procedure is difficult due to the nature of the fixed point problem. Instead, I report bootstrapped standard errors.

7.4 Mapping Model to Data

Based on survey data, I am able to identify dates of job moves to the precision of four-month periods of the year.[25] The transition parameters then represent rates of job arrival for each period, which we can translate into a yearly rate. Based on the period, I choose a discount rate of $\beta = 0.97$ which translates into a 9.5% yearly discount rate.

The sector of a job is determined by it's formality status, verified in the MiB database by the reported factory names (MIB, 2023). If a respondent could not name the factory, I use their self report of it's compliance status to fill in the value. If a factory named by a respondent is not found in the MiB database, I assume it is an informal factory. The survey team verified this procedure by visiting a selection of factories named by respondents and double checking for any misclassification.

I assume amenities at jobs do not change over time and that they can differ even within the same reported firm. For example, two workers who report working at the same factory

[25]See Appendix D.2 for details on this procedure.

may work with different supervisors and have different experiences. In Appendix I.1, I show that the results are robust even if amenities are restricted to be the same firm-wide.

Wages are allowed to grow over time if respondents reported getting annual increments, minimum wage bumps, or a promotion. The survey asks for start and end wages as well as the reason for wage increasee. Appendix D.3 explains my procedures for imputing wages to the periods in between. Wage trends are important to account for because workers who have stayed at jobs for a long time would otherwise be counted as working for a relatively lower wage.

I set the unemployment benefit b in the model equal to 2500 BDT a month. The choice of this number is difficult to justify using real world metrics since it combines both monetary compensation in unemployment and the workers' disamenity of work. The level of benefits offered by government programs lies between 250-1000BDT per month. However, setting the unemployment benefit to a value in this range would not account for the disamenity of working. To choose a number in a more principled way, I estimate the model at different values of the unemployment benefit and choose the one that best rationalizes unemployment data. A model estimated with $b = 3.39$ (equivalent to 2500 per month in monetary compensation) best predicts the unemployment rate I observe in the sample.

Data in the retrospective panel are restricted to prevent outliers from dominating the estimation. I drop observations from years before 2016. This truncates the job histories of the few individuals who have worked at a job for a long time. It also makes sure the sample period starts after the structural transformation in the labor market after the Rana Plaza disaster in 2013. Because of increasing pushes towards formalization in the period immediately after the disaster, it is likely the market was changing rapidly. Models of job search like the one in this paper generally assume structural invariance of market conditions. Avoiding the period from 2013-2016 makes the data more likely to align with this assumption.

8 Parameter Estimates

Results from the model can be split into three parts: transition parameters, offer distributions, and valuation of amenities. Table 11 reports transition parameters from the estimation. Separation rates in the formal sector are lower than in the informal sector. Translating to yearly rates, workers have a 9% chance of losing formal job and an 18% chance of losing an informal job. Workers searching for jobs from unemployment are successful. Workers have a 71% chance yearly of being offered a formal sector job and a 93% chance of being offered an informal job. These numbers square with the dynamism of the informal sector, which both has more churn in the entry and exit of firms and also generally has more availability of jobs.

The sector-specific job arrival rates for on-the-job search show a slight pattern of state-dependence. Formal sector offers are less likely to arrive to those working in the informal sector, though these differences are not statistically significant. The yearly rates for on-the-job offer arrival range from 9-18% and have overlapping confidence intervals. The on-the-job arrival rates reported here are lower than similar studies (Meghir et al., 2015), but this may be due to the unique nature of job search in the industry. Since job search usually involves being physically present at factory gates, it is harder to successfully search for jobs while already employed.

Table 11: Separation and Arrival Rates

Parameter Description	**Notation**	**Estimate**	**95% CI**
Separation Rates			
Formal job loss rate	δ_1	0.031	[0.027, 0.034]
Informal job loss rate	δ_2	0.067	[0.058, 0.076]
Offer Rates			
Rate of formal offers when unemployed	λ_{01}	0.340	[0.279, 0.420]
Rate of informal offers when unemployed	λ_{02}	0.591	[0.498, 0.676]
Rate of formal offers in formal sector	λ_{11}	0.044	[0.024, 0.060]
Rate of informal offers in formal sector	λ_{12}	0.067	[0.026, 0.108]
Rate of formal offers in informal sector	λ_{21}	0.013	[0.003, 0.071]
Rate of informal offers in informal sector	λ_{22}	0.048	[0.030, 0.071]

Note: Model was estimated on a final dataset of $N = 604$ unique individuals and a total of 7,344 observations. Periods in the model correspond to thirds of a year. 95% CIs reported in square brackets from the 2.5th and 97.5th percentile estimates of 200 bootstrap replications.

Marginal offer distributions for both sectors differ in wages and overtime rates offered. Figure 2 displays these offer distributions, including 95% CI based on bootstrap replications. Formal sector jobs offer higher pay in general, which makes sense given that they are more likely to sell products to international markets and tend to be in larger, higher productivity firms. However, the wage distributions do have substantial overlap.

The correlation between wages and amenities offered in the two sectors is different, as demonstrated in Table 12. Formal jobs that offer higher wages area also likely to offer high overtime rates, which is true to a lesser degree in the informal sector. Additionally, good supervisors are positively correlated with high wages in the informal sector but unrelated in the formal sector. Anecdotes from our focus groups verify that workers often feel that the high stress production environments of formal factories may encourage worse supervisors from a worker's perspective. This suggests that there are informal jobs that may be attractive to workers.

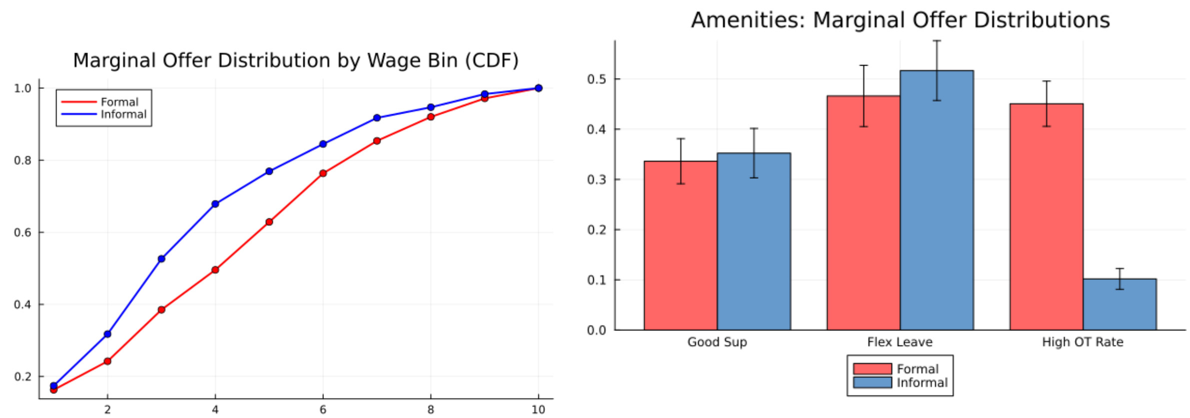

Figure 2: Estimated Marginal Wage and Offer Distributions

Table 12: Correlation in Wages and Amenities Offered in Each Sector

Formal Offers	Wage	Sup.	Leave	OT Rate
Wage	1			
Sup.	-0.010	1		
Flex. Leave	-0.223	-0.010	1	
OT Rate	0.532	0.144	-0.195	1

Informal Offers	Wage	Sup.	Leave	OT Rate
Wage	1			
Sup.	0.151	1		
Flex. Leave	0.019	0.064	1	
OT Rate	0.358	0.043	-0.131	1

Finally, the model-predicted valuations of amenities are presented in Table 13. The log-linear specification of flow utilities allows us to read the estimates of preferences as a willingness-to-pay for each amenity. As in the choice experiment, latent class 1 is salary-seeking, class 2 is formality-seeking, and class 3 is supervisor-seeking. Workers in class 1 do not exhibit strong preferences towards any amenity. Workers in class 2, who make up a slight majority of workers, are willing to pay up to 37.4% of their salary in exchange for a formal. Meanwhile workers in class 3 are willing to pay up to 28.6% of their salary for a good supervisor.

Table 13: Results on Willingness-to-Pay for Amenities

Latent Class	**Good Sup.**	**Flex. Leave**	**High OT Rate**	**Formality**
Class 1	0.002	-0.003	0.003	-0.058
(11.1%)	[-0.016, 0.022]	[-0.020, 0.024]	[-0.037, 0.027]	[-0.105, 0.000]
Class 2	0.111*	0.026*	-0.048*	0.374*
(53.3%)	[0.086, 0.134]	[0.006, 0.048]	[-0.066, -0.023]	[0.319, 0.429]
Class 3	0.286*	0.040*	0.058*	0.019
(35.6%)	[0.258, 0.311]	[0.013, 0.058]	[0.033, 0.084]	[-0.035, 0.075]

Note: Model was estimated on a final dataset of $N = 604$ unique individuals and a total of 7,344 observations. Periods in the model correspond to thirds of a year. 95% CIs reported in square brackets from the 2.5th and 97.5th percentile estimates of 200 bootstrap replications. Stars mark significance at this level.

8.1 Model Channels for Sectoral Sorting

In order to understand how each piece of the model contributes to sorting, I shut each channel down one at a time. In Figure 3, I show how each exercise affects worker sorting. There are four main exercises:

1. Low search frictions: Reduce search frictions so that both on-the-job, workers have a 20% chance of receiving an offer from each sector in all periods

2. No dynamics: Workers make myopic decisions in this version of the model with infinite discounting (i.e. $\beta = 0$)

3. Equal offer distributions: The informal offer distribution is set to be the same as the formal offer distribution

4. No preferences: Setting $\xi(x) = 0$, workers will now select jobs purely on wages.

Shutting down search frictions does not impact worker sorting between sectors. There are two competing forces at play—lower on-the-job search frictions reduce the value of unemployment, but increase the probability of workers accepting jobs that do not have their ideal mix of wages and amenities.

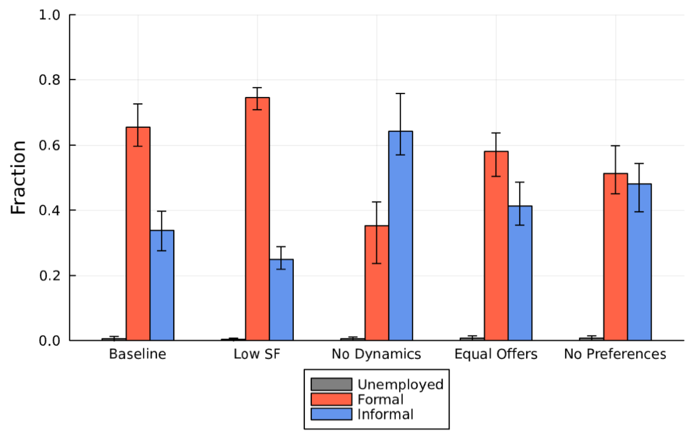

Figure 3: Worker Sorting under Different Model Scenarios

Removing dynamics from workers' decision-making results in worker sorting towards the informal sector. If workers are not considering the option value of each sector and the discounted future benefits, then the informal sector is attractive. Informal jobs arrive more often and can sometimes offer wages as high as the formal sector.

Equalizing the offer distributions does not change the distribution of workers between sectors. In Figure A3, I show how this policy affects each latent class. Primarily, salary-seeking individuals are more likely to be in informal jobs. Meanwhile the other groups, making up the majority of the market, do not change their behavior.

Finally, shutting down preferences slightly increases sorting into the formal sector. At first glance, it is surprising that there is not a more pronounced effect on worker behavior. However, Figure A4 provides some context. Salary- and supervisor-seeking workers are slightly more likely to be in the formal sector. Meanwhile formality-seeking workers, when no longer searching for jobs based on their preferences, are more likely to be in the formal sector than before.

9 Policy Analysis

Having characterized the dual-sector labor market in the garment industry, we can now turn to policy counterfactuals. An important concern for governments is to find ways to improve worker welfare, especially among those working in informal jobs out of the reach of government regulation.

In this section, I first look at a naïve policy scenario that eliminates the informal sector. Given that many governments aim towards this goal, it is interesting to see what the welfare effects of ideal implementation of such policies would be. I then look at more targeted policies to improve worker welfare in the form of various unemployment benefit programs.

To calculate welfare, I first simulate data from the steady state of the model for each counterfactual scenario. I then sum the present value of jobs that workers have in the simulated data. I disaggregate the welfare gains or losses by latent class as well as reporting the overall number across the labor market.

9.1 Counterfactuals: Eliminating Informality

While most governments cannot perfectly eliminate the informal sector, they often state this as the idealized goal. This section takes that goal seriously and investigates two scenarios of informal sector shut down. In the first scenario, I assume that every informal firm exits the market. As a result, the total rate of offer arrival decreases and job mobility decreases. In the second scenario, I assume that every informal firm is able to formalize and continue operating with no change to firm profits. In this scenario, there is no change in offer arrival rates, but only in the offer distribution that workers draw from. These two scenarios provide a lower and upper bound, respectively, on the types of welfare effects we might see from a more realistic policy targeting informality.

Table 14 shows that in the case of complete informal firm exit, overall welfare declines by 8.88%, with salary-seeking individuals most acutely affected. Alternatively, if there was perfect informal firm transition into formality with no other costs, workers would experience a 1.73% increase in welfare. This second scenario is a “best case” of sorts against which we can compare other policies to improve worker welfare.

A more realistic implementation of policies targeting informality would either raise the cost of informality, sweeten the benefits of formality, or increase enforcement. There is little empirical evidence that any of these approaches actually work in practice (Ulyssea, 2020), but even if they do the welfare gains are not as vast as we might expect. Any of the practical implementations described above would fall within the lower and upper bounds described above.

Table 14: % Change in Welfare by Counterfactual Scenario

	Elim. Inf. (firm exit)	**Elim. Inf (firm transition)**	**Cash Transfer**	**Unemp. Benefit**	**Unemp. Insurance**
Class 1 ("Salary seekers")	-11.41%	0.84%	0.47%	-0.004%	-0.71%
	[-12.366, -6.292]	[-0.045, 1.536]	[-0.574, 2.401]	[-0.807, 1.989]	[-1.950, 0.410]
Class 2 ("Formality seekers")	-7.96%	1.96%	1.50%	0.30%	-0.53%
	[-9.787, -5.883]	[1.060, 2.703]	[0.416, 2.540]	[-0.940, 1.446]	[-1.579, 0.368]
Class 3 ("Supervisor seekers")	-9.44%	1.64%	1.68%	1.05%	-0.42%
	[-11.002, -6.762]	[0.502, 2.114]	[0.407, 2.625]	[-0.634, 1.932]	[-1.343, 0.590]
Overall Welfare	-8.88%	1.73%	1.47%	0.56%	-0.51%
	[-10.324, -6.445]	[0.800, 2.253]	[0.392, 2.522]	[-0.662, 1.604]	[-1.505, 0.408]

Note: This table reports changes in welfare under different coutnerfactual scenarios. Each scenario is calculated by changing the model enviornment (e.g. by shutting down the informal sector) and simulating from the model to a steady state. Then, welfare is calculated by summing the present value in utility of the jobs in steady state. Within-class and overall numbers are reported as percentage changes from the baseline model (i.e. the model simulated at the point estimates of the parameters from Section 8). 95% CIs are reported in brackets below the estimates.

9.2 Counterfactuals: Social Safety Net Policies

A second policy lever with which to improve worker welfare is to provide a social safety net that facilitates better job search. Rather than accepting the first job offered to them, workers who are given unemployment support will be able to find jobs that better match their needs. The Bangladeshi government is currently trying to find ways to roll out unemployment insurance or similar protections. During the COVID-19 pandemic, for example, the government used cash transfers to support affected workers. Policies of this nature are thus generally feasible for the government.

However, implementing these policies in a highly informal economy is difficult for several reasons. For one, it is hard to identify workers' employment status, making it hard to prevent informal workers from using benefits meant for the unemployed. In fact, it is possible that the introduction of some of these policies will push workers into the informal sector. Second, even if the government can target formal workers, there may be spillover effects onto the informal sector as workers move between jobs.

I consider three types of social benefit policies in this setting: 1) a pure cash transfer to all workers, 2) a cash transfer conditional on unemployment, and 3) an unemployment insurance policy that pays workers half of the minimum wage in the RMG industry for four months after their employment is terminated. The first policy is the easiest to implement since it involves no targeting and would operate like a universal basic income. For the second policy, I assume that the government is unable to differentiate between informal and unemployed workers, so both groups receive a transfer. The third policy is a more classic

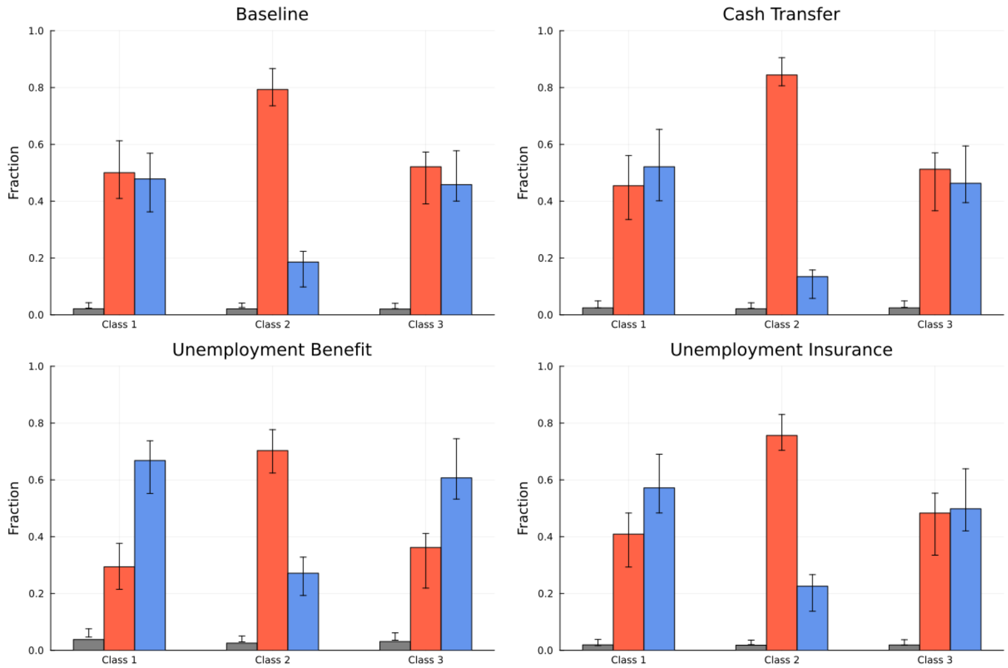

Figure 4: Sectoral Sorting by Class Under Different Scenarios

unemployment insurance setup in which formal workers receive unemployment benefits for a short time after their employment is terminated. Due to the lack of information about informal workers' salaries, they would not receive similar advantages.

I remain agnostic about the funding sources for the first two cash transfer policies. The Bangladeshi government has a budget for social safety policies that is presumably funded by redistributive taxes. The vast majority of workers in my sample fall below the minimum income threshold for paying income taxes, so would likely be pure beneficiaries in these scenarios. In the case of the third policy, I assume that the unemployment insurance is funded by a payroll tax on formal sector employees which amounts to 5% of income.

In Figure 4, I plot the distribution of workers by latent class in each sector in each policy scenario. A cash transfer to all workers does not significantly change how workers sort. An unemployment benefit—or a transfer targeted to the unemployed and informal workers—greatly increases the percentage of salary-seeking (Class 1) and supervisor-seeking (Class 2) workers in the informal sector. An unemployment insurance funded by a payroll tax has more modest effects, but still pushes workers, especially salary-seeking workers, into informal employment.

Additionally, Table 14 calculates the changes in welfare from each of the policies described. A cash transfer to all employees is the most welfare improving policy, increasing overall welfare by 1.47%. This policy realizes 84% of the gains of the best case scenario of eliminating the informal sector by transitioning all informal jobs to formal. Unemployment benefits and unemployment insurance policies have more ambiguous impacts. In general, unemployment benefits seem to have a slight positive effect, while unemployment insurance seems to negatively affect welfare. It is possible that this is because unemployment insurance imposes payroll taxation that are not sufficiently offset by the benefits.

10 Conclusion

This paper studies the determinants of worker sorting between formal and informal sectors. Using data on Bangladeshi garment workers, I build and estimate a partial equilibrium model of hedonic labor search. In this context, evidence for skills-based sorting is scarce. However, search frictions, especially in on-the-job search are significant. Additionally, workers have strong and heterogeneous preferences for job amenities.

In this dual-sector market with heterogeneous preferences, policies to help workers move to better jobs affect all workers regardless of the degree of targeting. Additionally, there are distinct impact on workers by group. Formality-seeking workers preferring to stay in the formal sector in nearly all scenarios, while salary-seekers are much more likely to choose informal jobs when there are high unemployment benefits.

The policy scenarios in this paper tell a partial story of informal labor markets. Firms' costs of providing amenities and their decision to post jobs in the formal or informal sector are left unmodeled. Without matched data on worker preferences and firm amenities, it is difficult to study firm job posting and amenity provision. Nonetheless, this paper provides important evidence on the forces affecting a worker's job search. It shows that well-designed policies in labor markets with informality need to account for search frictions and worker preference heterogeneity.

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A Additional Graphs

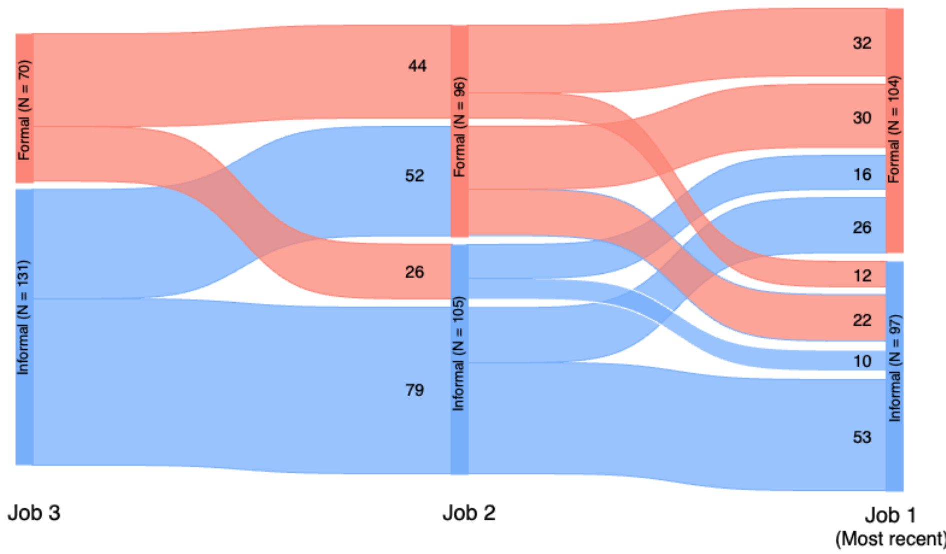


Figure A1: Flows Between Sectors

Note: This figure describes flows between formal and informal sector for the subset of workers who have at least three jobs.

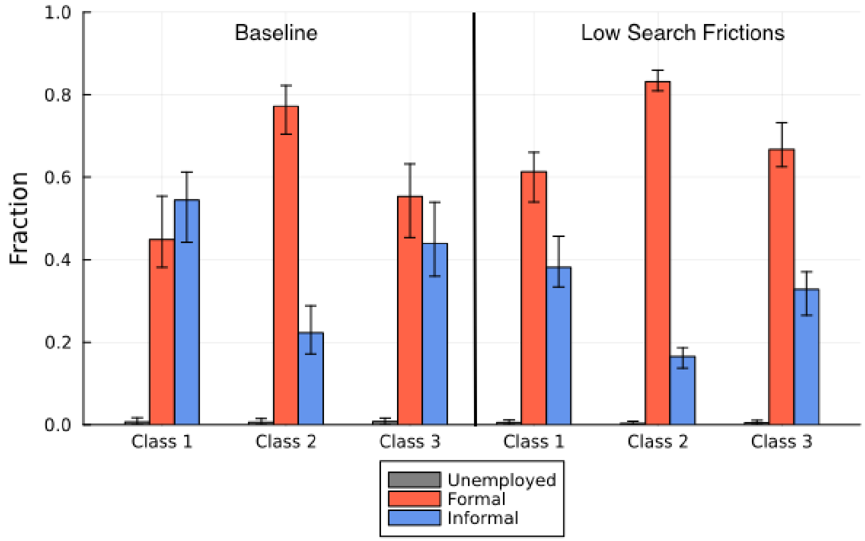


Figure A2: Sorting by Latent Class: Low Search Frictions

Note: This figure describes sectoral sorting and informal sector size in the baseline model vs. a model with lower search frictions. Class 1 are salary-seekers, Class 2 are formality-seekers, and Class 3 are supervisor-seekers.

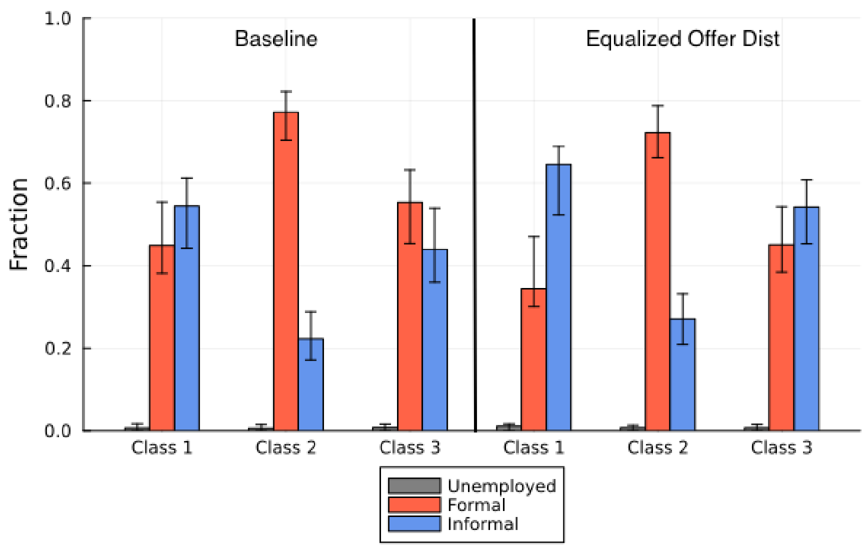


Figure A3: Sorting by Latent Class: Equalized Offer Distributions

Note: This figure describes sectoral sorting and informal sector size in the baseline model vs. a model with equalized offer distributions. Class 1 are salary-seekers, Class 2 are formality-seekers, and Class 3 are supervisor-seekers.

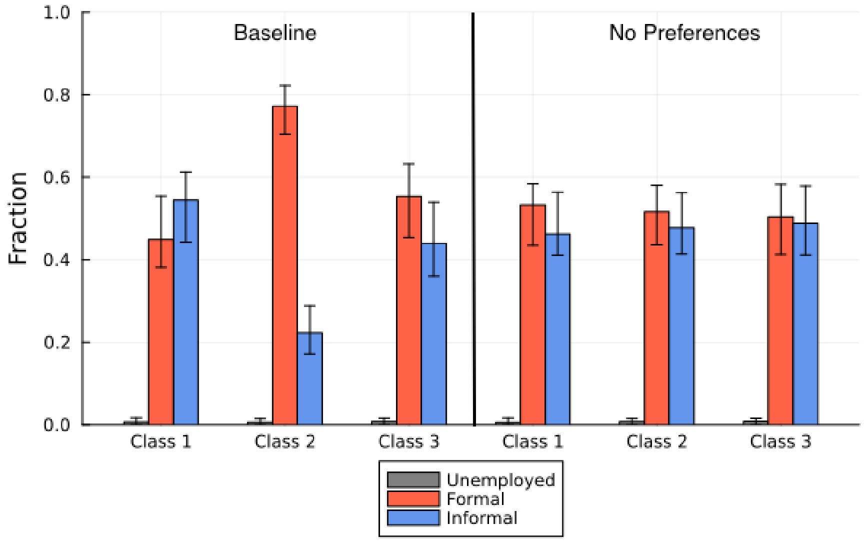


Figure A4: Sorting by Latent Class: No Preferences

Note: This figure describes sectoral sorting and informal sector size in the baseline model vs. a model with no preferences. Class 1 are salary-seekers, Class 2 are formality-seekers, and Class 3 are supervisor-seekers.

B Additional Tables

Table A1: Sectoral Transition Parameters: Primary Education

A: Uncond'l Transitions

	Form	Inf	N
Form	0.994	0.006	4577
Inf	0.044	0.956	1329

Rows sum to one

B: Cond'l on Move

	Form	Inf	N
Form	0.789	0.211	128
Inf	0.604	0.396	96

Rows sum to one

C: % Wage ↑ & Voluntary

	Form	Inf	N
Form	73.2	80.0	66
Inf	71.2	85.5	130

Note: Panel A reports the unconditional period-to-period transition matrix between sectors, which includes people who may stay at their job. Panel B reports the same matrix conditional on a move. Panel C reports the % of wage improving *voluntary* moves. A wage improving move $\equiv \Delta$ real wage $> -3\%$ (in case of reporting errors)

Table A2: Sectoral Transition Parameters: Secondary Education

A: Uncond'l Transitions

	Form	Inf	N
Form	0.993	0.007	2708
Inf	0.037	0.963	647

Rows sum to one

B: Cond'l on Move

	Form	Inf	N
Form	0.800	0.200	95
Inf	0.444	0.556	54

Rows sum to one

C: % Wage ↑ & Voluntary

	Form	Inf	N
Form	75.4	78.9	76
Inf	77.5	64.6	90

Note: Panel A reports the unconditional period-to-period transition matrix between sectors, which includes people who may stay at their job. Panel B reports the same matrix conditional on a move. Panel C reports the % of wage improving *voluntary* moves. A wage improving move $\equiv \Delta$ real wage $> -3\%$ (in case of reporting errors)

Table A3: Sectoral Transition Parameters: Low Numeracy Score

A: Uncond'l Transitions

	Form	Inf	N
Form	0.995	0.004	2854
Inf	0.042	0.958	636

Rows sum to one

B: Cond'l on Move

	Form	Inf	N
Form	0.827	0.123	81
Inf	0.614	0.386	44

Rows sum to one

C: % Wage ↑ & Voluntary

	Form	Inf	N
Form	71.6	80.0	70
Inf	94.7	73.3	34

Note: Panel A reports the unconditional period-to-period transition matrix between sectors, which includes people who may stay at their job. Panel B reports the same matrix conditional on a move. Panel C reports the % of wage improving *voluntary* moves. A wage improving move $\equiv \Delta$ real wage $> -3\%$ (in case of reporting errors)

Table A4: Sectoral Transition Parameters: High Numeracy Score

A: Uncond'l Transitions

	Form	Inf	N
Form	0.993	0.007	4401
Inf	0.041	0.959	1337

Rows sum to one

B: Cond'l on Move

	Form	Inf	N
Form	0.775	0.225	142
Inf	0.519	0.481	106

Rows sum to one

C: % Wage ↑ & Voluntary

	Form	Inf	N
Form	72.1	76.0	111
Inf	78.7	75.0	88

Note: Panel A reports the unconditional period-to-period transition matrix between sectors, which includes people who may stay at their job. Panel B reports the same matrix conditional on a move. Panel C reports the % of wage improving *voluntary* moves. A wage improving move $\equiv \Delta$ real wage $> -3\%$ (in case of reporting errors)

Table A5: Characteristics of Older Workers by Sector of Current or Most Recent Job

	Formal Mean	**Informal Mean**	**Difference**	**N**
Age	29.88	30.46	-0.586	244
Female (%)	85.71	85.53	0.188	244
Married (%)	91.67	82.89	8.772**	244
Some Primary Education (%)	50.00	57.89	-7.895	244
Some Secondary Education (%)	37.50	31.58	5.921	244
Numeracy Score	1.79	1.68	0.110	242
Noncognitive skill: Extraversion	5.24	5.33	-0.094	244
Noncognitive skill: Agreeableness	6.22	6.15	0.072	244
Noncognitive skill: Conscientiousness	5.54	5.56	-0.018	244
Noncognitive skill: Emotional Control	4.48	4.40	0.078	244
Noncognitive skill: Openness	5.30	5.22	0.080	244
Years of RMG Sector Experience	7.03	6.06	0.977	244

Note: This table displays differences between the demographics of those who worked in the formal vs. informal sectors in their current or most recent job. Sample is restricted to workers who are >25 years old

C Sampling and Survey Description

C.1 Sampling Strategy

Randomly Drawing Clusters

The survey team aimed to interview 650 RMG industry workers in the Mirpur area. Mirpur and its neighboring wards were chosen as the neighborhood hosts both formal and informal factories as well as a residential areas. The wards considered included Adabor, Darus Salam, Kafrul, Mirpur, Pallabi, Shah Ali, and Sher-e-bangla Nagar.

I first developed a strategy relying on satellite data to randomly sample from areas workers tend to live. The lack of an available sampling frame for the neighborhoods of interest make this strategy necessary. Previous national labor force surveys showed that garment workers largely lived in low-lying, makeshift buildings (LFS, 2017). Using the Global Human Settlement Layer (GHSL), I identified areas in Mirpur and surrounding wards that were predicted to be residential areas with buildings less than 6m tall (Kemper et al., 2021). I then used the map of factories provided by Mapped in Bangladesh to plot factories and identify areas within 2km of a garment factory. The 2km buffer was chosen since this the majority of workers likely live within this distance of their workplace. From the intersection of these two areas—low-lying residential settlments and areas within 2km of a factory—I randomly select 100 GPS points. I then draw a 200m buffer around each area to determine each sampling cluster.

Taking the 100 randomly selected GPS clusters, I first conducted a count census of each area. The census first allowed us to rule out clusters that were obviously in areas that were either uninhabited or were unlikely to contain garment workers. Since the GHSL model I was using was from 2018, some of the areas selected had since been built into schools or apartments for government employees. Secondly, the census provided a sense of the number of households in each cluster so that the number of interviews per cluster could be chosen accordingly. Enumerators of the census were asked to give an estimated number of households and likelihood of garment workers living in the cluster.

Based on the count census, I drew the number of interviews to be conducted in each cluster. Some clusters were left out by chance due to the low number of garment workers living there. In the end, 46 clusters were chosen with varying number of interviews assigned, as shown in Table A8.

Sampling Protocol

Survey teams of interviewers and supervisors travelled to the centroid of each cluster. They then conducted a random walk approaching each household to identify whether there was a garment worker who matched the eligibility criteria for the study. Usually this step was conducted in the middle of the day, which was when many garment workers were still at their factories. Enumerators were told to write down the time each worker would return to follow up with them. In households with multiple eligible workers, one was selected randomly for the interview.

Survey respondents were told the survey would take roughly 1 hour of their time. They were also given a compensation of 200taka (roughly 2USD) for their time. Workers were allowed to stop the interview at any time. These respondents were counted as refusals.

Table A8 reports the number of refusals in each clusters. If a household refused the interview, the next eligible household was selected. If the selected eligible garment worker in a household was unavailable, enumerators were instructed to contact them again twice. Once after work hours on weekdays, and once on Fridays—their only Weekend day off from work. If respondents were not at home both times, the household was replaced in our sample. The last column of Table A8 shows the number of households replaced in each cluster.

Sample Adjustment

While the initial goal was to survey 650 workers, some enumerators accidentally interviewed workers who had less than 6 months of experience in the garment sector. Generally, these workers were unable to provide much information about their job and had no job history. As a result, these 28 workers were dropped from the final sample used in this paper.

Table A8: # Interviews and Response Rates Across Clusters

	Interviews	**Refusals**	**% Refusals**	**Replaced**	**% Replaced**
Mean	14.17	0.72	5.17	0.33	1.94
SD	12.82	1.08	9.83	0.86	6.93
Min	3	0	0	0	0
Max	38	4	50	5	45.46

Note: This table summarizes the number of interviews, refusals, and replaced respondents across clusters. A refusal counts whether an eligible individual was approached and refused to respond to the interview. A replacement counts cases where enumerators attempted to interview the selected eligbile respondent two times, including once on a weekend, but were unable to find the individual at home.

C.2 Survey Instrument

The survey instrument administered to respondents contained the following sections:

1. Respondent demographics: gender, age, birth location, date of move to Dhaka (if applicable), religion, marital status, tribal status, educational attainment, vocational training, relationship to household head.

2. Household characteristics: household composition (including age and working status of every household member), household construction materials, source of light/drinking water/cooking fuel, average monthly household income, receipt of government assistance, amount of land owned, whether they owe money on a loan, nature of the loan (expected–e.g. for a wedding–vs. unexpected—e.g. for a health shock), use of bank/-mobile money account

3. Current job search: for those who are unemployed at present: whether they search for only garment sector jobs, how they are searching, which benefits they are searching for, whether they are searching for jobs with contracts, whether they are searching for jobs at compliant factories

4. Job history module:

    - Job start/end dates: Respondents were asked to recall exact year and month. If they were unable to recall the month, they were asked whether it was before or after Eid-ul-Adha, Eid-ul-Fitr, or Pohela Boisakh (Bangla New Year). They were also asked which Bangla season (6 per year) the move may have occurred.
    - Type of work: private vs. public employer vs. self-employment, whether it was garments work
    - Factory details: name of company, size of factory
    - Job details: position title, grade of position, department at factory, job tasks, number of processes
    - Formality details: compliance status of factory, whether job has ID card, type of contract (written vs. verbal vs. none), benefits stated in contract
    - Earnings and promotion: average monthly earnings at start, position at start, average monthly earnigns at end, position at end, reason for earnings increase
    - Hours at work: hours per week, number of times worked overtime
    - Work location: neighborhood of workplace, time to get to work

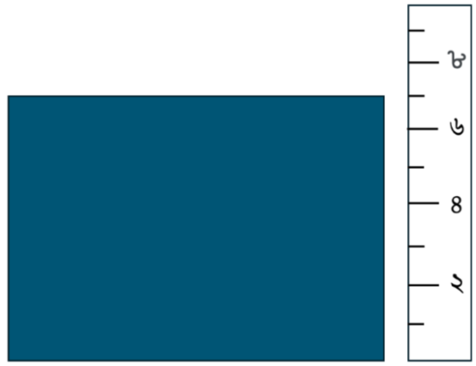
- Amenities: We asked respondents whether each of the following amenities were offered at their jobs and in what way: termination notice, childcare at work, food subsidy/free canteen, housing subsidy, maternity leave, bonus, overtime pay, training opportunities, provident fund, health facilities, travel subsidy, number of sick/casual leave days, supervisor rating at the job, whether they were abused by supervisor
- Start of work history:
  - When they first started working relative to leaving education
  - Details about first RMG industry job: questions about formality, leave policy, supervisor quality, start/end dates

5. Questions about Last Job Search: for currently employed: whether they chose between multiple offers, whether they looked for jobs with contracts, whether they looked for jobs at compliant factories, how they searched, whether offers matched actual conditions, which benefits mattered in search, knowledge about the minimum/maximum/average monthly wage of other workers in same position
6. Skills module: Numeracy + cognitive skills. Described in more detail in Section C.3
7. Choice experiment:
   - The design of the experiment is described in Section 5
   - Follow up questions: what are the benefits of compliant factories if salary, leave, overtime, and supervisor are all the same?, in general, what are the benefits of compliant factories.

C.3 Skill Measures

C.3.1 Job-relevant Numeracy Test

1. Here is a drawing of a piece of cloth with a measuring tape next to it. What is the measurement in inches of this piece of cloth? (Numbers in Bangla on the side of the ruler)



2. You are given a 30 meter long piece of cloth and are asked to cut it in half. How long are each of the remaining pieces of cloth after you cut it?
3. Let us say a garment worker can make 7 pieces in 1 hour. They work 9 hours a day. How many pieces do they make in one day?

Panel A of Table A9 describes the variation of this numeracy measure in the sample. In my analysis, I aggregate the number of correct responses on all three questions. Panel B of Table A9 shows the distribution of people getting between 0 to 3 questions correct. Respondents who answered that they didn't know were counted as incorrect for both questions. Respondents who refused to answer the question are excluded.

Table A9: Correct Answers by Question and Numeracy Score

A. % Correct by Question

Question #	% Correct
1	41.16%
2	93.89%
3	46.95%

B. Numeracy Score Distribution

Numeracy Score	% of Sample
0	4.05
1	33.17
2	38.35
3	24.43

Note: This table shows the percentage of correct answers by question and the distribution of numeracy scores across the sample.

C.3.2 Noncognitive Skills

I use the culturally-adapted Big 5 scale developed by (Islam, 2019) for Bangladeshi contexts. Respondents are asked to choose whether they think each description applies to their personality on a scale from 1 to 7. The scale was coded as follows: 1) Totally disagree, 2) Roughly

Table A10: Distribution of Noncognitive Skills in the Sample

Feature	Mean	SD
Openness	5.312	1.320
Conscientiousness	5.532	1.350
Extraversion	5.165	1.350
Agreeableness	6.145	0.985
Emotional Stability	4.642	1.293

disagree, 3) Somewhat disagree, 4) Neutral (neither agree nor disagree), 5) Somewhat agree, 6) Roughly agree, 7) Totally agree

Respondents were then asked to apply the scale to evaluate how much each of the following descriptions applied to them:

Q	Trait
1	Friendly, Active
2	Complicated, quarrelsome
3	Reliable, Self-controlled
4	Anxious, Easily upset
5	Eager to explore, Creative
6	Serious, Silent
7	Compassionate, Sincere
8	Messy, Careless
9	Sober, Calm
10	Traditional, Not Creative

The constructs in the Big 5 scale correspond to the acronym OCEAN—openness to experience (Q5, Q10), conscientiousness (Q3, Q8), extraversion (Q1, Q6), agreeableness (Q2, Q7), and neuroticism (Q4, Q9). In the adapted Big 5 scale, neuroticism is reverse coded to represent emotional stability. To calculate scale values, I take the average rating for each pair of questions corresponding to the same construct. Table A10 shows the distribution of each underlying construct in the sample.

D Data Preparation Choices

D.1 Defining Formality

In order to define what a formal factory is, I use data on reported factory names and locations. Respondents remember and report a factory name for 88% of jobs. For these, my survey team and I hand-cleaned factory names. We attempted to match reported factory name and neighborhood to factories reported in the Mapped in Bangladesh database (MIB, 2023). This database has the vast majority of compliant factories, listing which regulatory organization inspects them. It also contains a few informal factories that have been mapped in specific areas. For 52% of the jobs with factory names, we were able to find a match in the database. Of those, xx% were recorded as formal factories (i.e. inspected by one of Alliance, Accord, or National Initiative) in the database. If a job had a reported company name not matched in the database, I assume this is an informal factory.

The remaining jobs where respondents were unable to name factories require more work. For these jobs, I use two pieces of evidence about the factory's formality status. The first is whether the respondent had an ID card. ID cards are a unique feature of factories that are registered with the government. The second piece of evidence is whether the respondent reported that the factory was visited by an inspector. This matches the second part of our definition of formality—that the factory is inspected by a regulatory body.

D.2 Triangulating Job Move Periods

If the respondent was able to report the exact month and year of job move, this responses was preferred. For respondents who do not remember year of move, we cannot impute their move period. Overall, 3% of respondents report jobs for which they are unable to report either start or end years. For the current or most recent job, none of the respondents have missing start or end years.

For respondents who do not remember month of job move, we ask follow-up questions to triangulate their period of move. First, respondents are asked whether they moved before or after Eid-ul-Fitr. The dates of the two Eid festivals move each calendar year, but for years 2007-2024, Eid-ul-Fitr fell before Eid-ul-Adha. If a respondent said they moved in that year range after Eid-ul-Fitr, they were asked about the job move in relation to Eid-ul-Adha. The reverse was true in years before 2007. Then respondents were asked whether they moved before or after Pohela Boisakh, which falls in April. Respondents were next asked if they remembered the season of the Bangla calendar in which they moved. The seasons are Grishshô (April-June), Bôrsha (June-August), Shôrôd (August-October), Hemonto (October-December), Sheet (December-February), and Bôsôntô (Spring). Finally, respondents were asked about their move in relation to the beginning or end of the year (i.e. January vs. December). Based on responses to these questions, respondents were binned into a 4 month period of the year. Using this strategy, I am able to assign 96% of reported jobs to specific periods.

For remaining jobs that still had missing move periods, I impute them using data from non-missing observations in the retrospective panel. In this panel, I calculate the median duration of unemployment and nonparticipation in the panel from non-missing observations. Based on responses to whether the respondent was unemployed or not participating in the labor market, I assign them the median duration of that type of spell after a job. For example, consider a person with a missing job end date for Job 2 and who was unemployed between Job 2 and Job 1 (current job). Their end date for job 2 would be assigned so that the break between Job 2 and Job 1 was one period long.

D.3 Imputing Wage Growth

In many treatments of job search models with infrequent panel data, researchers use earnings at the start of the job as a fixed characteristic of the job over time. In this survey, I elicit information about both starting and ending earnings as well as the reason for salary increase. I use this information to impute the path of wage growth during the course of a position. This is especially important at formal sector jobs that sometimes have a short-term trial period for the job where workers may be earning very little. After the trial period, however, salaries jump significantly.

The three main reasons that a wage increase happens is: 1) promotion, 2) minimum wage bump, and 3) annual increment. Based on the stated reason given by respondents, I impute wage paths. If a respondent receives the same income over time, then they are simply assigned starting earnings in every period they are at the job.

If respondents report having a promotion, I assign their promotion to the middle period of their job duration. For workers with job durations under three years, if they experience a salary increase of more than 50%, I assume that they started the job on a trial basis. As a result, I code the promotion as happening after one four-month period.

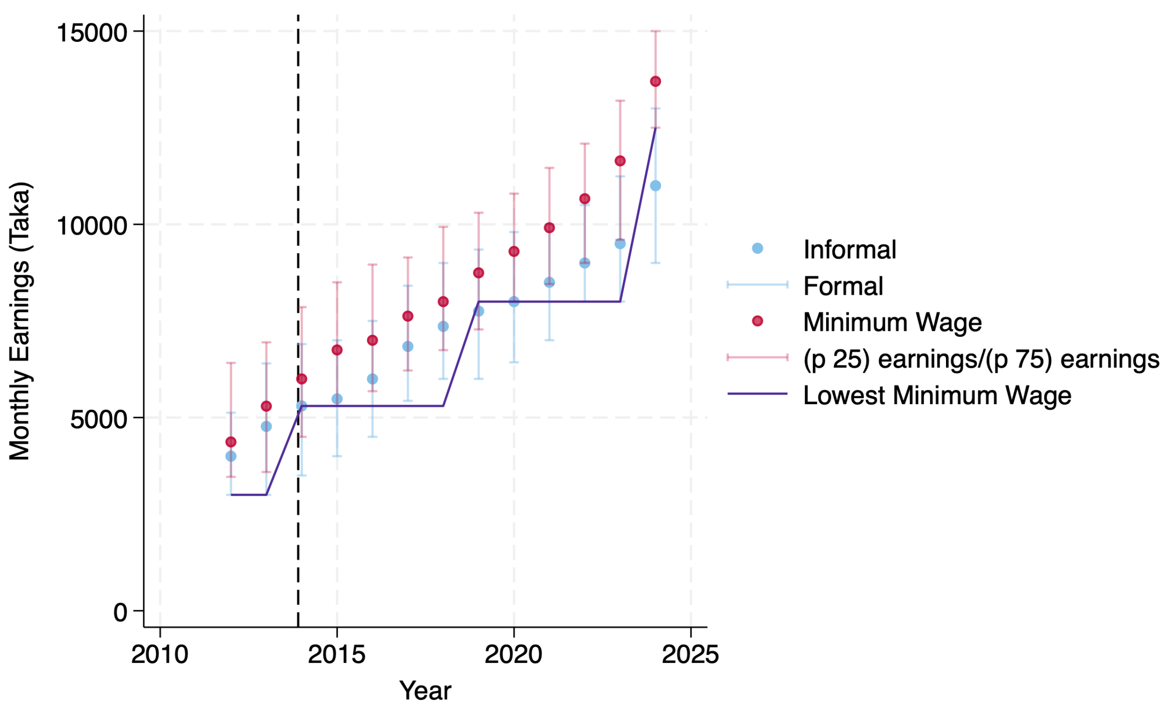
If respondents report a minimum wage bump, I change their wages everytime minimum wages were adjusted nationally over the duration of their job. Minimum wages are reported in Bangladeshi government schedules by position of the job. Based on what the worker told me their starting and ending positions are, I can thus assign them to the appropriate minimum wage level.

Finally, if respondents report an annual increment, I linearly impute wages year-to-year. As an example, consider a respondent started at 10,000 taka per month and ended at 16,000 taka per month over the course of a 2 year job. Then every third period, I would increase their salary by 1,000 taka (i.e. periods 1-2 have earnings of 10,000, periods 3-5 have earnings 13,000, and period 6 has earnings 16,000).

Respondents who have missing values for ending earnings despite citing a reason for wage increase are assigned to have stable earnings throughout the job duration. Alternatively, respondents who do not cite a reason for wage increase are assumed to be getting annual increments since this is the most common wage growth path among RMG workers.

As a verification of whether the imputation exercise reflects wage trends accurately, I compare against the formal sector minimum wage. Figure A5 plots the distribution of earnings by sector in each year and shows that earnings are above the lowest minimum wage (i.e. the minimum wage for entry-level helpers). The imputed wages keep pace with increases in the minimum wage in the formal sector. The informal sector also has wages that are increasing over time, but are less bound by minimum wage constraints, as we would expect.

Figure A5: Distribution of Earnings by Year and Sector



D.4 Imputing Missing Amenities

In addition to imputing the growth of wages, I impute missing values for certain amenities. 20% of jobs have missing values for overtime rate values and 18% of jobs have missing values for sick leave policy. These two amenities are crucial to model estimation given the choices available in the choice experiment. Missing values may not be at random—for example, respondents may be less likely to recall amenities at older job or less formal jobs that did not have a stated policy. As a result, I impute missing values using a logistic regression.

The imputation is done at the job level and includes both job and respondent characteristics. In the imputation equation, I include: job earnings, reported job formality status, job's reported export registration status[26], secondary education completion, gender, age, marital status, number of jobs worked, number of dependents in the household, household size, household ratio of dependents, household income, household debt, full-time work status, and job's ID card requirement. I also impute based on other reported amenities at the job: termination notice, holiday bonus, maternity leave, and overtime. Finally, I include start year and month fixed effects.

After running a logistic regression including all the covariates listed above, I predict whether that job has: 1) high overtime rate and 2) a flexible leave policy. This exercise allows me to fill in missing values based on patterns in the data. As a robustness check, I rerun results without imputation and report the results in Section I.1.

[26]This is an important determinant of factory size and a prerequisite for being a compliant factory by the standards of the three regulating bodies.

F Latent Class Logit Mixture Approach

The latent class logit approach I use in the paper draws from (Bhat, 1997). It uses information from the choice experiment to group respondents into C different latent classes while also modeling class membership according to demographic characteristics. The C classes are a metaparameter chosen by the researcher, which I set to 3 in this paper. Assuming C different latent classes with 5 different choice experiment questions asking respondents to choose between alternatives $m = 1, 2$, we can write the likelihood of the choice experiment as:

$$\mathcal{L}_i^{CE} = \prod_{q=1}^{5} \prod_{m=1}^{2} \left\{ \frac{\exp\left(\beta_c x_{qm}\right)}{\sum_{k=1}^{2} \exp\left(\beta_c x_{qk}\right)} \right\},$$

where x_{qm} are the features that are being varied in the choice experiment (e.g. flexible leave policies). Class membership can then be modeled with individual-specific covariates z_i as:

$$\mathbb{P}(i \text{ in class } c) = \frac{\exp\left(\theta_c z_i\right)}{1 + \sum_{d=1}^{C} \exp\left(\theta_d z_i\right)}.$$

The two levels of this model are estimated sequentially in an expectation-maximization algorithm. The algorithm is iterated until the parameter guesses converge.

G Derivation of Discretized Value Functions

$$V_k^1 = u_k + \beta \Bigg\{ \delta_1 \Bigg(\lambda_{01} \mathbb{E}_1 \left[\gamma + \ln\!\big(\exp\{V_{k'}^1\} + \exp\{V^0\} \big) \right] + \tag{A.1}$$

$$\lambda_{02} \mathbb{E}_2 \left[\gamma + \ln\!\big(\exp\{V_{k'}^2\} + \exp\{V^0\} \big) \right] + (1 - \lambda_{01} - \lambda_{02}) V^0 \Bigg)$$

$$(1 - \delta_1) \Bigg(\lambda_{11} \mathbb{E}_1 \left[\gamma + \ln\!\big(\exp\{V_{k'}^1\} + \exp\{V_k^1\} \big) \right] +$$

$$\lambda_{12} \mathbb{E}_2 \left[\gamma + \ln\!\big(\exp\{V_{k'}^2\} + \exp\{V_k^1\} \big) \right] + (1 - \lambda_{11} - \lambda_{12}) V_k^1 \Bigg) \Bigg\}$$

$$V_k^0 = u_k + \beta \Bigg\{ \delta_1 \Bigg(\lambda_{01} \mathbb{E}_1 \left[\gamma + \ln\!\big(\exp\{V_{k'}^1\} + \exp\{V^0\} \big) \right] + \tag{A.2}$$

$$\lambda_{02} \mathbb{E}_2 \left[\gamma + \ln\!\big(\exp\{V_{k'}^2\} + \exp\{V^0\} \big) \right] + (1 - \lambda_{01} - \lambda_{02}) V^0 \Bigg)$$

H All Conditional Transition Probabilities

Conditional transition probabilities are model-derived probabilities of observing a respondent move from Job m to Job ℓ given their preferences and job arrival probabilities. A job m is indexed by wage-amenity bundle (w_m, a_m) and sector s_m. We can define 11 different move types (MT) representing transitions to and from different sectors and write their model-derived probabilities as follows. These equations include job-to-job or job-to-unemployment transitions if there was a move in that period ($M = 1$) as well as people who stay employed at the same job or who stay unemployed ($M = 0$).

1. Formal to formal job-to-job transition

$$\mathbb{P}(w_\ell, a_\ell, s_\ell = 1 | w_m, a_m s_m = 1, M = 1) = \delta_1 \lambda_{01} p_{1\ell} + (1 - \delta_1)\lambda_{11} p_{1\ell} \frac{1}{1 + \exp\{v_m^1 - v_\ell^1\}}$$

2. Formal to informal job-to-job transition

$$\mathbb{P}(w_\ell, a_\ell, s_\ell = 2 | w_m, a_m s_m = 1, M = 1) = \delta_1 \lambda_{02} p_{2\ell} + (1 - \delta_1)\lambda_{12} p_{2\ell} \frac{1}{1 + \exp\{v_m^2 - v_\ell^1\}}$$

3. Informal to formal job-to-job transition

$$\mathbb{P}(w_\ell, a_\ell, s_\ell = 1 | w_m, a_m s_m = 2, M = 1) = \delta_2 \lambda_{01} p_{1\ell} + (1 - \delta_1)\lambda_{21} p_{1\ell} \frac{1}{1 + \exp\{v_m^1 - v_\ell^2\}}$$

4. Informal to informal job-to-job transition

$$\mathbb{P}(w_\ell, a_\ell, s_\ell = 2 | w_m, a_m s_m = 2, M = 1) = \delta_2 \lambda_{02} p_{2\ell} + (1 - \delta_2)\lambda_{22} p_{2\ell} \frac{1}{1 + \exp\{v_m^2 - v_\ell^2\}}$$

5. Respondent stays at a formal job (no move)

$$\begin{aligned}\mathbb{P}(w_m, a_m, s_m = 1 | M = 0) = (1 - \delta_1)\Bigg(&\lambda_{11} \sum_{i=1}^{K} p_{1i} \frac{1}{1 + \exp\{v_i^1 - v_\ell^1\}} + \lambda_{12} \sum_{i=1}^{K} p_{2i} \frac{1}{1 + \exp\{v_i^2 - v_\ell^1\}} \\ &+ (1 - \lambda_{11} - \lambda_{12})\Bigg)\end{aligned}$$

6. Respondent stays at an informal job (no move)

$$\mathbb{P}(w_m, a_m, s_m = 2|M = 0) = (1-\delta_2)\Bigg(\lambda_{21}\sum_{i=1}^{K} p_{1i}\frac{1}{1+\exp\{v_i^1 - v_\ell^2\}} + \lambda_{22}\sum_{i=1}^{K} p_{2i}\frac{1}{1+\exp\{v_i^2 - v_\ell^2\}} + (1-\lambda_{21}-\lambda_{22})\Bigg)$$

7. Respondent moves from formal job to unemployment

$$\mathbb{P}(s_\ell = 0|w_m, a_m, s_m = 1, M = 1) = \delta_1(1-\lambda_{01}-\lambda_{02}) + \delta_1\lambda_{01}\sum_{i=1}^{K} p_{1i}\frac{1}{1+\exp\{v_i^1 - v^0\}} + \delta_1\lambda_{02}\sum_{i=1}^{K} p_{2i}\frac{1}{1+\exp\{v_i^2 - v^0\}}$$

8. Respondent moves from informal job to unemployment

$$\mathbb{P}(s_\ell = 0|w_m, a_m, s_m = 2, M = 1) = \delta_2(1-\lambda_{01}-\lambda_{02}) + \delta_2\lambda_{01}\sum_{i=1}^{K} p_{1i}\frac{1}{1+\exp\{v_i^1 - v^0\}} + \delta_2\lambda_{02}\sum_{i=1}^{K} p_{2i}\frac{1}{1+\exp\{v_i^2 - v^0\}}$$

9. Respondent moves from unemployment to formal job

$$\mathbb{P}(w_\ell, a_\ell, s_\ell = 1|s_m = 0, M = 1) = \lambda_{01}\frac{1}{1+\exp\{v_0 - v_\ell^1\}}$$

10. Respondent moves from unemployment to informal job

$$\mathbb{P}(w_\ell, a_\ell, s_\ell = 2|s_m = 0, M = 1) = \lambda_{02}\frac{1}{1+\exp\{v_0 - v_\ell^2\}}$$

11. Respondent remains unemployed (no move)

$$\mathbb{P}(s_m = 0, M = 0) = (1-\lambda_{01}-\lambda_{02}) + \lambda_{01}\sum_{i=1}^{K} p_{1i}\frac{1}{1+\exp\{v_i^1 - v^0\}} + \lambda_{02}\sum_{i=1}^{K} p_{2i}\frac{1}{1+\exp\{v_i^2 - v^0\}}$$