Essays on Macroeconomics and Risk

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Economics)
in The University of Michigan
2023

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ACKNOWLEDGEMENTS

I am deeply grateful to the many people who supported me on this long journey. First, I would like to thank my incredible dissertation committee: Pablo Ottonello, Matthew Shapiro, Charlie Brown, and Toni Whited. I have learned so much from Pablo in my various roles as a student, teaching assistant, research assistant, co-author, and advisee. I am grateful for his willingness to advise on questions big and small, our many meetings that always ended with concrete lists of next steps, and his persistent optimism. Matthew ensured each of my papers has a beginning, middle, and end. His structure and guidance were crucial for getting me through each milestone, but especially the challenges of the last year. Charlie always prefaced that he is not a macroeconomist before giving some of the best comments on my work. His insights were invariably delivered with kindness and a sense of humor. Toni got me through the weeds of my model with a combination of shared codes and reassurances that I could do it even though it was frustrating. Her emails after my presentations always brightened my mood. I would also like to thank my other coauthors on my third chapter, Matias Moretti and Diego Perez, who have helped me become a better researcher through our work together.

In addition to my committee, I am thankful for the village of advisors in labor and macro at Michigan. I had many helpful meetings, conversations, and comments in lunch workshops that helped shape my dissertation. I also am indebted to the support of the current and past administration team in the economics department, especially Julie Heintz, Lauren Pulay, Laura Flak, and Chris Mueller. Thank you for ensuring my funding was processed smoothly, sending loads of recommendation letters, and processing my countless room requests to spare my officemates from listening to my Zoom meetings. Thanks also to Kai Petainen for helping me navigate Bloomberg and Dawn Reed for all of the scheduling assistance.

I am grateful to funding from the NSF Graduate Research Fellowship Program under grant number 1256260. Any opinions, findings, and conclusions or recommendations expressed in this material are my own and do not necessarily reflect the views of the National Science Foundation. I am also thankful for the opportunities provided by the AEA Summer Fellowship Program and the Federal Reserve Banks of Chicago and Richmond. These experiences introduced me to some excellent mentors and allowed me to develop my confidence as a presenter. I am especially thankful to Laura Murphy and Seula Kim for getting me through the push of the pre-job market summer.

I have been fortunate to meet many incredible colleagues and friends through this program, whose support in coursework, research, and life have been immeasurable. I am especially grateful to Leticia Juarez for sharing every minute detail of the job market process together; Tyler Radler and Katherine Richard for all of the study sessions, research chats, and practice presentations, but mostly the dinners and wine; Erin Markiewitz for the research dates and macro moral support; Nate and Faith Mather for sharing the joys and stress of this program, the job market, and pandemic wedding planning and re-planning; Aaron Kaye for being ready for a coffee break at the drop of a hat. I would also like to thank the 2017 cohort, my officemates, my gym/running buddies, and all of the others I have gotten to know, especially María Aristizábal Ramírez, Lea Bart, Erin Gibson, Chris Hollrah, Emily Horton, Max Huppertz, Stephanie Karol, Jennifer Mayo, Emir Murathanoglu, Hanna Onyshchenko, Shwetha Raghuraman, Nikhil Rao, Michael Ricks, Brock Rowberry, and Iris Vironi.

Finally, I am grateful to my family. Mom, thank you for all of the chats on my walks home from school. Dad, I hope this finally answers your question of what is in my dissertation. Grandma and Grandpa, our weekend phone calls were the highlight of my week. Erin, Mikey, Megan, and the Tranfaglias, thanks for being the best cheering squad. Lastly, thank you to my husband, John, for following me to and from Ann Arbor, weathering each phase of this process by my side, and celebrating each milestone. Cheers.

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ABSTRACT

This dissertation contains three self-contained essays in the field of macroeconomics that tackle various aspects of risk in the economy. Chapter I examines how employment risk varies by race and firm size in recessions and booms. Chapter II studies the effects of parental experiences on risk-taking in occupation choice. Chapter III studies how fluctuations in the global risk premium affect firms' investment decisions and the implications for understanding the transmission of external crises.

Chapter I studies the role of firms in the long-observed pattern that Black workers are more exposed to business cycle risk than white workers, even after adjusting for differences in industry and other cycle exposure factors. There are persistent differences in the job-finding and separation rates of Black and white workers across firms of different sizes. Black workers face higher separation rates and lower job-finding rate on average, with more extreme disparities at *small* firms. Meanwhile, when the labor market is weak, the job-finding rate falls more for Black workers, with the biggest drop coming from *large* firms. A search model with employer size-specific information frictions that captures these patterns. The abundance of available workers during downturns encourages firms to be more selective about the workers they hire, leading to worse hiring outcomes for minority workers at all firms. This selection effect can produce larger changes in hiring rates for the disadvantaged workers at firms with better screening technology, because these firms are able to capture a higher share of the matching market and they are more susceptible to general equilibrium effects.

Chapter II starts from the observation that children whose parents experience negative labor market shocks go on to earn less in adulthood. The chapter explores whether this earnings gap can be explained by the occupations that the affected children choose. The first part of the paper constructs new measures of the return and risk of expected lifetime earnings specific to initial occupation. A \$1 increase in expected lifetime earnings risk is associated with a \$1.4 increase in expected return. The next section uses linked parent-child data to exploit quasi-exogenous variation in parent experiences to study the effect of negative parental shocks on children's young adult earnings and riskiness of first occupation choice. Parents' layoffs lead children to sort into less risky occupations on average, accounting for up to 13 percent of the total gap in young adult earnings.

Chapter III studies the transmission of external crises through the microlevel patterns of firms' adjustments. The first section develops an open-economy model with heterogeneous firms that finance their investment using debt subject to default risk and face fluctuations in the risk premium required by foreign investors. The model reveals that the differential responses of firms by default risk is informative about the channels through which global risk premium fluctuations affect the economy. The next section uses firm-level data for a panel of emerging markets and show that while investment of risky firms contracts in response to increases in the global risk premium, that of risk-free firms expands. The findings imply that exchange rate depreciations play a stabilizing role during external crises for most firms in the economy, owing to more favorable prices. Devaluations are contractionary only for heavily indebted firms, for which the negative balance-sheet effects dominate the stabilizing effects of lower costs.

CHAPTER I

Firm Heterogeneity and Racial Labor Market Disparities

1.0 Abstract

Black workers are more exposed to business cycle employment risk than white workers, even after adjusting for differences in industry and other cycle exposure factors. This paper introduces a new channel to explain the excess sensitivity of Black employment: employer heterogeneity in hiring. There are persistent differences in the job-finding and separation rates of Black and white workers across firms of different sizes. Black workers face higher separation rates and lower job-finding rates on average, with more extreme disparities at *small* firms. Meanwhile, when the labor market is weak, the job-finding rate falls more for Black workers, with the biggest drop coming from *large* firms. The second half of the paper introduces a search model with employer size-specific information frictions that captures these patterns. The abundance of available workers during downturns encourages firms to be more selective about the workers they hire, leading to worse hiring outcomes for minority workers at all firms. This selection effect can produce larger changes in hiring rates for the disadvantaged workers at firms with better screening technology, because these firms are able to capture a higher share of the matching market and they are more susceptible to general equilibrium effects.

1.1. Introduction

The Black population in the U.S. faces persistently lower rates of employment than the white population. Additionally, Black employment responds more to macroeconomic conditions, rising more during expansions but also falling more during contractions. For example, over the peak to trough of the Great Recession, the Black employment rate fell by 4.5 percentage points whereas the white employment rate fell by 3.2 percentage points. Understanding the differences in exposure to aggregate labor market risk is important both for addressing persistent racial economic disparities and also for designing equitable stabilization policies in response to downturns.

This paper explores the role of firm heterogeneity and information frictions in explaining the higher aggregate employment volatility for Black workers. The empirical section shows that Black workers face especially higher separation rates and lower job-finding rates at small firms, consistent with the fact that Black workers are more likely to be employed by large firms. Meanwhile, when the economy contracts, the reduction in job-finding for Black workers at large firms is the strongest driver of the worsening employment gap. Motivated by existing micro-level research, the second half of the paper builds a model in which heterogeneous workers and firms meet in a labor market with information frictions. Minority workers face more severe information frictions, particularly at small firms, which generates a lower minority employment rate and a higher propensity for minority workers to be employed by large firms. The model is also consistent with the pattern that large firms contribute most to the worsening employment gap when the economy is weak.

In the empirical section, I document differences in employer-type specific transition rates by race and how they vary with aggregate conditions. I use micro-level data to adjust for differences in industry composition, geography, and other factors. Over my sample period of 1996 to 2012, the Black separation rate was 0.09 percentage point higher on average than the white separation rate, after controlling for worker and job characteristics. This headline number masks considerable heterogeneity across employer types, with separations at large firms roughly twice as high and separations at small firms three times as high. Meanwhile, the rate at which Black workers moved from nonemployment to employment was 0.76 percentage point lower than for white workers, with -0.59 percentage point of that gap coming from small firms and only -0.07 percentage point from large firms.

Next, I examine how these patterns change with aggregate conditions in the economy. When the headline unemployment rate is high, separations increase and job-finding decreases. For Black workers, the drop in the job-finding rate at large firms is especially large, falling by nearly twice as much as the job-finding rate for white workers. Given the already high separation rate for Black workers, the decrease in job-finding is especially important, contributing to the lower overall employment rate during these periods.

In Section 4, I develop a model to study how information frictions in the hiring process across firms contribute to the patterns in the data that Black workers are more likely to work for large firms and that large firms contribute more to the worsening of the the job-finding gap when the labor market is weak. I start with a canonical random search model and introduce three main ingredients: endogenous firm size, uncertain worker productivity, and differences in screening technology across worker groups and firm sizes. The first two ingredients create a trade-off for firms between recruiting intensity and selectivity. If firms choose a high selectivity strategy, they pay high search costs but the workers they recruit are very likely to be productive so the cost of turnover is lower. Alternatively, if they choose a low selectivity strategy, they pay lower search costs but higher turnover means they pay more wages to workers who end up separating quickly.

I assume that small firms have worse screening technology than large firms and that all firms receive noisier signals about minority worker productivity. The first assumption implies that the benefit of screening workers is lower for small firms and they will choose a lower selectivity strategy than large firms. This produces higher turnover rates at small firms. The second assumption generates the lower employment rate for minority workers. More noise in the signal for minority worker productivity means firms identify fewer minority workers who satisfy their hiring criteria, leading to negative job-finding gaps at both types of firms. The combination of both assumptions generates the higher share of minority employment at large firms and more severe job-finding gaps at small firms.

The model predicts that the racial employment gap can worsen with lower aggregate productivity. Decreased demand for labor leads to a decrease in market tightness, allowing firms to attract more applicants per unit of search intensity. Thus, the relative cost of the high selectivity strategy decreases, which negatively affects minority workers. The effect is more severe at large firms because their more efficient screening technology enables them to capture more of the market for matches and makes them more sensitive to general equilibrium effects on wages.

Related literature

This paper contributes to several major strands of the literature. First, there is an extensive literature studying the excess sensitivity of Black employment to macroeconomic conditions (Couch and Fairlie, 2010; **?**; **?**; **?**; to name a few). Most of these papers focus on the stylized fact that the Black unemployment rate is roughly double the white unemployment rate and this ratio is constant over the business cycle. They conclude that this pattern is maintained because Black workers are last hired and first fired in response to shocks. My finding that the job-finding margin is the most gap for Black workers during downturns is consistent with recent evidence by Forsythe and Wu (2021) and Kuhn and Chancí (2021). Another related area of research is considering the effects of monetary policy on racial inequality (see Bartscher et al., 2021; Lee et al., 2022; Bergman et al., 2020; Thorbecke, 2001; **?**; Zavodny and Zha, 2000). This literature demonstrates the policy interest of understanding how racial differences evolve over the business cycle. My paper contributes to this literature by introducing the role of employer heterogeneity, which is interesting on its own for understanding how shocks permeate through the economy, but also could have important implications for economic policies that interact with the firm size distribution.

Second, there is a large micro literature documenting racial disparities and discrimination in the labor market (see **?** for an overview). The fact that Black workers are more likely to be employed by large firms was documented by **?** and has more recently been emphasized by **?** and **?**. Morgan and Várdy (2009) shows that if firms are sufficiently selective, then differences in "discourse systems" that make it harder for firms to evaluate minority workers will lead to underrepresentation of minorities. **?** uses this framework to show that differences in referral networks can lead minority workers to disproportionately sort to large firms (Okafor (2022) highlights a similar mechanism without firm size). My paper builds on this literature by evaluating the role of this type of information friction with endogenous firm size and endogenous wages. My model could be easily adapted to study disparities along other dimensions besides race, whenever one group faces stronger information frictions due to differences in professional networks or other reasons.

Finally, the macro literature has studied the role of firm heterogeneity in labor market fluctuations. Empirically, **?** and Haltiwanger et al. (2018) show the importance of job creation at large firms for aggregate employment fluctuations. Other papers have introduced firm heterogeneity and endogenous size in the canonical random search model (Elsby and Michaels, 2013), and shown that information frictions are important in this context (**?**). My paper extends these findings to show that firm heterogeneity and information frictions are important to understanding both the persistence of racial employment gaps and their relationship to aggregate economic conditions.

Outline

The rest of the paper proceeds as follows. Section 1.2 describes the data and background empirical facts. Section 1.3 provides empirical evidence of job flows by race and firm size. Section 1.4 introduces the model and describes the channels through which employer composition affects employment fluctuations by race. Section 1.5 describes the model calibration and results. Section 1.6 provides counterfactuals. Section 1.7 concludes.

1.2. Background Empirical Facts

1.2.1 Data

Survey of Income and Program Participation (SIPP)

My primary data source is the Survey of Income and Program Participation (SIPP), which provides high-frequency information on workers' transitions between employment states and employer types in combination with details about worker occupations, education, and other characteristics. Relative to the Current Population Survey (CPS), which is commonly used to study employment transitions, the SIPP is a smaller survey and is designed to be representative at the national level but not the state level. The main advantage of the SIPP is that it asks workers about the size of their employer, which can be matched to the employment transitions data. I define large firms as those with 100 employees or more, as firms above that threshold are not further disaggregated during my sample period. By this definition, roughly 60% of privately employment is at large firms over the course of my sample. I primarily use this dataset for studying worker transitions between employment states.

The SIPP is a rotating panel that interviews households every four months for approximately 3-4 years. Each panel has a nationally representative sample of households, leading to a sample size of about 80,000 to 100,000 adults per panel. Interviews are staggered such that one quarter of the sample is interviewed during each month. In each interview, household members are asked about their weekly labor force status over the previous 18 weeks. Employed workers are asked to provide details about up to two jobs per interview period, including start and end date, firm size, occupation, industry, and type of employer (e.g. private employer or government). They are also asked about similar details for up to two businesses they own. Both jobs and businesses are assigned an identifier so that they can be tracked across interview waves.

I will be using data from the 1996, 2001, 2004, and 2008 panels.[1] For most of my analysis I will be focusing on individuals aged 20 or older who self-identify as non-Hispanic white or Black. This gives me a sample of about 286,000 individuals who I observe for an average of 22 months.

In order to study differences in employment rates and transition rates by employer type, I start by assigning each person to a monthly labor force state using their labor force status for week corresponding to the BLS convention, as described by **?**. I first assign workers as either employed or non-employed (either unemployed or out of labor force). I am choosing to

[1]For the 2008 panel, I only use waves 1-10 of 16 due to a change in the firm size survey instrument. See Appendix A.1.1 for details on the construction of firm size and the discrepancy in the later waves of the 2008 panel.

focus on non-employment rather than unemployment because I want to focus on differences between employers rather than differences in labor force participation behavior over the business cycle. To address the problem of seam bias, whereby respondents are more likely to report employment transitions over the months between survey waves, I exclude the first month of each four-month panel (**?**).

For workers who are employed, I use the job and business history information, particularly start and end dates, to match their employer characteristics to their employment status. I assign each employed worker-month observation to one of four mutually exclusive employer classifications: large firm, small firm, government, or self-employed. For workers who are simultaneously employed by two jobs, I select the job that has higher reported hours, with longer tenure used as a tie-breaker. I only classify a worker as self-employed if they do not work for another employer during that month. I am able to classify 99% of workers who report being employed to their employer type. This classification is not 100% because some workers have more than two employers over the four month survey period so I only observe the two that they choose to describe in the interview, or there may be inconsistencies in the start/end dates.

Current Population Study (CPS)

For additional motivation, I use the CPS to show aggregate employment patterns by race. As with the SIPP, I include all individuals aged 20 and older.

As a validation for my measures of firm size in the SIPP, I use the March Annual Social and Economic Supplement (ASEC), which provides an annual snapshot of employment and employer composition, but lacks the detailed transition dynamics from the SIPP. The survey asks questions about all household members' current employment status, as well as more detailed questions about the main job they held in the previous year. This includes industry, occupation, earnings, and notably, firm size. The firm size variable is also more detailed than the variable in the SIPP, allowing me to present sorting patterns with alternative thresholds. My sample covers individuals aged 18-65 for calendar years 1987-2019. The sample size varies from about 75k to 115k adults per year.

1.2.2 Employment over the Business Cycle

The Black employment-to-population ratio is consistently lower than the white employment-to-population ratio. The solid orange line in Panel (a) of Figure 1.1 plots the level difference in these ratios for the Black relative to the white population. Additionally, the gap exhibits strong business cycle sensitivity, tending to become more negative around the shaded NBER recession periods. The correlation with the headline unemployment rate is -0.8, meaning that when the unemployment rate is higher, the Black employment rate tends to fall by more.

Some of the difference in employment rates can be explained by differences in demographics, occupation, industry, or geography, but the cyclical pattern cannot. The dashed blue line in Figure 1.1 shows the conditional gap, which is the portion of the gap that cannot be explained by observable worker characteristics within each month.[2] To estimate this conditional gap, I use a Oxaca-Blinder decomposition within each month, described in Appendix A.1.2. If the Black employment rate tended to fall more during downturns because Black workers were more likely to work for volatile industries, for example, then the cyclical pattern should disappear after controlling for time-specific industry effects. As seen in Figure 1.1, this is not the case. The conditional gap has a lower absolute value mean and the variance is lower, but the correlation with the business cycle is still high. For example, the correlation between the conditional employment gap and the headline unemployment rate is -0.81.

For comparison, Panel (b) shows that the Hispanic employment rate has exceeded the white employment rate over the last couple of decades, as seen in the solid blue line. However, it is still slightly lower than would be predicted by worker characteristics, and is countercyclical, with a correlation of -0.5 with the headline unemployment rate.

Appendix Figure A.2 reports the raw and conditional employment gaps separately by gender. Although the raw gaps exhibit substantially different patterns by gender, the conditional gaps are similar. Appendix Table A.1 summarizes these gaps and their correlations with the unemployment rate. The countercyclical employment gap for Black workers also holds when measured in logs rather than levels. Appendix Figures A.3 and A.4 show the employment gaps across and within genders in logs rather than levels, and Table A.2 summarizes. Appendix A.1.2 provides more details and discussion about each of these exercises.

1.2.3 Heterogeneity in Employer Composition

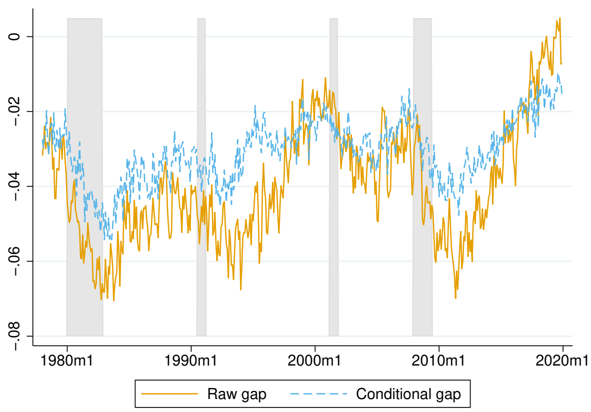
To illustrate the differences in employer composition, I plot the average distribution of employers for non-Hispanic white and Black and Hispanic employed workers over 1988 to 2019. Figure 1.2 shows that for both white and Black workers, large firms make up the majority of employers, but this difference is even larger for Black employees. Meanwhile, Hispanic workers are overrepresented in small firms.

To evaluate how much of this difference in employer composition is attributable to

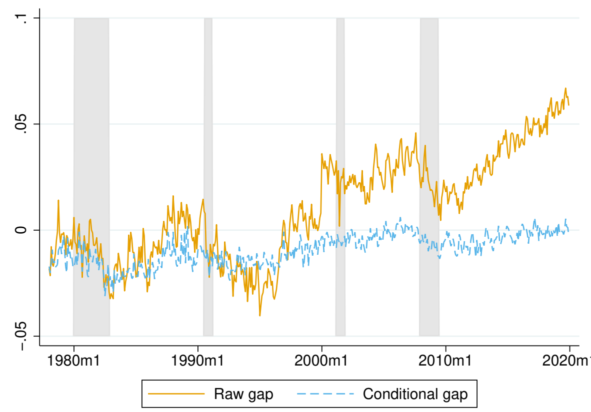
[2] The controls are an age quadratic by gender, marital status by gender, occupation, industry, state, and metro area size.

Figure 1.1: Employment-to-population ratio relative to white

(a) Black



(b) Hispanic



Source: CPS.
The solid (Raw gap) line plots the employment-to-population ratio for the Black and Hispanic populations relative to the white population. The mean is -3.9 percentage points and standard deviation 1.6. The dashed (Conditional gap) line plots the within-month employment gap, conditional on an age quadratic by gender, marital status by gender, occupation, industry, state, and metro area size. The mean is -3.1 percentage points and standard deviation 0.9.

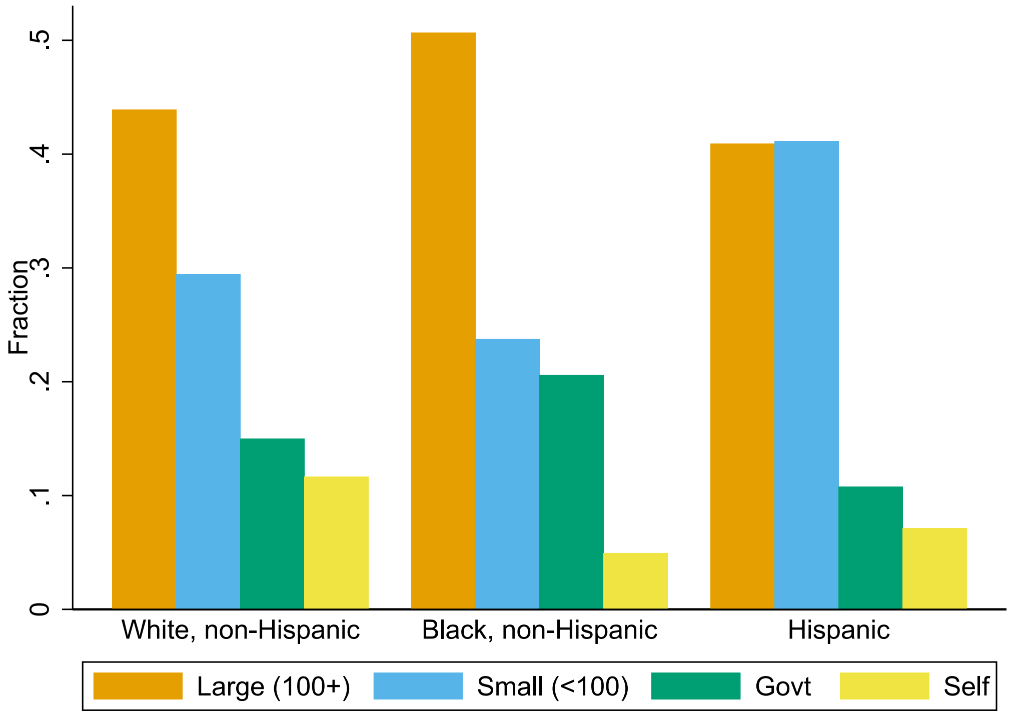
differences in industry, occupation, location, and other observable features, I use a linear probability model and regress an indicator for working for each type of employer on a number of observable worker characteristics and a race/ethnicity-specific dummy variable. Figure 1.3 shows that while differences in government and self employment are somewhat explained by differences in observable variables, the gap in firm size is not. Appendix Table A.3 reports similar patterns using a higher threshold and with data from the SIPP.

Meanwhile, the massive gap in the likelihood of working for small firms for Hispanic workers is largely explained by differences in industry and other characteristics. Due to these different patterns in the employment gap over time and employer composition, I will limit my focus to Black and white non-Hispanic workers, though there is clearly more heterogeneity to be explored in future work by examining other racial and ethnic groups. The limited sample size of the SIPP and limited detail about race and ethnicity also make it difficult to expand further to other minority groups with precision.

1.3. Empirical Evidence

The previous section showed that Black employment is more cyclically sensitive than white employment and that Black workers are more likely to work for large firms. This section will show how differences in job-finding and separation rates vary by race and firm size both on average and over the business cycle.

Figure 1.2: Employer composition by race and ethnicity



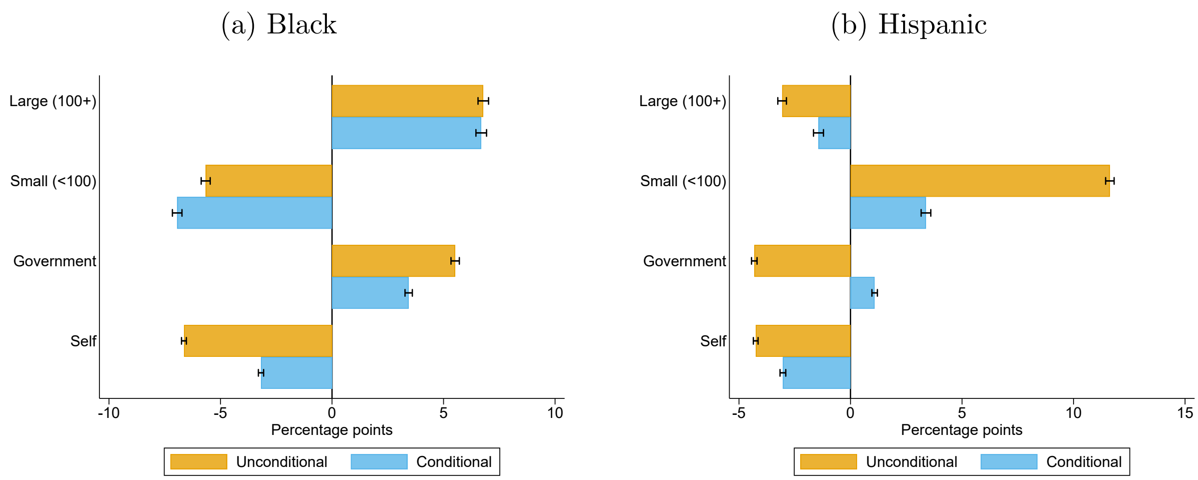
Source: ASEC supplement to the CPS
Bars represent the average annual fraction of workers who report each employer type as their primary job over the prior year. The sample covers the adult population aged 18-65 from 1988-2020.

1.3.1 Transition rates by race

Before exploring heterogeneity by firm size, I start by documenting patterns in employment transitions by race in the SIPP and how they vary with aggregate conditions in the economy. In particular, I define high UR months as those in which the difference between the headline unemployment rate and its time-varying noncyclical rate of unemployment is in the top third of monthly observations.[3] Of the 181 months in my sample, 55 are considered high UR by this measure. I choose this binary measure as the baseline specification rather than the continuous gap because it maps better to the steady state comparison in the model. Additional results using continuous measures are reported in Appendix A.2. I choose to focus on the top third of unemployment deviations from trend rather than the top half to isolate more severe periods.

[3]The noncyclical rate of unemployment replaced the natural rate of unemployment, published by the Congressional Budget Office. I construct the thresholds using the full sample of data from 1949 to 2023.

Figure 1.3: Employment composition relative to white



Source: CPS.
Conditional estimates control for age, age-squared and education by gender, occupation, industry, state, and metro area size.

I start with a linear probability model, with the following specification,

$$s_{it}^N = \alpha + \alpha^B \text{Black}_i + \beta \text{HighUR}_t + \beta^B \text{Black} \times \text{HighUR} + \Gamma X_{it} + \epsilon_{it}, \tag{1.3.1}$$

where s_{it}^N is an indicator equal to 1 if individual i is nonemployed in month t conditional on being employed in month $t-1$; Black_i is a racial dummy variable; HighUR_t is an indicator for whether month t is in the top tercile of unemployment gap deviations from trend; and X_{it} is a vector of worker and lagged job characteristics. Worker characteristics are age, age-squared, and marital status, all interacted with gender; education; geographic region; and an indicator for large metro area. Job characteristics are industry; occupation; and length of employment spell in years. I also include fixed effects for calendar month. Given that the variation is at the month level, I cluster standard errors by time.

The point estimates for the main coefficients of interest are reported in Panel (a) of Table 1.1. Starting in column 1, Black workers are 0.09 percentage points more likely to separate from employment than white workers in the reference periods. Moving to columns (2)-(3), this gap is somewhat smaller when we consider men and women separately, but still positive. In high unemployment months, all workers are about 0.05 percentage points more likely to separate from employment, with this effect being driven by men. Finally, separations for Black workers do not rise disproportionately in the SIPP data during high unemployment months.

Next, I document the patterns for job-finding rates, where I use the model,

$$f_{it} = \alpha + \alpha^B \text{Black}_i + \beta \text{HighUR}_t + \beta^B \text{Black} \times \text{HighUR} + \Gamma X_{it} + \epsilon_{it}, \tag{1.3.2}$$

where f_{it} is an indicator if worker i becomes employed in month t after not being employed in month $t-1$; X_{it} includes the same worker characteristics as in the separations model, but instead of job characteristics, it includes the length of the nonemployment spell in years; an indicator for whether the spell started before the sample; and an indicator for new entrants to the labor market.[4] I include fixed effects for calendar month to capture seasonal dynamics. Standard errors are clustered by month.

The main coefficient results are shown in Panel (b) of Table 1.1. Starting in first row, Black workers are 0.76 percentage points less likely to move from nonemployment to employment in the reference periods. This effect is strongest for Black men, who are 1.3 percentage point less likely to move from nonemployment to employment than white men. In high unemployment months, the average job-finging rate decreases by 0.62 percentage point, with a stronger effect for men at 0.77 percentage point. Black workers face an especially low job-finding probability in high unemployment months. For the full sample, Black workers are an additional 0.23 percentage point less likely to move into employment, which adds about 30% to the average racial gap. The results are much weaker for men, with a negative but statistically insignificant coefficient on the interaction term. For Black women, the effect is especially strong, with the job-finding rate falling by 0.29 percentage point, or about 80% of the average racial gap.

1.3.2 Transition rates by race and firm size

Given the aggregate patterns of transition rates in the SIPP, I next study how these vary with firm size.

For separations, I modify the framework above to allow for size-specific interactions on the main coefficients of interest,

$$s^N_{ijt} = \alpha_j + \alpha^B_j \text{Black}_i + \beta_j \text{HighUR}_t + \beta^B_j \text{Black} \times \text{HighUR} + \Gamma X_{ijt} + \epsilon_{ijt}, \tag{1.3.3}$$

where s^N_{ijt} is the probability that worker i moves from employment at type j firm in month $t-1$ to nonemployment in month t; worker and job characteristics, X_{ijt} are the same as above.

The results are reported in Panel (a) of Table 1.2. Column (1) repeats the result from

[4]For nonemployment spells that start before the survey period, respondents are asked when they last held a job, up to two years earlier. This indicator captures those individuals whose spell length is longer than two years prior to the start of the survey.

Table 1.1 for comparison. Columns (2)-(5) report the size-specific coefficents of interest from equation (1.3.3). The higher separation rate for Black workers is coming from large and small firms, with Black workers facing a 0.18 percentage point higher separation rate at large firms relative to white workers at large firms, and 0.27 percentage point gap at small firms. In high unemployment months, the separation rate generally increases, with the largest increase coming from small firms. The gap in separation rates between Black and white workers does not appear to worsen in high unemployment months, with negative and statistically insignificant coefficients for both large and small firms. Separations from self employment appear to worsen for Black workers.

Turning next to job-finding rates, I modify the linear model to include separate outcome variables for moving into employment at each type of firm,

$$f_{ijt} = \alpha_j + \alpha_j^B \text{Black}_i + \beta_j \text{HighUR}_t + \beta_j^B \text{Black} \times \text{HighUR} + \Gamma_j X_{it} + \epsilon_{it}, \tag{1.3.4}$$

where f_{ijt} is the probability of worker i moving from nonemployment in month $t-1$ into employment at a type j firm in month t. The sum of these firm-type specific job-finding rates is equal to the total job-finding rate, $f_{it} = \sum_j f_{ijt}$.

The results are reported in Panel (b) of Table (1.2). Column (1) repeats the coefficients from the aggregate model, given by equation (1.3.2), for comparison. Black workers face lower job finding rates relative to white workers with similar characteristics across all types of employers except government. The gap in job-finding rates at small firms is especially wide, with Black workers facing a 0.59 percentage point lower probability of moving into employment at a small firm. In high unemployment months, the job-finding rate decreases across all types of employers. The gap in job-finding rates between Black and white workers worsens in high unemployment months, with the effect entirely driven by the change in job-finding at large firms. Black workers are 0.23 percentage point less likely to move into any type of employment and 0.24 percentage point less likely to move into large firm employment in high unemployment months.

1.3.3 Alternative specification

The results that job-finding rates are especially low for Black workers in high-unemployment months and that this is driven by large firms are robust to using a logit model rather than the linear model.

In particular, I use the following model for separations,

$$s_{it}^N = \frac{\exp\left(\alpha^B \text{Black}_i + \beta \text{High UR}_t + \beta^B \text{Black} \times \text{High UR} + \Gamma X_{it}\right)}{1 + \exp(\alpha^B \text{Black}_i + \beta \text{High UR}_t + \beta^B \text{Black}_i \times \text{High UR}_t + \Gamma X_{it})} \tag{1.3.5}$$

in which s_{it}^N is the probability of worker i moving to nonemployment in month t, conditional on being employed in month $t-1$, and controls are the same as the linear version. Standard errors are clustered by month. The estimates for the main coefficients of interest are reported in Panel (a) of Table 1.3. The first column pools all workers and the second two re-estimate the model separately by gender. Black workers have consistently higher separations to nonemployment than white workers, as seen by the positive coefficient on the Black dummy variable, with a particularly higher rate of separations for Black men. The coefficients can be interpreted as the log difference in the ratios of the separation probability to the job-staying probability for each indicator, for Black relative to white workers. The ratio of separating to job-staying is about 6.5 percent higher for Black workers. This ratio increases by about 4.9 percent when the unemployment rate is high, with the increase concentrated among men. However, we observe negative and statistically insignificant interactions effects for Black workers in high unemployment periods.

Next, I use the following model for job finding,

$$f_{it} = \frac{\exp\left(\alpha^B \text{Black}_i + \beta \text{High UR}_t + \beta^B \text{Black}_i \times \text{High UR}_t + \Gamma X_{it}\right)}{1 + \exp(\alpha^B \text{Black}_i + \beta \text{High UR}_t + \beta^B \text{Black}_i \times \text{High UR}_t + \Gamma X_{it})} \tag{1.3.6}$$

in which f_{it} is the probability of worker i moving to employment in month t, conditional on being nonemployed in month $t-1$, and controls are again the same as in the linear model, with standard errors clustered by month. The estimates for the main coefficients of interest are reported in Panel (b) of Table 1.3. Conditional on observable characteristics, the Black job-finding rate is significantly lower in general, especially for Black men. Considering the first column, the ratio of job finders to those staying nonemployed is 28% lower for the Black population. In the high unemployment state, the ratio of job-finders to those staying in nonemployment is about 28% lower as well. For the Black population, that ratio is an additional 8% lower, indicating that the changes in job-finding are particularly important for the changes in Black employment in high-unemployment months.

I modify the model of separations to nonemployment to allow for separate effects by employer type,

$$s_{ijt}^{N} = \frac{\exp\Big(\alpha_j + \alpha_j^B \text{Black}_i + \beta_j \text{High UR}_t + \beta_j^B \text{Black}_i \times \text{High UR}_t + \Gamma X_{it}\Big)}{1 + \exp\Big(\alpha_j + \alpha_j^B \text{Black}_i + \beta_j \text{High UR}_t + \beta_j^B \text{Black}_i \times \text{High UR}_t + \Gamma X_{it}\Big)} \tag{1.3.7}$$

in which s_{ijt}^N is the probability of worker i moving to nonemployment in month t, conditional on being employed at a type j employer in month $t-1$. I estimate coefficients on the race variable and macroeconomic conditions separately by employer type. The worker and firm characteristics are the same as above. To avoid overfitting the model, I do not estimate these separately by firm size. Standard errors are clustered by month.

The results are shown in Panel (a) of Table 1.4. The first column repeats the results from estimating equation (1.3.5), as shown in Table 1.3. The next four columns report the coefficients interacted with firm size or employer type, from equation (1.3.7). Black workers face higher separation rates across employers, with the exception of government employers, and the results are all statistically significant. For the difference in separation rates by high-unemployment months, the results are similarly noisy. Separation rates tend to be higher on average in high unemployment months but lower for Black workers, similar to the aggregate pattern.

Moving next to job-finding rates, I modify the logit model to incorporate multiple outcome variables,

$$f_{ijt} = \frac{\exp\Big(\alpha_j^B \text{Black}_i + \beta_j \text{High UR}_t + \beta_j^B \text{Black}_i \times \text{High UR}_t + \Gamma_j X_{it}\Big)}{1 + \exp\Big(\alpha_j^B \text{Black}_i + \beta_j \text{High UR}_t + \beta_j^B \text{Black}_i \times \text{High UR}_t + \Gamma_j X_{it}\Big)}, \tag{1.3.8}$$

where f_{ijt} is the probability of moving from nonemployment in month $t-1$ to employment at a type j firm in month t, and the sum of these probabilities across types of employers sums to the total, $\sum_j f_{ijt} = f_{it}$. The individual controls are the same as in the aggregate specification. Standard errors are clustered by month.

Panel (b) of Table 1.4 reports the results. Column (1), again, repeats the results from equation (1.3.6). Columns (2)-(5) report the coefficient results from equation (1.3.7). To interpret the baseline differences, the relative probability of moving to a large firm rather than staying nonemployed is about 8.5 percent lower for Black workers than for white workers. The same relative probability for small firms is about 63 percent lower for Black workers. Thus the baseline differences in job-finding rates at each type of firm are quantitatively large, consistent with the strong sorting patterns shown earlier.

Next, looking at the differences by high-unemployment months, the probability of moving to a large firm relative to staying nonemployed decreases by about 27 percent for white workers in high unemployment months. The decrease in this ratio for small firms is relatively similar at 28 percent. Meanwhile, for Black workers, the decrease in the relative probability of moving to a large firm falls by an additional 12 percent. Given that the proportional changes are similar for white workers between small and large firms, this change cannot be simply explained by the higher exposure of Black workers to larger firms.

1.3.4 Heterogeneity by separation type

I explore the separation findings in more detail using individuals' self-reported reasons for jobs ending. For this exercise, I consider all workers employed by large or small firms based on their job start and end dates. I define a separation as the month of the job end date. I then classify each separation as voluntary or involuntary based on the reasons workers report. I compare how these separations change with firm size, race, and aggregate conditions with the following regression,

$$s^k_{ijt} = \alpha_j + \alpha^B_j \text{Black}_i + \beta_j \text{HighUR}_t + \beta^B_j \text{Black} \times \text{HighUR} + \Gamma X_{ijt} + \epsilon_{ijt}, \qquad (1.3.9)$$

$k \in \{all, vol, invol\}$, and s^k_{ijt} is the total (all), voluntary (vol) or involuntary ($invol$) separation probability for worker i from firm size j in month t; X_{ijt} contains standard worker worker characteristics–age, age-squared, and marital status by gender, education, geographic region, metro area size–as well as job-specific characteristics–job tenure in years, log wage, hours, union membership, and industry.

The main coefficients are reported in Table 1.5. Starting with total separations reported in Column (1), there is little difference in separation rates for Black workers relative to white workers at either small or large firms. However, Columns (2)-(3) show that there are meaningful differences in separations by type. Black workers are 0.71 percentage point less likely to voluntarily separate from small firms, whereas they are 0.56 percentage point more likely to separate involuntarily. These patterns are smaller in magnitude at large firms with voluntary separations -0.48 percentage point lower and involuntary separations 0.38 percentage point higher.

Similarly, total separations decrease in high unemployment months, by roughly the same amount at large and small firms. This effect is driven by voluntary separations, which decrease by more at small firms, whereas involuntary separations increase at both types of firms, but especially at small firms, with an increase of 0.92 percentage point. There does not appear to be a meaningful extra difference in separations for Black workers at either type of firm in high unemployment months, even when comparing voluntary and involuntary.

1.3.5 Empirical Summary

Overall, the evidence in this section shows two main patterns. First, Black workers face higher separation rates and lower job-finding rates across firms, but particularly at small firms. Second, in a slack labor market, Black workers face especially lower job-finding rates, particularly at large firms. Appendix A.2 reports additional results. Appendix Tables A.4 and A.5 report the results from Table 1.2 separately by gender. Appendix Tables A.6 and A.7 report the results from Table 1.5 separately by gender. Appendix Table A.8 repeats the main results with a continuous interaction term with the unemployment gap rather than an indicator for top tercile months. Appendix Table A.9 presents results with the state-level unemployment rate. The results are robust across measures of aggregate conditions and generally stronger for women than men.

The remainder of the paper will focus on one explanation for why we observe more Black workers employed at large firms and evaluate whether this mechanism generates the two patterns described. I choose to focus on the role of information frictions in the hiring process because it is an explanation that has empirical support in the literature and emphasizing hiring is intuitive, given the importance of the job-finding margin in the empirical results presented. **?** show that referral networks are important for new hires at small firms, and that given racial differences in entrepreneurship, Black workers have less developed networks at these firms. As firms grow, these referrals become less important and the racial gap in hiring narrows. I will model this mechanism in a concise way as a difference in the precision of the signal about a worker's productivity that varies by race and firm size. This mechanism is also consistent with large firms having more sophisticated human resources departments or experienced hiring managers that allow them to evaluate workers more equitably.

In the model, the only difference between Black and white workers will be this difference in information quality in the hiring process. Thus, the model is not designed to capture the full scope of racial differences in hiring and separations because it fails to explicitly model the many other factors that create disparities in the labor market between Black and white workers, such as employer prejudice (**?**), intergenerational wealth (Toney and Robertson, 2021), interactions with the criminal justice system (Holzer et al., 2005), to name just a few. Nonetheless, it is informative to see that the model directionally produces the empirical finding that job-finding rates for Black workers at large firms are especially sensitive to aggregate conditions in the labor market.

The model will be disciplined by average moments from the data, such as the job-finding rate by firm size and the Black share of employment by firm size. In order to make these moments consistent with the setting of the model, I make two adjustments to the raw data. First, I take the means for white workers in low-unemployment periods as given and then back out the means for Black workers using the gap after conditioning on worker and job characteristics, as described earlier in this section. Given that I do not have differences in industry and education in the model, I want to consider the difference in rates between Black and white workers that cannot be explained by these factors. Second, I restrict my sample to individuals who are nonemployed or employed by a large or small firm in the current period and who were in one of these three categories in the previous period, i.e. I exclude workers who moved into nonemployment from a government employer. I rescale the reference-group mean job-finding rates by a factor of $1/(0.79)$ to account for the fact that large and small firms make up 79% of job-finding for white workers, as reported in the means in Table 1.2. The conditional gaps and reference-group means are reported in Table 1.6. I use these estimates and the Black share of the population in the SIPP to construct a set of average moments that will be used in disciplining the model and evaluating its fit. The moments are reported in Table 1.7.

Table 1.1: Transition rates by race and aggregate unemployment

(a) Separations: E to N			
	(1)	(2)	(3)
	All	Men	Women
Black	0.09	0.08	0.08
	(0.03)	(0.04)	(0.04)
High UR	0.05	0.14	-0.04
	(0.04)	(0.05)	(0.04)
Black × High UR	-0.08	0.01	-0.13
	(0.05)	(0.07)	(0.07)
N	3,701,235	1,900,483	1,800,752
R^2	0.01	0.01	0.01
Black mean	1.60	1.52	1.66
White mean	1.30	1.17	1.44

(b) Job-finding: N to E			
	(1)	(2)	(3)
	All	Men	Women
Black	-0.76	-1.30	-0.36
	(0.06)	(0.09)	(0.07)
High UR	-0.62	-0.77	-0.53
	(0.09)	(0.11)	(0.07)
Black × High UR	-0.23	-0.10	-0.29
	(0.09)	(0.14)	(0.10)
N	2,226,789	837,928	1,388,861
R^2	0.04	0.05	0.04
Black mean	2.65	2.81	2.53
White mean	2.39	3.01	2.01

The table reports differences in separation and job-finding rates by race and macroeconomic conditions. The units are percentage points. Panel (a) reports the estimates for separation rates from equation (1.3.1). Panel (b) reports the estimates for job-finding rates from equation (1.3.2). All specifications include controls for age, age-squared, and marital status (interacted with gender in column (1)); education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table 1.2: Transition rates by race, aggregate unemployment, and firm type

(a) Separations: E to N					
	(1)	(2)	(3)	(4)	(5)
	All	Large	Small	Government	Self
Black	0.09	0.18	0.27	-0.30	0.01
	(0.03)	(0.05)	(0.07)	(0.04)	(0.07)
High UR	0.05	0.07	0.10	0.07	-0.01
	(0.04)	(0.05)	(0.06)	(0.08)	(0.04)
Black × High UR	-0.08	-0.11	-0.21	0.05	0.29
	(0.05)	(0.08)	(0.14)	(0.09)	(0.15)
N	3,701,235	3,701,235			
R^2	0.01	0.01			
Black mean	1.60	1.69	2.20	0.82	0.82
White mean	1.30	1.27	1.79	0.96	0.47
(b) Job-finding: N to E					
	(1)	(2)	(3)	(4)	(5)
	All	Large	Small	Government	Self
Black	-0.76	-0.07	-0.59	0.01	-0.08
	(0.06)	(0.04)	(0.03)	(0.02)	(0.01)
High UR	-0.62	-0.26	-0.22	-0.04	-0.04
	(0.09)	(0.04)	(0.03)	(0.01)	(0.01)
Black × High UR	-0.23	-0.24	0.04	-0.03	0.02
	(0.09)	(0.06)	(0.04)	(0.03)	(0.02)
N	2,226,789	2,226,789	2,226,789	2,226,789	2,226,789
R2	0.04	0.02	0.02	0.01	0.00
Black mean	2.65	1.42	0.74	0.28	0.09
White mean	2.39	1.03	0.87	0.26	0.13

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions. The units are percentage points. Panel (a) reports the estimates for aggregate separations rates from equation (1.3.1) in column (1) and the interacted coefficients with employer type from equation (1.3.3) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (1.3.2) in column (1) and the estimates for equation (1.3.4) with an outcome variable for each employer type in columns (2)-(5). All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table 1.3: Transition rates by race and aggregate unemployment, logit

(a) Separations: E to N	(1) All	(2) Men	(3) Women
Black	0.07	0.09	0.04
	(0.02)	(0.03)	(0.02)
High UR	0.05	0.13	-0.03
	(0.03)	(0.04)	(0.03)
Black × High UR	-0.05	-0.02	-0.06
	(0.03)	(0.05)	(0.05)
N	3,701,235	1,900,483	1,800,752
Pseudo R^2	0.07	0.07	0.06
Black mean	1.60	1.52	1.66
White mean	1.30	1.17	1.44

(b) Job-finding: N to E	(1) All	(2) Men	(3) Women
Black	-0.27	-0.37	-0.19
	(0.02)	(0.03)	(0.03)
High UR	-0.28	-0.29	-0.27
	(0.05)	(0.05)	(0.05)
Black × High UR	-0.08	-0.06	-0.09
	(0.04)	(0.05)	(0.05)
N	2,226,789	837,928	1,388,861
Pseudo R^2	0.21	0.22	0.20
Black mean	2.65	2.81	2.53
White mean	2.39	3.01	2.01

The table reports differences in separation and job-finding rates by race and macroeconomic conditions from a logit model. Panel (a) reports the estimates for separation rates from equation (1.3.5). Panel (b) reports the estimates for job-finding rates from equation (1.3.6). All specifications include controls for age, age-squared, and marital status (interacted with gender in column (1)); education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table 1.4: Transition rates by race, aggregate unemployment, and firm type, logit

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.07	0.12	0.12	-0.31	0.23
	(0.02)	(0.03)	(0.03)	(0.05)	(0.09)
High UR	0.05	0.06	0.07	0.08	-0.06
	(0.03)	(0.04)	(0.04)	(0.09)	(0.06)
Black × High UR	-0.05	-0.07	-0.11	0.10	0.37
	(0.03)	(0.05)	(0.07)	(0.10)	(0.17)
N	3,701,235	3,701,235			
Pseudo R^2	0.07	0.07			
Black mean	1.60	1.69	2.20	0.82	0.82
White mean	1.30	1.27	1.79	0.96	0.47

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-0.27	-0.10	-0.62	0.06	-0.62
	(0.02)	(0.03)	(0.03)	(0.06)	(0.10)
High UR	-0.28	-0.27	-0.28	-0.13	-0.34
	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)
Black × High UR	-0.08	-0.12	0.01	-0.17	0.13
	(0.04)	(0.05)	(0.05)	(0.11)	(0.17)
N	2,226,789	2,226,789			
Pseudo R^2	0.21	0.17			
Black mean	2.65	1.42	0.74	0.28	0.09
White mean	2.39	1.03	0.87	0.26	0.13

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions using a logit model. Panel (a) reports the estimates for aggregate separations rates from equation (1.3.5) in column (1) and the interacted coefficients with employer type from equation (1.3.7) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (1.3.6) in column (1) and the estimates for the multinomial logit given by equation (1.3.8) with an outcome variable for each employer type in columns (2)-(5) and remaining nonemployed as the reference outcome. All specifications include controls for age, age-squared, and marital status (interacted with gender in column (1)); education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table 1.5: Separation rate heterogeneity

	(1) All	(2) Voluntary	(3) Involuntary
Large	-0.08	-0.07	-0.04
	(0.05)	(0.08)	(0.06)
Small × Black	-0.05	-0.71	0.56
	(0.12)	(0.18)	(0.16)
Large × Black	-0.01	-0.48	0.37
	(0.07)	(0.12)	(0.09)
Small × HighUR	-0.26	-0.99	0.92
	(0.07)	(0.10)	(0.09)
Large × HighUR	-0.22	-0.82	0.63
	(0.05)	(0.07)	(0.06)
Small × Black × HighUR	-0.10	-0.08	-0.06
	(0.20)	(0.28)	(0.30)
Large × Black × HighUR	-0.19	-0.26	-0.06
	(0.12)	(0.17)	(0.16)
N	1,566,300	1,556,118	1,556,118
R^2	0.02	0.02	0.01
Black mean	2.38	2.31	1.93
White mean	2.15	2.41	1.48

The table reports differences in size-specific and reason-specific separation rates by race and macroeconomic conditions given by equation (1.3.9). The units are percentage points. The sample includes all workers who report a job at a large or small firm. The outcome variable in column (1) is an indicator equal to 1 if the worker reports the job ending that month. The outcome variables in columns (2)-(3) are indicators equal to 1 if the worker reports the job ending and gives an involuntary or voluntary reason for it, respectively. All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects; job tenure in years; log wage; hours; union membership; and industry. Standard errors are clustered by month.

Table 1.6: Regression results for fitting the model (re-scaled)

	(1) Large Job-finding	(2) Small Job-finding	(3) Large Separation	(4) Small Separation	(5) Large share of employment	(6) Employment
Conditional gaps:						
Black	-0.21	-0.70	0.18	0.28	10.26	-6.22
	(0.04)	(0.03)	(0.04)	(0.08)	(0.44)	(0.35)
High UR	-0.49	-0.39	0.07	0.11	0.92	-2.77
	(0.02)	(0.02)	(0.02)	(0.04)	(0.27)	(0.17)
Black × High UR	-0.28	0.01	-0.11	-0.20	-0.29	-0.99
	(0.06)	(0.04)	(0.07)	(0.14)	(0.69)	(0.53)
Reference group mean						
White, Low UR	1.37	1.17	1.40	1.53	62.86	57.35
	(0.02)	(0.01)	(0.01)	(0.02)	(0.15)	(0.15)

The table reports conditional gaps from the data to be used in the model analysis. The reference group mean reports the mean outcome variable for white workers in non-high unemployment periods. The mean job-finding rates in columns (1) and (2) are scaled up by a factor of 1/(0.79) to account for the fact that large and small firms make up 79% of job-finding for white workers, as reported in the means in Table 1.2. Columns (1)-(2) and (3)-(4) replicate the results from Table 1.2 with the sample excluding non-private firm employees. Standard errors are constructed using a block bootstrap by person, within each SIPP panel.

Table 1.7: Data moments for model

Large firm share of employment	64.10	(0.15)
Job-finding rate	2.40	(0.02)
Large	1.34	(0.02)
Small	1.06	(0.01)
Separation rate	1.47	(0.01)
Large	1.43	(0.01)
Small	1.56	(0.02)
Black share of population	13.26	(0.10)
Nonemployment	14.90	(0.15)
Large firm employment	13.68	(0.16)
Small firm employment	8.97	(0.15)

The table reports moments from the data to be used in the model analysis. I use the Black share of the population and the results from Table 1.6 to construct all other moments. For example, using column (5) of Table 1.6, the Black employment rate is .51, constructed by adding the reference group mean in the bottom row to the conditional gap in the top row, .57-.06. Then the Black share of nonemployment is $\frac{.13\times(1-.51)}{.13\times(1-.51)+(1-.13)\times(1-.57)}$. I use the Black share of nonemployment to weight the job-finding rates in columns (1) and (2), and so on. The remaining moments are constructed in a similar fashion. Standard errors are estimated using a block bootstrap by person, within each SIPP panel.

1.4. Model

The empirical results demonstrate that Black workers face persistently lower job-finding rates at small firms, in excess of what would be predicted by worker characteristics. When the economy contracts, the job-finding rates for Black workers at large firms decrease proportionately more than the job-finding rates at small firms. In this section, I develop a quantitative model that embeds information frictions in the hiring process as a mechanism for contributing to these patterns. The model features heterogeneous firms, heterogeneous workers, and a frictional labor market. It is set in discrete time.

1.4.1 Environment

1.4.1.1 Workers

A unit mass of infinitely-lived workers are endowed with one indivisible unit of labor. They share a common discount factor, β, with linear preferences for consumption. They produce and consume a single homogeneous good. Workers have no disutility of labor but may be unemployed due to frictions in the labor market. Let u_t denote the mass of nonemployed workers at the start of period t (with $1 - u_t$ the mass of employed workers). Nonemployed workers receive flow utility b. Firms are owned by workers with dividends distributed in lump sum.

There are two types of workers, $g \in \{W, B\}$, with (a fixed) fraction $\pi < \frac{1}{2}$ in B (minority group). Let π_t^u be the share of B workers in the nonemployed population (u_t) at time t, which is determined endogenously by separations and hiring decisions by firms. Group membership will only affect the access workers have to matching technology, to be described in the next section.

1.4.1.2 Firms

There are two types of firms indexed by their (fixed) idiosyncratic productivity z. They share a common aggregate productivity a_t, which will be subject to shocks. They use labor to produce a single good with decreasing returns to scale production technology,

$$y_t = a_t z n_t^{\alpha}$$

1.4.1.3 Matching and hiring process

This is a random search model with information frictions in the hiring process (**?**, **?**). Firms post vacancies (v) to attract matches. This vacancy posting can be interpreted as recruiting intensity. The more vacancies the firm posts, the more candidates it has to choose from when deciding who to hire. The matching rate between vacancies and nonemployed workers depends on market tightness, θ_t, where the probability that a vacancy attracts a worker is $q(\theta)$, the probability a nonemployed worker meets a firm is $\theta q(\theta)$, and $\theta = \frac{V}{U}$ is market tightness. Given that this is random search, workers do not target particular types of firms and firms cannot target their vacancies to particular workers. A worker matches to a type z firm proportional to their share of vacancies, while a firm matches to a type g worker proportional to their share in the nonemployed pool.

When workers and firms meet, both parties face uncertainty around the worker's productivity, which is revealed at the production stage if the worker is hired. Workers can either be a productive type, contributing one unit of labor to the firm's production function, or unproductive, contributing zero. Each time a worker meets a firm, they draw a new match quality from the same distribution, ($\tilde{F}(\tilde{x})$), which determines the likelihood the worker will be productive. The match quality is unobservable to the worker and the firm, but both observe a signal of the match quality, (s). The signal follows the inspection technology form of Menzio and Shi (2011), where the firm observes the true match quality with probability $p(g, z)$, which depends on worker group g and firm type z. With probability $1 - p(g, z)$, the firm observes another iid draw from the same distribution. Thus, the firm forms a posterior belief (x) about the worker's productivity conditional on their signal, according to

$$x = p(g, z)s + (1 - p(g, z))\mathbb{E}[s] \tag{1.4.1}$$

This friction is meant to capture differences in referral networks that affect the information firms have about potential hires, as in **?**. It is similar to the statistical discrimination literature (e.g. Black (1995), **?**). These papers aim to explain racial wage gaps through differences in signal quality.

Using these beliefs, the firm must decide which matches to hire. The firm chooses a group-specific threshold rule, $x^*(g, z)$ such that it hires all matches from that group with an expected productivity above the threshold. Once workers are hired, wages are bargained using Stole and Zwiebel (1996) and then wages are paid, production occurs, and new hire types are revealed.

At the start of the next period, all of the unproductive hires from the end of the previous period separate and an exogenous share δ of the productive hires separate. These newly separated workers are not able to search until the following period.

1.4.2 Optimization

1.4.2.1 Firms' Problem

The firm chooses vacancies v and hiring standards x_B, x_W, which implicitly define the number of hires $\{h_g\}$, the expected productivity of the hires $\{\hat{x}(x_g, p(g, z))\}$, and next period employment $\{n_g'\}$ for each group

$$J_t(n_B, n_W, z) = \max_{v\geq 0, x_g} - c_v(z)v + a_t z(n')^\alpha \tag{1.4.2}$$
$$- \sum_g \Big((1-\delta)n_g w^n(n', z, g) + h_g w^h(x_g, n', z, g)\Big) + \beta \mathbb{E}_t J_{t+1}(n_B', n_W', z)$$

s.t.

$$n' = \sum_g n_g' \tag{1.4.3}$$
$$n_g' = (1-\delta_t)n_g + \hat{x}(x_g, p(g, z))h_g \tag{1.4.4}$$
$$h_g = \frac{u_{gt}}{u_t} q(\theta_t) v (1 - F(x_g|p(g, z))) \tag{1.4.5}$$
$$\bar{x}(p(g, z)) - p(g, z) \leq x_g \leq \bar{x}(p(g, z)) \tag{1.4.6}$$

where $\bar{x}(p)$, $F(x|p)$, and $\hat{x}(x, p)$ capture features of the distribution of posterior beliefs a firm forms about match productivity, given the quality of the signal p and the exogenous distribution of match productivity, $F(\cdot)$.

$$\bar{x}(p) = p + (1-p)\mathbb{E}[x] \tag{1.4.7}$$

$\bar{x}(p)$ is the maximum posterior belief about match productivity the firm receives, given its signal quality p. For example, if the firm receives no information about match productivity ($p = 0$), the posterior belief about the worker with the highest observed signal is the unconditional expectation, whereas if it receives full information about match productivity ($p = 1$), the worker with the highest signal will be productive with probability 1.

$$F(x|p) = F\left(\frac{x - (1-p)\mathbb{E}[x]}{p}\right) \tag{1.4.8}$$

$F(x|p)$ is the cumulative distribution of posteriors conditional on signal quality p, and $\hat{x}(x, p)$ is the expected productivity of a hire conditional

$$\hat{x}(x, p) = \frac{\int_x^{\bar{x}(p)} y dF(y|p)}{1 - F(x|p)} \tag{1.4.9}$$

where $F(\cdot)$ is the exogenous distribution of match quality.

Vacancies costs are linear but I allow the vacancy cost to vary with fixed firm productivity, z, with the assumption that $\frac{\partial c_v(z)}{\partial z} < 0$. Thus firms with higher productivity (which will be endogenously larger) have lower vacancy costs. In a two-firm model, this specification delivers the intuition that larger firms can have larger human resources departments or other economies of scale that lets them screen applicants at a lower marginal cost without introducing complications in the bargaining problem with workers.

Note that firms cannot target their vacancies to a particular group. This implies that if firms hire both types of workers, then

$$q(\theta_t)v = \frac{h_B}{\frac{u_{Bt}}{u_t}(1 - F(x_B|p(B,z)))} = \frac{h_W}{\frac{u_{Wt}}{u_t}(1 - F(x_W|p(W,z)))} \tag{1.4.10}$$

1.4.2.2 Worker's Problem

Let $V_t^u(g)$ be value of nonemployment for a worker from group g at the end of the period, $V_t^n(g,z)$ be the value of a worker employed at a firm of type z that is known to be productive,

$$V_t^n(g,z) = w_t^n(n', z, g) + \beta \mathbb{E}_t \left[V_{t+1}^u(g) + (1-\delta)(V_{t+1}^n(g,z) - V_{t+1}^u(g)) \right] \tag{1.4.11}$$

Newly hired workers can be paid different wages and face higher separation rates, captured in the value function $V_t^h(g,z)$[5]

$$V_t^h(g,z) = w_t^h(x_g(z), n', z, g) + \beta \mathbb{E}_t \left[V_{t+1}^u(g) + \hat{x}(x_g(z), p(g,z))(1-\delta)(V_{t+1}^n(g,z) - V_{t+1}^u(g)) \right] \tag{1.4.12}$$

where $\hat{x}(x_g(z), p(g,z))$ is the probability that the worker is productive conditional on the firm's hiring threshold $x_g(z)$ and signal quality $p(g,z)$. For nonemployed workers, the value function is

$$\begin{aligned} V_t^u(g) &= b + \beta \mathbb{E}_t V_{t+1}^u(g) \\ &\quad + \underbrace{\beta \mathbb{E}_t \left[\theta_{t+1} q(\theta_{t+1}) \sum_z \frac{\mu(z) v^(z)}{V} (1 - F(x_g(z)|p(g,z)))(V_{t+1}^h(g,z) - V_{t+1}^u(g)) \right]}_{\Omega_t(g)} \end{aligned} \tag{1.4.13}$$

where $v(z)$ is the equilibrium number of vacancies posted by a firm of type z, $\mu(z)$ is the mass of type z firms per worker in the economy, V is the aggregate number of vacancies, and $x_g(z)$ is the firm's equilibrium threshold rule.

[5]For simplicity, I am going to ignore differences in individual productivity probabilities across new hires within the same group and firm. From the firm's perspective, the problem would be unchanged if I allow wages and value functions to depend on an individual's specific x.

1.4.2.3 Wage bargaining

Wages are set via Stole and Zwiebel (1996) bargaining in which firms bargain with each worker sequentially and failure to negotiate with a worker requires them to go back and bargain again with the others. This is a standard bargaining rule in models with endogenous firm size, such as **?** and Elsby and Michaels (2013). Let $D_t(\{\tilde{n}_g\}, \{h_g\}, \{x_g\}, z)$ be the firm value after vacancy posting is sunk and hiring thresholds have been set,

$$\begin{aligned} D_t(\{\tilde{n}_g\}, \{h_g\}, \{x_g\}, z) =& a_t z(n')^\alpha - \sum_g \Big(\tilde{n}_g w^n(n', z, g) + h_g w^h(x_g, n', z, g)\Big) \\ &+ \beta \mathbb{E}_t J_{t+1}(n'_B, n'_W, z) \\ &\text{s.t.} \\ &n'_g = \tilde{n}_g + \hat{x}(x_g, p(g, z))h_g \end{aligned} \tag{1.4.14}$$

where $\tilde{n}_g = (1-\delta)n_g$ is the number of existing employees, h_g is the number of new hires as defined in equation (1.4.5), and $\hat{x}(x_g(z), p(g, z))$ is the expected productivity of new hires as defined in equation (1.4.9).

Firms and workers split the surplus according to the following rules

$$\phi D_{t,\tilde{n}_g} = (1-\phi)\left(V_t^n(g, z) - V_t^u(g)\right) \tag{1.4.15}$$

$$\phi D_{t,h_g} = (1-\phi)\Big(V_t^h(g, z) - V_t^u(g)\Big) \tag{1.4.16}$$

where the left-hand-side is the marginal surplus to the firm of having one more employee from that group multiplied by the worker bargaining power, and the right-hand-side is the marginal surplus to the worker of being employed by a type z firm rather than nonemployed, multiplied by the firm bargaining power.

Using the firm and worker value functions with the sharing rules, we get the following equilibrium wage functions,

$$w^n(n', z, g) = \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z n'^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) \tag{1.4.17}$$

$$w^h(x_g, n', z, g) = \hat{x}(x_g, p(g, z)) \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z n'^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) \tag{1.4.18}$$

where $\Omega_t(g)$ is the value of searching next period for a worker from group g as defined in equation (1.4.13). This term is included in addition to the flow value of nonemployment, b, because workers who separate are not able to search in the following period. Notice that if firms have full bargaining power, $\phi = 0$, then all workers will be paid their outside option, b, and the value of search will disappear, $\Omega_t(g) = 0$.

The full details are provided in Appendix A.3.

1.4.2.4 Aggregation

Let $\mu(z)$ be the mass of type z firms (relative to a unit mass of workers). The aggregate nonemployment rate for the minority group evolves according to

$$u_{gt+1} = 1 - \frac{1}{\pi(g)} \sum_z \mu(z) \left(n'_g(z) + h_g(z)(1 - \hat{x}(x_g(z), p(g, z))) \right) \tag{1.4.19}$$

where $\pi(g)$ is the share of group g in the population, $\mu(z)$ is the mass of firms of type z, and the second term in the sum represents the number of hires who will separate in the next period because they are revealed to be unproductive. These workers are not able to search in the following period and should be excluded from the nonemployment rate.

The distribution of employment across firms is given by

$$\Gamma(z) = \frac{\mu(z) \sum_g \left((1-\delta) n_g(z) + h_g(z)\right)}{\sum_{\tilde{z}} \mu(\tilde{z}) \sum_g \left((1-\delta) n_g(\tilde{z}) + h_g(\tilde{z})\right)} \tag{1.4.20}$$

1.4.3 Equilibrium

1.4.3.1 Equilibrium definition

Given exogenous masses of firms $\mu(z)$, a recursive competitive equilibrium for this economy is a list of functions: (i) value functions for firms, $J(n_B, n_W, z)$, (ii) decision rules for vacancies and hiring standards, $v(z), x_g(z)$, (iii) value functions for workers $V^n(g, z)$, $V^h(g, z)$, $V^u(g)$, (iv) wage functions $w^n(n', g, z)$, $w^h(x_g, n', g, z)$, and (v) worker outside option functions $\Omega(g)$, and market tightness θ, a stationary distribution of employment across firms, $\Gamma(z)$, and a stationary distribution of minority workers in unemployment and each employer type, π^u, π^z.

1. *Firm optimization*: Given θ, $\lambda(u)$, $\Omega(g)$, $w^n(n', z, g)$, $w^h(x_g, n', z, g)$, the set of decision rules $v(z), x_g(z)$ solve the firm problem

2. *Worker optimization*: Given $\theta, \Gamma(z)$, $w^n(n', z, g)$, $w^h(x_g, n', z, g)$, and $v(z), x_g(z)$, worker value functions $V^n(g, z)$, $V^h(g, z)$, and $V^u(g)$ solve the worker problem and $\Omega(g)$ is consistent with value functions

3. *Wage bargaining*: $w^n(n', z, g)$, $w^h(x_g, n', z, g)$ solve the bargaining problem

4. *Consistency*: The stationary distribution of employment $\Gamma(z)$ is consistent with firm optimization

5. *Market clearing*: The labor market clears and the distribution of minority workers across unemployment and employer types, π^u, π^z is consistent with firm optimization

1.4.3.2 Firm problem solution

With the wage equations, the firm's problem can be rewritten as choosing the number of productive workers from each group, subject to a cost minimization problem,

$$
\begin{aligned}
J_t(n_B, n_W, z) = & \max_{n'_g \geq (1-\delta)n_g} -C_t\left(\Delta_B, \Delta_W\right) \\
& + \frac{1-\phi}{1-\phi+\alpha\phi} a_t z (n')^{\alpha} - \sum_g (1-\delta) n_g \Big((1-\phi)(b+\Omega_t(g))\Big) + \beta \mathbb{E}_t J_{t+1}(n'_B, n'_W, z) \\
& \text{s.t.} \\
& \Delta_g = n'_g - (1-\delta) n_g
\end{aligned}
$$

where

$$
C_t(\Delta_B, \Delta_W) = \min_{\{x_g\}} \sum_g \frac{\Delta_g}{\hat{x}(x_g, p(g,z))} \left(\frac{c_v(z)}{q(\theta_t)(1-F(x_g|p(g,z)))} + (1-\phi)(b+\Omega_t(g)) \right) \tag{1.4.21}
$$

$$
\text{s.t.} \ (1.4.10)
$$

and $C_t(\Delta_B, \Delta_W)$ can be understood as the total cost of hiring $\Delta_B + \Delta_W$ *productive* workers.

For an interior solution, the firm's problem is characterized by two first order conditions. For each group,

$$
\begin{aligned}
\frac{\partial C_t(\Delta_B, \Delta_W)}{\partial \Delta_g} & + \beta(1-\delta)\mathbb{E}_t\left[(1-\phi)(b+\Omega_{t+1}(g))\right] \\
& = \frac{\alpha(1-\phi)}{1-\phi+\alpha\phi} a_t z (n')^{\alpha-1} + \beta(1-\delta)\mathbb{E}_t\left[\frac{\partial C_{t+1}(\Delta'_B, \Delta'_W)}{\partial \Delta'_g}\right]
\end{aligned} \tag{1.4.22}
$$

This condition shows that the firm will hire workers from group g until the marginal cost (left) is equal to the marginal benefit (right). The marginal cost of hiring a productive worker is the hiring cost plus the expected discounted compensation cost for this worker in the next period. The marginal benefit is the effective marginal product of labor (subtracting the share paid to workers as wages) plus the savings to the firm from hiring $(1-\delta)$ fewer workers in the next period.

Using the first order condition from the cost minimization problem, the marginal hiring cost simplifies to

$$\frac{\partial C_t(\Delta_B, \Delta_W)}{\partial \Delta_g} = \frac{(1-\phi)(b+\Omega_t(g))}{x_g} \tag{1.4.23}$$

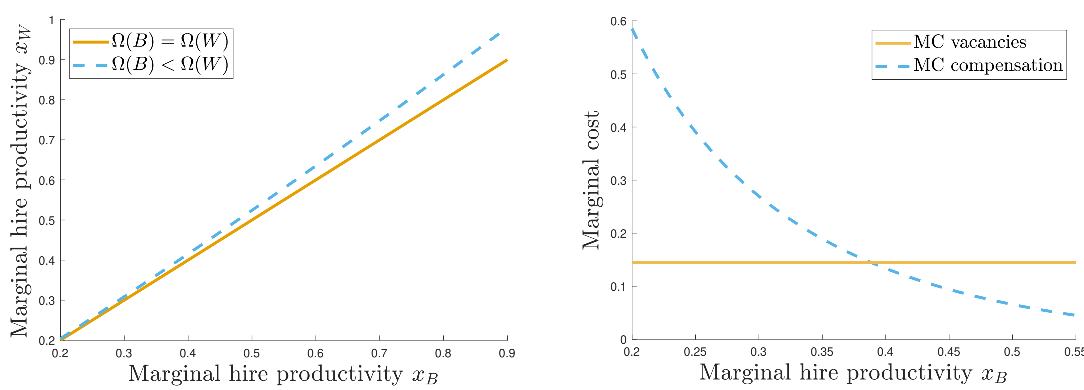
which can be interpreted as the compensation cost for the marginal hire, as the firm needs to hire $\frac{1}{x_g}$ workers to hire the last productive worker.

Equations (1.4.22) and (1.4.23) can be combined to show the relationship between the hiring thresholds for the two groups.

$$\begin{aligned} 0 =& \frac{(b+\Omega_t(B))}{x_B} - \beta(1-\delta)\mathbb{E}_t\left[(b+\Omega_{t+1}(B))\frac{1-x'_B}{x'_B}\right] \\ &- \frac{(b+\Omega_t(W))}{x_W} + \beta(1-\delta)\mathbb{E}_t\left[(b+\Omega_{t+1}(W))\frac{1-x'_W}{x'_W}\right] \end{aligned} \tag{1.4.24}$$

Panel (a) of Figure 1.4 shows this relationship in steady state where $\Omega_t(g) = \mathbb{E}[\Omega_{t+1}(g)] = \Omega(g)$, using the calibration discussed in the next section. First, the orange (solid) line shows that if the outside options of both groups are equal, then the firm will choose the same marginal hire productivity across groups. If the outside option of the minority group is lower $\Omega(B) < \Omega(W)$, as shown by the blue (dashed) line, the firm is willing to choose a lower productivity threshold for the minority group because they can compensate them less. Notice that this relationship

Figure 1.4: Marginal hire productivity between groups



(a) (b)

between x_B and x_W is determined by market conditions and all firms in the economy face the same tradeoff between marginal hire productivities. However, firms may choose to locate at different points on the frontier, depending on the solution to the cost minimization problem.

Given the relative number of workers a firm wants to hire from each group, the cost minimization solution is given by

$$\frac{c_v(z)}{q(\theta_t)} = \sum_g \frac{u_{gt}}{u_t}(1-\phi)(b+\Omega_t(g))\frac{\left(\hat{x}(x_g, p(g,z)) - x_g\right)}{x_g}(1 - F(x_g|p(g,z))) \tag{1.4.25}$$

The left side of equation (1.4.25) is the marginal vacancy cost, which is constant due to the linear vacancy technology. The right side of equation (1.4.25) is the marginal benefit of posting an additional vacancy, which can be thought of as the marginal cost of compensation. If the firm posts an extra vacancy, it can maintain the same level of hiring by being more selective about the workers it hires, thus reducing the compensation paid to unproductive workers. In the limit, if firms hired only the workers with the highest expected productivity, this cost would go to zero. As they lower the threshold, they accept more workers who will separate. Thus the compensation cost is decreasing with firm selectivity. The firm's optimal decision is at the intersection of these two curves, shown in Panel (b) of Figure 1.4.

1.5. Calibration

I calibrate the model at a monthly frequency. I first fix a set of parameters using moments from the data or external estimates. Then, I choose the remaining parameters to match moments from the data.

I need two functional form assumptions before describing the parameters. I use a Cobb-Douglas matching function as in Petrongolo and Pissarides (2001)

$$q(\theta) = \zeta\theta^{-\psi}$$

I also need an exogenous distribution of match quality. I will use the functional form assumption from **?**,

$$F(y) = (y)^{1/(\gamma-1)}$$

with $\gamma > 1$ and $y \in [0, 1]$. This distribution is convenient because it is governed by a single parameter. The unconditional mean of match quality is $1/\gamma$. Higher values of γ will imply that screening is more valuable because the ex ante quality of the pool is lower.

1.5.1 Fixed parameters

Table 1.8 summarizes the values of fixed parameters and their sources. Given the monthly frequency, I set the discount factor β to 0.996 to match a quarterly interest rate of 0.012. I set the production curvature α to 0.677 as in **?**. I use a standard Cobb-Douglas matching technology with matching elasticity ψ 0.6 as in Petrongolo and Pissarides (2001).

I set the share of large firms to 0.02 to match the share of firms with 100 or more employees, excluding firms with zero employment, from 1997 Census data, as reported by **?**. This is the same threshold for defining large firms that I use in the SIPP, and the time period is consistent with my sample that starts in 1996. The aggregate productivity a scales the absolute value of firm size up, and I choose a value of 4.2, which corresponds to small firms having about 30 employees in equilibrium and large firms having 2700. The minority share of the population is fixed at 0.13 based on the share of Black relative to white population in the SIPP, as reported in Table 1.7.

The overall job-finding rate in the SIPP is the matching rate from the perspective of the worker, $\theta q(\theta)$ times the vacancy-weighted average hiring rate across firms and worker groups. Given a target for market tightness, θ and the fixed parameter value of ψ, this can be expressed as

$$\zeta\theta^{1-\psi}\sum_z\sum_g \frac{v(z)}{v}\frac{u_g}{u}(1-F(x(g,z)))$$

Thus given a target of the job-finding rate from the data, ζ governs how selective the firm is. If ζ is low, then the share of matches that are hired increases, whereas if ζ is high, this share decreases. As a baseline, I select ζ such that the weighted average of the hired share of matches is 8%, which corresponds to the inverse of the average number of applications received per hire in Barron et al. (1997). This parameter choice is important because when firms are more selective, this leads to a more negative gap in hiring between minority and majority workers.

Finally, I choose a normalization for the signal quality for majority workers. I use the same normalization across large and small firms because I am allowing vacancy costs to vary by firm size and I cannot separately identify these parameters. What matters is the gap in signal qualities between workers across groups within the same firm.

1.5.2 Fitted parameters

The remaining parameters are chosen in two parts. For the first four, I use moments from other papers to solve for parameters that affect scaling of the model, given the other

Table 1.8: Fixed Parameters

Parameter	Meaning	Value	Source
β	Discount factor	0.996	Quarterly interest rate 0.012
α	Production curvature	0.677	**?**
ψ	Matching elasticity	0.6	Petrongolo and Pissarides (2001)
υ	Share of large firms	0.02	**?**
a	Aggregate productivity	4.2	Relative sizes
π	Minority share population	0.133	SIPP
ζ	Matching scale	.342	Avg. hired share 0.08
p_W	Majority signal quality	0.99	Normalization

parameter values. For the next six, I estimate them using generalized method of moments (GMM), allowing the scale parameters to update with each iteration. I construct the weight matrix for GMM using a block-bootstrapped variance-covariance matrix.

The scale parameters are reported in panel (a) of Table 1.9. I target a market tightness of 0.72 as in Elsby and Michaels (2013) by solving for the mass of firms per worker, μ, consistent with this value. Following the strategy of **?**, I normalize b such that the equilibrium value of nonemployment for the majority group ($b + \Omega(W)$) is equal to 1. I solve for the value of ϕ such that the ratio of b to average productivity (Y/N) is 0.73. The shape of the match quality distribution governs the relative selectivity at small versus large firms. I solve for γ such that large firms hire 5% of their matches, which is the inverse of the number of applications received per hire at firms with 100 or more employees in Barron et al. (1997). The equivalent figure at small firms is 10% and left as an untargeted moment.

The remaining six parameters affect all of the moments but I will discuss the identification intuition. Appendix A.4 provides additional details. The estimated values are reported in panel (b) of Table 1.9. The exogenous separation rate δ is identified by the average separation rate. The vacancy costs by firm size are identified by the job-finding rates by firm size. To see this, return to the firm's selectivity decision in Panel (b) of Figure 1.4. An increase in the vacancy cost shifts the marginal cost of vacancies up (blue line), which leads the firm to be less selective, or hire more of its matches, holding fixed the number of hires. This corresponds to a decrease in the number of vacancies the firm needs to post to attract that number of matches. These two effects together map to the job-finding rate at each firm. The relative productivity of large firms, $\frac{z(L)}{z(S)}$ is identified by the employment share at large firms. If the model had no heterogeneity other than differences in firm productivity, large firms would make the same decisions as small firms but with more workers, because $z(L)$ would lead them to hire until their marginal product of labor was the same.

The final estimated parameters are the signal gaps at large and small firms. These are

Table 1.9: Fitted Parameters

Parameter	Meaning	Value
(a) Scale parameters		
μ	Number firms/worker	0.007
b	Flow value unemp	0.998
ϕ	Bargaining power	0.259
γ	Match quality shape	3.28
(b) Estimated parameters		
δ	Exog. separation	0.012
$c_v(L)$	Vacancy cost	0.001
$c_v(S)$	Vacancy cost	0.060
$\frac{z(L)}{z(S)}$	Relative productivity	4.158
$\Delta_p(L)$	Signal gap, large	0.121
$\Delta_p(S)$	Signal gap, small	0.598

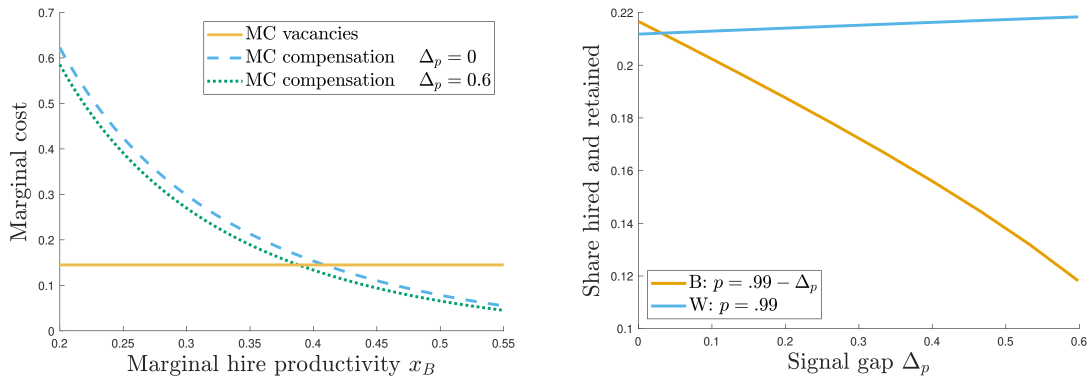
identified by the minority share of employment at each type of firm. Consider the partial equilibrium effects of increasing the signal quality gap between majority and minority workers for the firm's optimal threshold solution in equation (1.4.25). Holding fixed the minority share of nonemployment, workers' outside options, and market tightness, an increase in the signal quality gap will make firms slightly more lenient in their hiring, as the information is not as informative. This can be observed by the shift in the marginal cost of compensation curve in Panel (a) of Figure 1.5 from the blue (dashed) line to the green (dotted) line. Increasing the signal gap from 0 to 0.4 leads to a decrease in the optimal threshold of 0.01. The larger effect is that as the signal gap increases, there is a smaller mass of minority workers with a signal above the chosen threshold, and the average productivity conditional on being above that threshold also decreases.[6] The result is that the share of minority workers who are hired and retained in the next period drops, as seen in Panel (b) of Figure 1.5, and representation of minority workers falls.

1.5.3 Model fit

The model fits the targeted moments almost exactly, with values shown in Panel (a) of Table 1.10. Panel (b) shows the fit for untargeted moments. I match the average separation rate by construction, but the model matches the distribution across firm size reasonably well. I target the minority share of employment by firm size but not the gaps in job-finding

[6]To see this, consider the case where the majority worker has signal quality 1. The productivity of the hired majority workers will then range from x_W to 1, whereas the productivity of hired minority workers will range from $x_B < x_W$ to $1 - \Delta_p(1 - \mathbb{E}[x])$, which is decreasing in Δ_p.

Figure 1.5: Signal quality gap and firm's decision



(a) (b)

and separations that contribute to them. The model underestimates the job-finding gaps by both types of firms, but still captures that the gap is wider at small firms. Similarly, it captures that the separation gap is higher at small firms. It overestimates the small firm gap while underestimating the large firm gap, similar to the pattern in overall separations. The imperfect fit in terms of hiring and separation gaps is to be expected as the only difference between groups in the model is the hiring process, whereas in reality workers face differences in many other aspects of the employment process. Finally, the small firms in the model are less selective than in the survey estimates from the data, as reported in Barron et al. (1997).

1.6. Counterfactuals

1.6.1 Low vs. high productivity

I use the quantitative model to consider a permanent negative shock to aggregate productivity, a. Given that the Great Recession is a major source of the variation in my data, this type of shock is relevant. I choose the scale of the decrease such that the total drop in job finding for white workers matches the empirical average decrease in high unemployment period, as reported in Table 1.6.

Table 1.11 reports the results of this exercise for job-finding. By construction, the data and model match exactly in the first row for the total change in job finding for white workers. The next two rows show that the model is relatively consistent with the data in terms of the shares attributed to each type of firm, though the decrease in job-finding is less skewed towards large firms than it is in the data.

The second group of Table 1.11 shows the difference in the job-finding gap between steady states. In the data the job-finding gap is 28 basis points worse in the high unemployment

Table 1.10: Moments, percentage points

(a) *Targeted*

Moment	Data/Model
Separation rate	1.47
Employment share	
Large	64.10
Job-finding rate	
Large	1.34
Small	1.06
Minority share	
Large	13.68
Small	8.97
Hired share matches*	
Large	5.02

(b) *Untargeted*

Moment	Data	Model
Separation rate		
Large	1.43	1.28
Small	1.56	1.82
Job-finding gap (B-W)		
Large	-0.21	-0.07
Small	-0.70	-0.26
Separation gap (B-W)		
Large	0.18	0.11
Small	0.28	0.70
Hired share matches*		
Small	10.04	31.63

The units are percentage points. Panel (a) reports the moments that were targeted in the model calibration, which match the data exactly. Panel (b) reports untargeted moments in the model and the data. The data moments are all calculated in the SIPP, except for the hired share of matches, indicated by the *. These are imputed from the inverse number of applications received per hire by firms with over/under 100 employees, as reported by Barron et al. (1997).

periods and the model slightly overshoots that, with the gap worsening by 30 basis points. Looking at the split between large and small firms, the model captures that this difference is strongest for large firms. It predicts a small worsening of the job-finding gap at small firms that we do not see in the data. Because the model is not fully capturing the stronger decrease in job-finding for white workers at large firms, shown in the top panel, it may miss some of the mechanical effects on the job-finding gap if large firms adjust their hiring more in response to negative shocks and Black workers are more exposed to large firms. Nonetheless, it captures the general pattern that most of the change in the job-finding gap is coming from large firms. Using the model, we can decompose why the difference is larger for large firms. To start, the job finding gap at a firm of type z is

$$\underbrace{\theta q(\theta)}_{\text{matching rate}} \underbrace{\frac{\nu(z)v(z)}{\sum \nu(z)v(z)}}_{\text{vacancy share}} \underbrace{\Big((1-F(x_B|p(B,z))) - (1-F(x_W|p(W,z)))\Big)}_{\text{relative selectivity}} \tag{1.6.1}$$

which is a product of three terms. The first is the matching rate component, resulting from the decrease in market tightness, which is the same across all firms. The second is the vacancy share component. The last is the relative selectivity component, or the hiring gap conditional on matching at the type z firm.

These components are itemized in Table 1.12 for small and large firms in the high and low productivity states. Looking at the first column, we see the key pattern that although

Table 1.11: Steady state comparison

Changes: low - high productivity	**Data**	**Model**
White job finding rate	-0.873	-0.873
Large	-0.487	-0.463
Small	-0.386	-0.410
Job finding gap	-0.275	-0.300
Large	-0.281	-0.248
Small	0.006	-0.052

This table shows the comparison between the low productivity relative to high productivity steady state. The units are percentage points. The low productivity is 0.068 log points below high productivity, chosen such that the difference in the white job finding rate in the first row matches between data and model. The data counterparts are taken from the regression results in columns (1) and (2) of Table 1.6, which show the average difference in the size-specific job-finding rates when the unemployment gap is high.

Table 1.12: Job-finding gap components

	Total gap	Matching rate	Vacancy share	Relative selectivity
Large firm				
High a	-0.066	0.300	0.888	-0.246
Low a	-0.313	0.228	0.894	-1.537
Small firm				
High a	-0.260	0.300	0.132	-7.738
Low a	-0.312	0.228	0.127	-12.884

This table shows the components of the job-finding gap between Black and white workers in the model by firm size and aggregate productivity state. A negative gap means Black workers are finding jobs at lower rates than white workers. The first column, in percentage points, is the product of the next three columns, defined as in equation 1.6.1. The first two are expressed as fractions and the last is in percentage points.

the job finding gap is smaller at large firms than small firms in the high productivity steady state, it decreases by more when we move from high productivity to low productivity. This change is primarily driven by the decrease in relative selectivity at both types of firms, shown in the last column. In the high productivity steady state, large firms hired 0.25 ppt fewer Black matches than white, whereas small firms hired 7.7 ppt fewer. In the low productivity state, this gap widens to 1.5 ppt at large firms and 12.9 ppt at small firms. The change in selectivity is thus bigger in proportional terms at large firms, though it is bigger in levels at small firms. The change in selectivity at large firms is amplified by the the disproportionate share of vacancies posted by large firms.

The intuition for the worsening in relative selectivity at both types of firms can be understood by returning to the firm's marginal cost condition in equation (1.4.25). When market tightness is lower, firms match with more workers per vacancy, shifting the marginal vacancy cost curve down. This direct effect is illustrated in Panels (a) and (b) of Figure 1.6 as the difference between the solid and dotted orange lines. It is cheaper for firms to be selective about which workers they hire in the low productivity steady state. This is shown by the intersections of the dotted orange lines at higher marginal productivities of minority workers for both firms.

The selectivity decisions are also influenced by indirect effects, through workers' outside options and the minority share of nonemployment, which affect the marginal cost of compensation. These effects are much smaller for the small firms, as shown by the difference between the solid and dotted blue lines in Panel (a) relative to Panel (b). The shift in the marginal compensation cost curve is the result of two opposing forces. First, in the low productivity steady state, all workers face worse prospects if they join the nonemployed pool, which lowers the endogenous value of nonemployment, $\Omega(g)$, for both groups of workers. Thus, the terms inside the summation in equation (1.4.25) are smaller, driving down the marginal cost curve. The second effect is happening through a narrowing of the outside option gap. Because white workers enjoyed more surplus from employment, as this surplus decreases it causes this value to fall more for white workers than Black.[7] Equation (1.4.22) shows that the relative selectivity between Black and white workers depends on the gap in outside options. Because Black workers earn lower wages, firms are willing to set a lower marginal productivity threshold for this group. As the outside option gap narrows in the low productivity steady state, this incentive weakens, leading the firm to set marginal thresholds closer to equality between Black and white workers. Panels (c) and (d) show that this effect is stronger at large firms because they are more selective. This shift in relative selectivity causes the overall change in the marginal cost of compensation to be positive, as illustrated in Panels (a) and (b). Intuitively, for a given marginal productivity for Black workers, the firm is now going to hire more white workers with a lower likelihood of being productive, which drives up marginal compensation costs, in spite of average compensation being lower.

To summarize, the worse signal quality for minority workers at both types of firms means that they are hired less in response to a permanent negative productivity shock. At small firms, this is driven by the direct effect of becoming more selective due to the reduced marginal cost of vacancies. At large firms, this is driven by the indirect effect of compensation becoming more equal across groups. These nuances are summarized in Figure 1.7, which shows the relationship between firm selectivity and the racial hiring gap. The small firm hiring gap worsens in the low productivity state primarily due to movement along the solid

[7] The narrowing of the outside option gap can be thought of as a narrowing of the racial wage gap. **?** uses data from the CPS to show that the wage gap between Black and white workers is less severe with negative aggregate shocks, which would be consistent with the model prediction. I do not see a significant relationship in either direction between the racial wage gap and the business cycle in the SIPP.

high productivity curve (direct effect), whereas the large firm hiring gap worsens due to the shift from the solid high productivity curve to the dotted low productivity curve (indirect effect). These changes summarize the hiring gap conditional on matching at a firm. The total observed changed in the job-finding gap is worse at large firms because their low marginal cost of vacancy posting leads them to attract a disproportionate share of matches, thus amplifying the worsening of the hiring gap.

One limitation of this counterfactual and related dynamic exercises is that as firms get more selective, their separation rates fall. Thus, without further richness on the separations margin, I am not be able to replicate both job-finding and separation patterns with representative small and large firms.

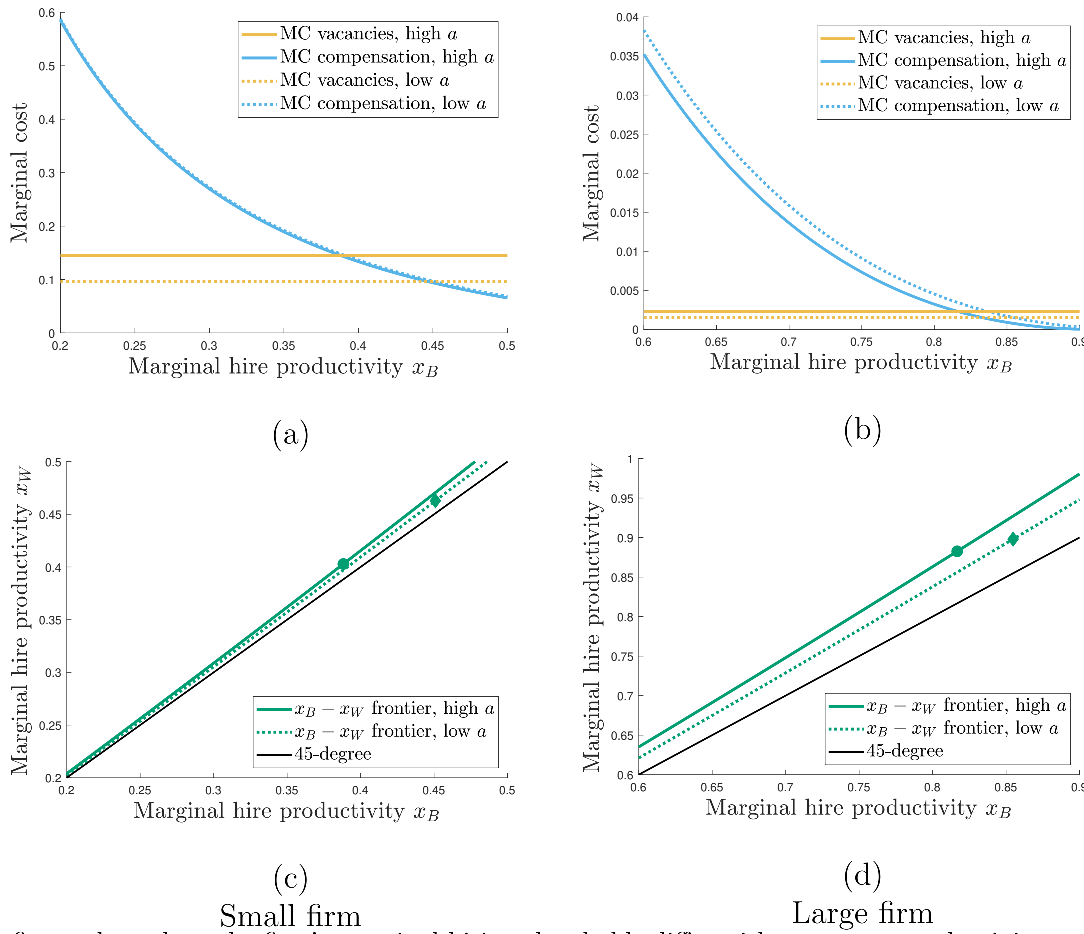
1.7. Conclusion

This paper starts by shedding light on the interactions between firm types and the Black-white employment gap over the business cycle. Consistent with other evidence on sorting between large and small firms, I show that the job-finding and separation gaps are worse for Black workers at small firms on average. However, when the economy contracts and the overall unemployment rate is higher, Black workers are disproportionately hurt by the drop in job-finding rates at large firms.

I showed that a model of information frictions in the hiring process can directionally generate both the sorting of Black workers towards large firms and the disproportionate impact of large-firm hiring changes on Black employment in response to aggregate productivity changes. Although the initial hiring gap is more negative at small firms, both firms worsen the hiring gap for Black workers when a decrease in productivity leads the economy to contract. The impact of the contraction at large firms is stronger overall because they make up a larger share of matches.

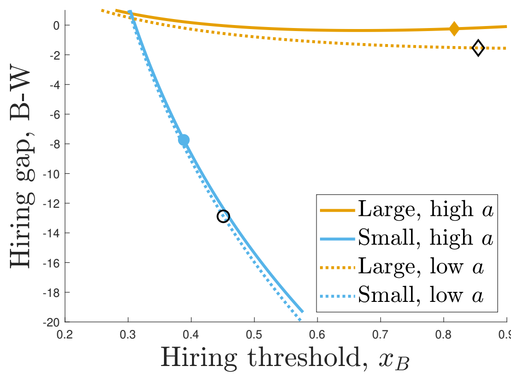
The general setup of this model could be used for any setting in which workers differ in their ability to communicate their productivity to potential employers. One such example could be differences in education. It could also easily include more than two groups. I showed in the background information that Hispanic workers are more likely to work at small firms. There is nothing specific to this model that says that small firms need to have the worse signal quality and indeed it would be interesting to see how the implications vary if another group of workers does not face this size-skewed disadvantage.

Figure 1.6: Change in selectivity with aggregate productivity



This figure shows how the firm's marginal hiring thresholds differ with aggregate productivity. Panels (a) and (b) show the tradeoff in the firm's decision between vacancy posting and selectivity. The orange lines are the marginal cost of vacancies, $c_v(z)/q(\theta)$. The blue lines are the marginal cost of compensation, defined as the right-hand side of (1.4.25). Both firms are more selective in the low productivity steady state, as the intersection of the dotted lines is to the right of the intersection of the solid lines. Panels (c) and (d) show how this affects selectivity for majority workers using the relationship in equation (1.4.22). In the low productivity state, the outside options become more equal and the frontier shifts closer to the 45-degree line, as shown by the dotted line. The dots represent the threshold choices in the high productivity state and the diamonds are the threshold choices in the low productivity state.

Figure 1.7: Hiring gap across firms



This figure shows how the hiring gap at each type of firm varies with the productivity threshold for minority workers. First, the orange and blue solid lines show the relationship between the threshold and the hiring gap at large and small firms in the high productivity steady state. The difference between these curves comes from the gap in signal quality for minority workers. The curve for small firms is generally much lower because the gap in signal quality is worse at these firms. The filled diamond and circle show the high productivity steady state threshold choice and hiring gap for each type of firm. The difference in the location of these points on the x-axis comes from differences in the marginal cost of vacancies. Large firms are more selective because they have a lower marginal cost of vacancies. Finally, the dashed orange and blue curves show the relationship between the threshold and hiring gap in the low-productivity steady state. The black diamond and circle show the low-productivity thresholds and hiring gaps. The hiring gap worsens at large firms primarily due to the indirect effects, shown by the shift from solid to dashed line. The hiring gap worsens at small firms primarily due to the direct effect of moving to the right along the solid curve.

CHAPTER II

Intergenerational Occupation Choice

2.0 Abstract

Children whose parents experience negative labor market shocks go on to earn less in adulthood. This paper asks whether this earnings gap can be explained by the occupations that the affected children choose. The first part of the paper constructs new measures of the return and risk of expected lifetime earnings specific to initial occupation. A \$1 increase in expected lifetime earnings risk is associated with a \$1.4 increase in expected return. The next section uses linked parent-child data to exploit quasi-exogenous variation in parent experiences to study the effect of negative parental shocks on children's young adult earnings and riskiness of first occupation choice. Parents' layoffs lead children to sort into less risky occupations on average, accounting for up to 13 percent of the total gap in young adult earnings. These results are similar for another measure of negative parental experience, measured as exposure to macroeconomic conditions using heterogeneity in parents' industry of employment and children's birth year. Children exposed to negative macroeconomic growth through either parent's employment earn less as adults and sort into less risky occupations. In both exercises the risk channel is larger for fathers' experiences than mothers.

2.1. Introduction

One of the big questions economists and policymakers confront is how inequality is transmitted from one generation to the next. Understanding these patterns in intergenerational mobility has important implications for designing equitable policies, and has thus been the subject of much research (see overviews by Solon (1999) and **?**). One strand of this research has shown that parents' labor market experiences have lasting effects on children's outcomes later in life (**?**). For example, **?** finds that children whose fathers lose their jobs due to exogenous firm closure go on to earn less than their otherwise similar peers as young adults.

My paper aims to explore this finding more deeply by asking whether negative parental experience leads to less risk-taking in children's occupation decisions and whether this can account for the decrease in earnings.

There are several channels through which we may expect parental experiences to affect the riskiness of children's occupation choices. First, there is the direct effect of lost access to parental financial resources. Children may anticipate decreased access to a financial safety net, thereby sorting into occupations that provide a safer stream of income (Boar (2021)). Reduced financial resources also likely affect human capital investment, particularly education. Whether or not this affects the riskiness of occupations chosen depends on the correlation between the education required for an occupation and its level of risk. Finally, children's willingness to take risks may change as a result of their parents' experiences.

In order to assess whether any of these channels are important, I must first develop a framework for defining occupation risk. I build on recent work that characterizes career choice as an investment in an income-generating process. Both Cubas and Silos (2017) and **?** develop measures of career risk and show that there exists a risk-return trade-off in career choice. Cubas and Silos (2017) aims to disentangle the industry risk premium from sorting based on industry-specific skills. **?** estimates a measure of occupation risk that allows for occupation switching as an insurance mechanism. As measurement of risk and return is not the primary subject of this paper, I aim to introduce a parsimonious measure that captures the central idea of investment in a starting occupation as a path to a stream of future income. I use a similar framework to Boar (2021) and define occupation return and risk as the mean and volatility of lifetime earnings in excess of what would be predicted by demographic characteristics. I find a positive relationship between return and risk using data on 22 occupation groups in the Panel Study of Income Dynamics (PSID). Section 2 discusses this measurement in greater detail.

After constructing measures of risk and return, I can evaluate whether parental experience affects these outcomes for young adults. I use the linked parent-child files from the PSID to identify roughly 4,600 parent-child pairs for whom the child is observed later as a working adult. I then create an indicator for whether the child's parent is ever laid off during ages 0 to 15. I regress income in early adulthood on parental job loss, controlling for demographics and parental education and employment characteristics. I confirm the finding that parental job loss leads to decreased earnings in early adulthood. Then, I use the same framework to evaluate the effect on the risk of the occupation these children choose. I find that children whose fathers are laid off choose less risky occupations, though I do not find significant results for mothers. Pooling both parents, I find that sorting into less risky occupations can explain at most 13% of the earnings gap in adulthood for children whose parents are laid off.

The focus on layoffs is a departure from the job displacement literature, which focuses on job losses that are due to firm closure, and therefore plausibly exogenous for the workers. I make this decision for two reasons. First, the number of displacements in my sample is small– about one-third the number of layoffs. I worry about drawing conclusions from such a small group of individuals. Second, research has shown that the negative consequences of job separation largely stem from periods of nonemployment in general rather than displacement in particular, and that people who are displaced are no more likely to experience periods of nonemployment than those separated for other reasons (Fallick et al. (2019)). However, focusing on layoffs generally runs the risk of conflating job loss with other parental characteristics. To alleviate this concern slightly, I exclude children whose parents were laid off more than one time and I use two variations of controls for parent characteristics. I also report results for the displaced subsample in the appendix.

As a further validation for the finding that negative parental experiences lead children to choose less risky occupations, I repeat my empirical analysis using relative exposure to negative macroeconomic conditions rather than layoffs. I find that this negative exposure leads children to earn 1-9 percentage points less in adulthood and choose 1-3 percentage points less risky occupations.

To my knowledge, this is the first paper to study how parent experience affects risk-taking in occupation choice. The most similar paper is Boar (2021), which studies whether parents' consumption decisions are influenced by the riskiness of the sector in which their children work. While her paper acknowledges that children's initial sector choice may be influenced by their family's financial resources, my paper tests this relationship more explicitly.

My work also relates to the large set of papers examining the long-term impacts of childhood experiences. A large body of work shows that health shocks during childhood can have lasting effects on outcomes in adulthood. See, for example, Almond et al. (2009), Almond and Mazumder (2011), and others. **?** and related papers have shown that the neighborhoods in which children grow up influence their adult outcomes. More specifically, my paper builds on the job displacement literature which studies how parental job loss during childhood affects adult labor market outcomes (**?**, **?**). My paper combines this childhood experience literature with the outcome of occupation risk and return to provide a potential mechanism for the observed earnings gaps.

This paper also touches on the literature about economic experience and risk taking. Several papers have studied heterogeneity in individuals' risk preferences and how they vary across families or correlate to observed behaviors, **?** and **?**. Shigeoka (2019) uses geographic variation in Japan to show how exposure to adverse economic conditions influences risk tolerance and some observed behaviors, such as business ownership. These papers rely on survey questions that elicit individuals' risk preferences by asking them how they would respond to hypothetical income trade-offs. My paper will advance this literature by taking occupation risk as given and studying how these heterogeneous preferences map into actual labor market choices. Malmendier and Nagel (2011) uses survey data to demonstrate that individuals' financial market experiences influence their future financial decisions. Poor past performance tends to make them less likely to take risks. My contribution is testing this finding in the labor market, which is a more consequential source of income for many people than financial markets.

The rest of the paper proceeds as follows. Section 2 discusses the measurement of occupation risk and return, section 3 describes the empirical framework, section 4 describes the data, section 5 presents results for parent layoffs, section 6 presents results for macroeconomic exposure, and section 7 concludes.

2.2. Characterizing occupations

2.2.1 Framework

As a starting point for my analysis, I assume that individuals enter the labor market and choose an initial occupation that will provide a stream of earnings over their career. The reason for focusing on starting occupation is two-fold. First, there is no obvious way to categorize individuals into occupations systematically, as they could theoretically change occupations every year. Characterizing occupations based on workers who stay in their occupations for long periods of time may not be appropriate as these workers might be better matched to their jobs than the general pool of workers to choose that occupation at any point in time. Since all workers must start somewhere, looking at first occupation provides a somewhat natural way of dividing the workforce into occupations, even if these are not permanent. It also makes sense from an entry-decision framework.

The second reason I focus on starting occupations is because I want to study the early-career decisions of individuals who had negative parental employment experiences in their childhood. If I characterize occupations based on the individuals who hold those occupations at the prime of their careers, ascribing those attributes to the young adults who choose those careers may be inappropriate, as young adults in particular tend to change occupations more than older individuals (**?**).

Next, I need to identify the salient characteristics of occupations that influence individuals' career choices. Using a similar framework to Boar (2021), I assume that individuals enter the labor market with a prediction of what their lifetime earnings will be based on their demographic characteristics and education. In particular,

$$y_{ijt} = \underbrace{f(\boldsymbol{X}_{it}, t)}_{\hat{y}_{it}} + \epsilon_{ijt}, \tag{2.2.1}$$

where y_{ijt} is real labor income of individual i who starts their career in occupation j in year t, $\boldsymbol{X}_{it}$ are observable demographic characteristics, including race, an age polynomial, gender, and educational attainment, but notably excludes occupation. Then ϵ_{it} may be interpreted as the annual real earnings of individual i in excess of what would be predicted by their demographics and macroeconomic conditions alone, which is captured by $\hat{y}_{it}$.[1]

For each individual, I aggregate (2.2.1) over the life cycle to construct lifetime earnings, expressed in annual terms

$$Y_{ij} := \frac{1}{T}\sum_t \frac{y_{ijt}}{R^{t-t_0}} = \underbrace{\frac{1}{T}\sum_t \frac{\hat{y}_{it}}{R^{t-t_0}}}_{\hat{Y}_i} + \underbrace{\frac{1}{T}\sum_t \frac{\epsilon_{ijt}}{R^{t-t_0}}}_{\varepsilon_{ij}}, \tag{2.2.2}$$

where Y_{ij} is lifetime earnings of individual i with starting occupation j, $\hat{Y}_i$ is predicted lifetime earnings of i conditional on demographics and aggregate conditions, and ε_{ij} is the excess lifetime return of individual i. Discount rate R is assumed constant for simplicity.

So far I have not conditioned on occupation in constructing $\hat{Y}_i$. Thus there is some portion of ε_{ij} that comes from the choice of occupation j. I use this observation to define the return and risk of occupation j as the mean and volatility of excess lifetime earnings (ε_{ij}),

$$\mu_j \equiv \mathbb{E}_j[\varepsilon_{ij}] \tag{2.2.3}$$

$$\sigma_j^2 \equiv \mathbb{V}_j[\varepsilon_{ij}] \tag{2.2.4}$$

To illustrate why these features are relevant, consider the perfect capital market benchmark

[1] Because I did not condition on occupation in $f(\cdot)$, the residuals need not be mean zero within occupation. Further, they are converted from logs to levels and therefore will not be centered around zero.

in which individuals choose occupations to maximize lifetime consumption,

$$\max_j \left\{ \mathbb{E} \sum_{\tau=0}^{T} \frac{u(c_\tau)}{R^\tau} \right\} \tag{2.2.5}$$

$$\text{s.t.}$$

$$\frac{1}{T} \sum_{\tau=0}^{T} c_\tau = \hat{Y}_i + \varepsilon_{ij}$$

$$\text{and (3) and (4)}$$

Then μ_j and σ_j are the relevant features of occupations if the discrete choice above can be rewritten as a function of these two characteristics.

2.2.2 Data and limitations

I estimate these measures using longitudinal data on labor income from the PSID.[2] My sample includes individuals with positive labor income for at least ten years. Labor income includes transfers from unemployment compensation and workers' compensation when available. I also restrict the sample to observations with positive hours unless they report non-zero unemployment or worker's compensation. I exclude retired individuals, students, and those are out of the labor force for other reasons during periods in which they are not labor force participants. I exclude individuals during years in which their occupation or industry is missing, unless they report being unemployed. I winsorize log income and exclude the top and bottom one percent.

I assign each individual to a starting occupation based on the first occupation in which they are observed working after finishing school and by age 30. My focus on starting occupations thus excludes individuals from the original survey who were over age 30 in 1968 and individuals who marry into PSID families after age 30. I define occupations using 22 groups of 2010 Census occupation codes, as described in table 2.1.

After all of these restrictions, I have a sample of 141,053 observations corresponding to 6,760 individuals. Table 2.2 shows some descriptive statistics of the sample.

If I observed every individual over their full lifetime, I could directly implement the measures discussed above. Instead, I often observe fragments of individuals' careers. In particular, my sample gets thinner at mid-career through retirement. In order to implement (2.2.2) in my sample directly, I must assume that the distribution of missing data points and the wage profile over the life cycle are not systematically different across occupations.

[2] I use waves from 1968 to 2017.

Table 2.1: Occupation categories

		Occupation	2010 Census codes	Number of entrants
1		**Management, business and financial**		
	1.1	Management	[0010,0430]	424
	1.2	Business and financial	[0500,0900]	131
2		**Professional and related**		
	2.1	Computer and math	[1000,1240]	85
	2.2	Engineering and architecture	[1300,1560]	146
	2.3	Sciences	[1600,1965]	62
	2.4	Community	[2000,2060]	73
	2.5	Legal	[2100,2160]	32
	2.6	Education	[2200,2550]	328
	2.7	Arts	[2600,2960]	102
	2.8	Health	[3000,3540]	241
3		**Services**		
	3.1	Healthcare support	[3600,3655]	233
	3.2	Protection	[3700,3955]	115
	3.3	Food	[4000,4160]	455
	3.4	Building maintenance	[4200,4250]	230
	3.5	Personal care	[4300,4650]	231
4		**Sales and office**		
	4.1	Sales	[4700,4965]	600
	4.2	Office	[5000,5940]	1,112
5		**Natural resources, construction, and maintenance**		
	5.1	Agriculture	[6000,6130]	89
	5.2	Construction and mining	[6200,6940]	409
	5.3	Installation, maintenance, and repair	[7000,7630]	233
6		**Production, transportation, and material moving**		
	6.1	Production	[7700,8965]	904
	6.2	Transportation	[9000,9750]	528

Table 2.2: Sample description

	Mean	SD	P5	P50	P95	N
Education						
High School	0.32	0.47	0	1	1	6760
Some College	0.30	0.46	0	1	1	6760
College	0.31	0.46	0	0	1	6760
Demographics						
Women	0.49	0.50	0	0	1	6760
White	0.65	0.48	0	0	1	6760
Min Age	22.9	3.04	18	23	29	6760
Birth year	1963	13.26	1943	1962	1985	6760
Income						
Real income	31,424	22,050	4,838	27,015	73,309	141,053

To the extent that these assumptions are valid, then this measure is an appropriate approximation of lifetime earnings. Indeed, under the strong assumption of perfect consumption smoothing and perfect capital markets, then annual lifetime earnings would be an appropriate measure of annual consumption. If the wage profile is different across occupations systematically, then the average measure would bias downwards the return of occupations that have lower early returns and bias upwards the risk. One way to address this would be to weight individuals more heavily the longer they appear in the sample. Given the relatively small sample sizes within each occupation bin, this does not seem practical in the current framework. Thus, my baseline measure relies on the assumption that the earnings profile is consistent across occupations.

2.2.3 Implementation

To implement these measures, I assume log earnings can be modeled as

$$\ln y_{ijt} = \underbrace{\beta X_{it} + \gamma_t}_{\ln \hat{y}_{it}} + e_{ijt}, \tag{2.2.6}$$

where $\ln y_{ijt}$ is log real labor income for individual i who starts their career in occupation j in year t, X_{it} includes race, age, age-squared, decade of birth, gender, availability of unemployment transfer data, four education bins, and interactions between gender and marital status and family size, and γ_t is a time fixed effect. To account for the sampling biases of the PSID, I weight observations using individuals' last non-zero weight in the sample.

Then e_{ijt} is the portion of earnings orthogonal to characteristics X_{it} and time. I map these results back to the framework given by equation (1),[3]

$$\epsilon_{ijt} = \exp\bigl(\ln \hat{y}_{ijt}\bigr)\bigl(\exp\bigl(e_{ijt}\bigr) - 1\bigr) \tag{2.2.7}$$

and apply sample analogs of (3) and (4) to construct the measures of return and risk. I assume a discount rate of $R = 1.04$, consistent with Boar (2021).[4]

Other papers in the literature, such as **?** and Cubas and Silos (2017), focus more on the log income generating process. They decompose e_{ijt} into an occupation-specific premium and a shock process,

$$e_{ijt} = \alpha_j + \nu_{ijt}, \tag{2.2.8}$$

where the occupation premium is modeled as $\alpha_j = \mathbb{E}[\beta_j X_{ijt} - \beta X_{ijt}]$, with β_j as occupation-specific returns to observable characteristics and an intercept. They then decompose the error term e_{ijt} into permanent and transitory components. I choose to take a more flexible approach and focus on levels for several reasons. First, I want to study relatively granular occupations and I have a limited sample with which to do that. Decomposing variance into permanent and transitory processes would require estimating at least two if not more parameters for each occupation, which would likely lead to noisy estimates. Estimating β_j separately for each occupation would run into similar precision concerns. Second, I have postulated that individuals consider the mean and variance of level lifetime earnings when choosing an occupation to enter. Thus there is a clear mapping between the mean and variance of ε_{ij} and the decision process that I consider. In particular, using the transformation in (2.2.7), return and risk are now measured in real US dollars, which is directly comparable to real earnings. Since the income generating process by occupation is not the primary focus of my paper, I choose to use this simpler framework to characterize occupations.

2.2.4 Risk-return trade-off

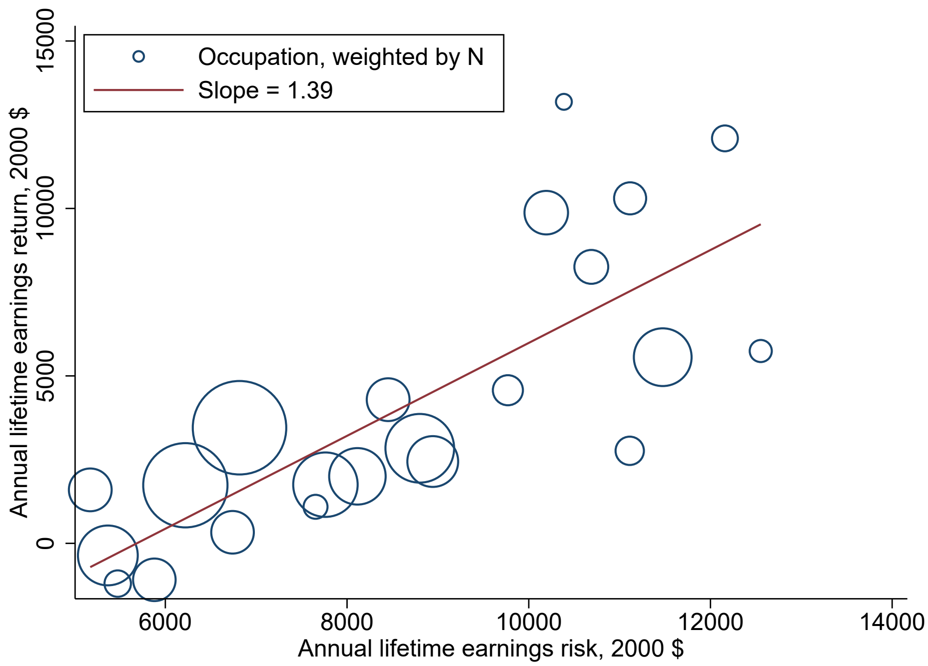
Using the methodology described above, I estimate lifetime earnings return and risk for the 22 occupations detailed in table 2.1. Figure 2.1 shows the relationship between average lifetime earnings return, μ_j, and risk, σ_j, as defined in equations 2.2.3 and 2.2.4. The upward sloping line suggests that occupations that have higher earnings in excess of demographics also tend to have greater volatility, which is consistent with a risk-return trade-off in starting

[3] If $y = \hat{y} + \epsilon$ and $\ln y = \ln \hat{y} + e$, then $\epsilon = y - \hat{y} = \exp(\ln y) - \exp(\ln \hat{y}) = \exp(\ln \hat{y} + e) - \exp(\ln \hat{y}) = \exp(\ln \hat{y})(\exp(e) - 1)$.

[4] The results are similar with $R = 1.03$ or $R = 1.05$.

occupations.

Figure 2.1: Risk-return trade-off.



Lifetime earnings return (μ_j) is the within-occupation expected value of annual average lifetime earnings in excess of what would be predicted by demographic characteristics. Lifetime earnings risk (σ_j) is the within-occupation standard deviation of annual average lifetime earnings in excess of demographic predicted earnings. Risk and return are measured in 2000 US dollars. Circles are weighted by the number of individuals in each occupation.

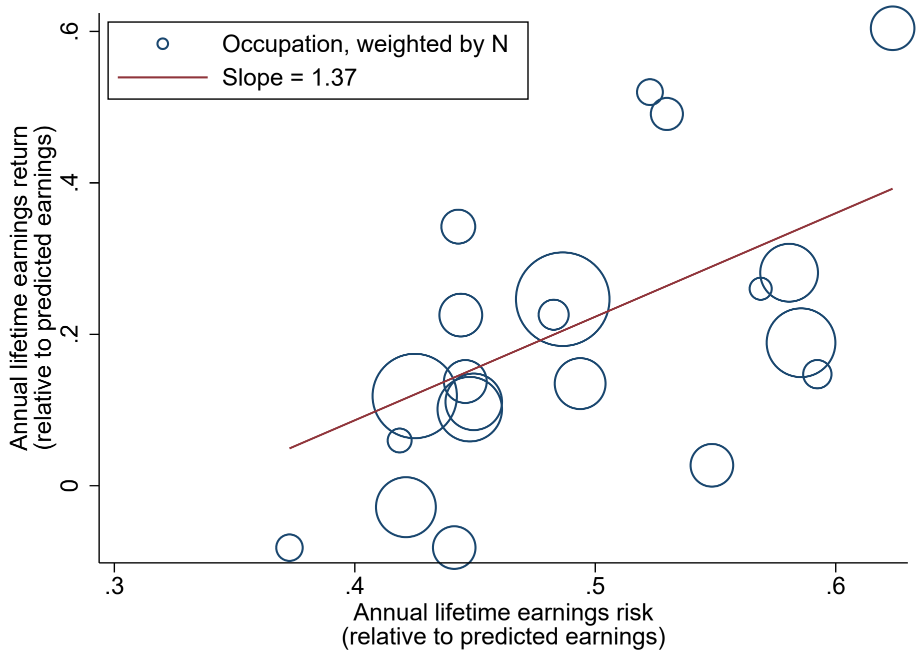
The measures introduced so far are unit-dependent. Due to the mapping to levels in (2.2.7), both risk and return could be mechanically higher if individuals have higher expected earnings. To account for this, I provide a unitless measure where I scale lifetime earnings risk σ_j and lifetime earnings return μ_j by the average predicted lifetime earnings of individuals in that occupation, $\hat{Y}_j$, where

$$\hat{Y}_j = \mathbb{E}_j[\hat{Y}_{ij}], \tag{2.2.9}$$

with $\hat{Y}_{ij}$ defined as in equation (2.2.2). Figure 2.2 displays the rescaled version of figure 2.1. The interpretation here is that after adjusting for differences in the composition of entrants to different occupations, higher return occupations are associated with higher risk. This result is sensitive to the assumption that occupations follow the same age profile of earnings.

The measures of risk and return that I have proposed aggregate among individuals who sort into a given occupation. A better measure of occupation risk and return would be

Figure 2.2: Risk-return trade-off in ratios.



Lifetime earnings return ($\mu_j/\hat{Y}_j$) is the within-occupation expected value of annual average lifetime earnings in excess of what would be predicted by demographic characteristics. Lifetime earnings risk ($\sigma_j/\hat{Y}_j$) is the within-occupation standard deviation of annual average lifetime earnings in excess of demographic predicted earnings. Risk and return are measured in 2000 US dollars and then scaled by predicted lifetime earnings, $\hat{Y}_j$. Circles are weighted by the number of individuals in each occupation.

measures specific to individual i. For example, the expected return of architects might be higher than demographics alone would suggest, but if an individual knows that they do not have the spatial reasoning skills required, their expected return could be much lower than the observed return. If individuals self-select into occupations that they are best at, under the strong assumption that occupation-specific skills are independently distributed across occupations, the observed expected return of the occupation should be an upper bound of the expected return for any individual considering that occupation, and similarly the volatility of lifetime earnings should be a lower bound of the underlying volatility if there is more downside risk in the population as a whole. If this assumption does not hold then I cannot assume a bound in either direction.

I use the results from figure 2.1 as my baseline measures of return and risk, as they have the clearest mapping back to the framework introduced earlier in this section and they have the interpretation that a \$1 increase in the risk of an occupation is associated with a \$1.4 increase in return. This relationship will be important for decomposing the effects of occupation sorting on adult earnings in the interpretation of my empirical results.

2.3. Empirical framework

There are many reasons to suspect that parental labor market shocks affect the occupation decisions of their children and particularly the riskiness of occupations chosen. However, there are many other reasons that individuals sort into different occupations, such as taste, talent, access, etc. Thus the first step in studying this question is to assess whether there is a noticeable difference in the characteristics of occupations chosen by children whose parents experience labor market shocks.

The ideal comparison would be the occupation choice of an individual whose parent experiences an economic shock compared to what that same individual would have chosen if the shock had not occurred. This thought experiment is of course impossible to carry out with data. As an alternative, I turn to the job displacement literature and compare the outcomes of individuals whose parents were laid off during their childhood to otherwise similar individuals whose parents maintained steady employment. In particular,

$$z_i = \gamma \cdot \text{experience}_i + \beta_1 X_i^c + \beta_2 X_i^p + u_i, \tag{2.3.1}$$

where z_i is the adulthood outcome of individual i, X_i^c is a vector of the child's characteristics, X_i^p is a vector of the parent's characteristics, and experience_i is an indicator for whether the individual's parent is laid off at any point during childhood. The exclusion restriction here is that after controlling for these parent and child characteristics we shouldn't expect any systematic differences between the two groups of children before the layoff occurred. This could be violated if the parent characteristics insufficiently control for parents' earning potential and likelihood of being laid off. To address these threats, I propose two sets of parental controls and I also include a robustness check focusing on the subset of parents who are displaced by firm or plant closure, as these are likely more exogenous to the household (after controlling for industry, etc.) than all layoffs.

The adult outcomes z_i I study are income in early adulthood and risk of first occupation choice, as defined in section 2. Child characteristics, X_i^c, include the decade in which the child was born and race. In my baseline specification I do not include the child's education, though this clearly affects their labor market outcomes in adulthood. One of the key channels through which negative parental experiences may affect children's outcomes is through their human capital accumulation. If I control for the child's education, then I am shutting down this channel. I also do not include the age at which I observe the child as an adult in my baseline specification, as this could also be related to education decisions.

Parental characteristics, X_i^p, include the parent's education and modal industry and occupation. Because lower income or lower educated individuals tend to experience layoffs at a higher rate than their higher income or educated counterparts, these parental characteristics are important to ensure that this framework is not just picking up socioeconomic characteristics of the parent. Ideally, one would like to measure the family's financial resources as well to better capture the child's socioeconomic upbringing. However, using average family income over childhood will likely absorb some of the financial channel through which parental job loss affects adult outcomes. Additionally, children experience the parental layoff at different ages. Thus it is not clear which age range of parental income is relevant. To that end, my baseline specification uses education, occupation, and industry fixed effects in lieu of family income. As a robustness check, I follow **?** and use the distribution of ages at which parental job loss occurs to randomly assign reference ages for the children whose parents are not laid off. This allows me to control for family income two to four years prior to the job loss to better control for the child's socioeconomic background.

2.4. Data

Using the parent linkage files from the PSID, I identify over 4,600 parent-child pairs. I identify the birth mothers for nearly all of these children and the birth fathers for roughly 3,000 of them. To be included in my sample, a child must be observed living with at least one parent for at least one year before age 15 and they must be observed again as an adult in the labor force, after finishing school.[5] The parent must be working for at least one year in order to observe occupation and industry.

In my baseline sample, I include all parent-child pairs that are observed at least once by the time the child is 15. There are several reasons a child-parent pair could appear for only part of the full childhood–if they are part of the original 1968 sample, if they move into a PSID family, if the family does not respond to the survey for some years but then returns, if the parents divorce and the child lives with just one of them after, if the child lives with a grandparent or other family member for part of childhood, etc. One might be concerned about censoring with including these pairs that we only observe for several years rather than the entirety of childhood. For example, in the PSID the parent might never be laid off but perhaps they were laid off before they entered the sample or during a period in which they did not respond to the survey. I choose to include all of these individuals because setting an ad-hoc minimum observation threshold could elimination important variation. For example, divorce rates have been shown to rise following layoffs (Charles and Stephens (2004)). If I exclude partial observations, I could be missing some of the children most affected by parent

[5]In order to observe the child's adult outcomes, they must be observed as the head or spouse of a split-off family unit. I also include young adults surveyed in the Transition to Adulthood Supplement for the 2005 to 2017 waves as long as they meet the criteria of being done with school and working.

layoffs. To alleviate concerns about censoring, I can repeat my analysis for the subsample of roughly 3,000 children I observe living with at least one parent for the entirety of childhood. However, these results should have the caveat that this sample likely has more stable family structure than the population as a whole.

Tables 2.3 and 2.4 show descriptive statistics for the parents and children in my matched sample.[6] The incidence of parental layoff in my sample is about 16 percent for fathers and 18 percent for mothers. About one third of total layoffs are displacements due to plant or firm closure.

Table 2.3: Matched parent data description

	Fathers		Mothers	
	Laid off	Others	Laid off	Others
Parent's education				
High school	.37	.29	.39	.35
	(.48)	(.45)	(.49)	(.48)
Some college	.24	.22	.35	.26
	(.43)	(.41)	(.48)	(.44)
College	.21	.38	.12	.29
	(.40)	(.49)	(.33)	(.46)
Parent's modal industry				
Manufacturing	.27	.26	.13	.11
	(.45)	(.44)	(.33)	(.31)
Public sector	.05	.08	.03	.05
	(.21)	(.27)	(.16)	(.21)
N	469	2537	789	3535

In table 2.3, I see that the parents who are laid off are generally less educated than the others. I highlight two industries of employment– first, the displacement literature often focuses on plant closures which predominantly affect the manufacturing industry. Since I am including all layoffs rather than just displacements, the laid-off parents in my sample are only slightly more likely to work in manufacturing than the non-laid-off group. To the extent that public sector jobs tend to have more job security than private sector jobs, it is unsurprising that I see relatively fewer laid-off parents working in the public sector.[7] These

[6] In my regression analysis I use sample weights to adjust for the oversampling of poor households in the PSID survey design. The means and standard deviations shown here are not weighted.

[7] These industries are measured as the mode over childhood, not the industry in which the parent was employed at the time of the layoff. The reason for this distinction is so that they are comparable to the non-laid-off parent measurement. It is unclear at what age to measure the industry for the parents who are not laid off, and comparing modes for one group to point-in-time measures for the other group does not seem appropriate.

Table 2.4: Matched child data description

	Fathers		Mothers	
	Laid off	Others	Laid off	Others
Demographics				
Age in adulthood (first)	22.6	22.9	22.1	22.9
	(3.1)	(2.9)	(3.0)	(3.0)
Woman	.51	.50	.53	.51
	(.50)	(.50)	(.50)	(.50)
White	.88	.87	.62	.83
	(.33)	(.34)	(.49)	(.37)
Birth year	1978	1981	1983	1978
	(9.9)	(11.2)	(8.6)	(11.0)
Education				
High school	.30	.19	.33	.21
	(.46)	(.41)	(.47)	(.41)
Some college	.27	.25	.35	.27
	(.45)	(.45)	(.48)	(.44)
College	.37	.53	.27	.48
	(.48)	(.5)	(.44)	(.50)
Adult outcomes				
Real earnings	17,907	19,648	14,496	18,710
(3-year average)	(13,111)	(12,637)	(10,558)	(12,794)
Occupation excess return	2,458	3,069	2,224	2,837
(μ_j)	(2,414)	(2,929)	(2,270)	(2,807)
Occupation risk	7,440	7,876	7,264	7,703
(σ_j)	(1,802)	(1,892)	(1,716)	(1,853)
N	469	2537	789	3535

statistics illustrate the importance of including controls for parental education and other employment factors in my regressions.

Table 2.4 shows characteristics of the children in my matched sample. The sample is broadly balanced in age, gender, and birth cohort. The slight difference in birth year for the mothers' sample could reflect shifts in labor force participation over the sample period, which is one of the reasons I choose to separate fathers and mothers rather than pool parents together. The children of laid-off parents are less white and go on to receive less education than their peers. Looking at the adulthood outcomes, the affected children earn less on average and start their careers in occupations that have lower risk and lower excess returns, as estimated in section 2.

As a validation for my measure of occupation risk, I turn to survey questions from the Transition to Adulthood Supplement. This supplement was administered from 2005 to

2017 and asked young adults questions about their career plans and their priorities in job characteristics. I focus on one question in particular: "On a scale of 1 to 7, where 1 means not at all important and 7 means very important, how important is it to you to have a job that is steady, with very little chance of being laid off?" For young adults who were surveyed more than once, I look at the first response they gave. My sample includes 2,300 individuals who responded to this question and can be assigned to a starting occupation. The survey responses are highly skewed with about 54% of respondents saying that it is very important for them to have a steady job. This skewness could come from a lack of trade-off in the survey design–respondents were asked to rate the importance of each job quality separately, rather than prioritize among a set of job characteristics. Although this measure is not perfect, it is closely related to what I am trying to study. Since the variation appears to be at the highest response, I define prioritizing a steady job as a response of 7.

Using this indicator for prioritizing steady employment, I try two validation exercises. First, I regress children's occupation risk on the steady job indicator. I find a very small (0.6 percentage point) decrease in risk for individuals who respond that a steady job is very important to them, though the standard error is high. Next, I regress the steady job indicator on parental layoff. I find that children whose parents are laid off are 3 to 5 percentage points more likely to respond that a steady job is very important, though again the difference is not statistically significant. Both of these exercises move in the direction I expect which is encouraging, though certainly not conclusive evidence of the mechanisms I suggest.

Table 2.5: Prioritizing steady employment

	Risk log σ_j	Prioritize steady job	
	(1)	(2)	(3)
Priorize steady job	-0.00584		
	(0.0101)		
Parent laid off		0.0486	0.0261
		(0.0312)	(0.0310)
Parent controls			X
Observations	2300	2323	2323
R-Squared	.0001443	.0017741	.0537735

Notes: Column 1 shows the correlation between prioritizing a steady job and observed occupation risk. Column 2 shows the correlation between parental layoff and prioritizing a steady job and column 3 shows the same correlation with controls for parents' education, occupation, industry, and race. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

2.5. Results

2.5.1 Adult earnings

Before examining the effect of parental job loss on occupation choice, I first demonstrate that this parental experience is important for adult outcomes. I estimate equation (2.3.1) with the child's log mean real earnings over the first three years in the labor force as the outcome of interest. I only include children who are observed for at least three years as adults since young adult earnings are typically noisy in one given year. As described in section 3, I include controls for parents' education, industry, and occupation. I use four education bins, six broad occupation groups described in table 2.1 and 15 industries.[8] I include controls for both parents when possible, and an indicator for not observing the second parent characteristics as necessary. For example, in a two-parent household I control for both parents' education, occupation, and industry. If the second parent is not working over the entirety of childhood, I still control for their education but I include indicators for missing industry and occupation. If I do not observe the second parent at all then I will have an additional indicator for missing education.[9]

Columns (1)-(3) of table 2.6 show the results of my baseline specification. Children whose parents are laid off go on to earn 12 percentage points less as young adults than their peers. Columns (4)-(6) show the results using family income instead of occupation and industry characteristics and show that parent's job loss leads to 9 percentage points lower income as adults. Overall, these estimates are broadly consistent with the finding of **?**, who find that parental job loss results in 10 to 11 percentage points lower earnings using an earlier sample from the PSID.

2.5.2 Occupation choices

Now that I have shown that parental job loss negatively affects earnings, I want to explore whether there is a difference in the riskiness of their occupation choices. I assign the children in my sample a level of occupation risk based on the measures estimated in section 2 and the first occupation these children work in. Table 2.7 shows the results of regressing occupation risk measured in log dollars on the indicator for parental layoff and the same controls as

[8]The industries are 1. Agriculture, 2. Mining, 3. Construction, 4. Manufacturing, 5. Wholesale trade, 6. Retail trade, 7. Transportation, 8. Utilities, 9. Information and communication, 10. FIRE, 11. Professional, 12. Education, health and social services, 13. Arts, entertainment and food services, 14. Other services, and 15. Public administration.

[9]For the effect of fathers' layoffs on children's outcomes, the results are similar with and without controls for mothers' characteristics. For mothers it is more important to control for father characteristics, likely because there are more single mothers and mothers' layoffs will be more important for single parent families than families in which the mother is a secondary earner.

Table 2.6: Effect of parent's job loss on adult earnings

	(1)	(2)	(3)	(4)	(5)	(6)
Father	-0.135***			-0.0987*		
	(0.0517)			(0.0539)		
Mother		-0.114**			-0.0530	
		(0.0481)			(0.0478)	
Either parent			-0.120***			-0.0869**
			(0.0360)			(0.0367)
Family income				0.299***	0.255***	0.251***
				(0.0383)	(0.0320)	(0.0290)
Mean ($)	18121	16803	16864	17456	16656	16765
Mean (log $)	9.56	9.47	9.47	9.52	9.46	9.46
SD (log $)	.75	.79	.79	.76	.79	.79
Observations	2477	3516	3852	2035	3001	3424
R-Squared	.15	.15	.15	.14	.15	.15

Notes: All columns include controls for child's decade of birth and race and parents' education. In columns (1)-(3), parent employment controls include dummies for 15 industries and 6 broad occupation categories, measured as mode over career. In columns (4)-(6), parent employment controls are replaced with the log of average real household income over the 2-4 years prior to child's reference age, defined as the age at which their parent was laid off or a randomly assigned age based on the distribution of ages at parent layoff. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

table 2.6. These results indicate that children whose parents are laid off tend to sort into occupations with about 2 percentage points lower risk, though the estimate varies by parent and attenuates with the inclusion of pre-layoff income controls.

Table 2.7: Effect of parent's job loss on occupation risk

	(1)	(2)	(3)	(4)	(5)	(6)
Father	-0.0364**			-0.0116		
	(0.0155)			(0.0160)		
Mother		-0.00630			0.0147	
		(0.0130)			(0.0134)	
Either parent			-0.0233**			-0.00432
			(0.0104)			(0.0107)
Family income				0.0656***	0.0534***	0.0557***
				(0.0115)	(0.00846)	(0.00811)
Mean ($)	8133	7936	7921	8063	7908	7907
Mean (log $)	8.97	8.95	8.95	8.96	8.95	8.95
SD (log $)	.25	.24	.24	.25	.24	.24
Observations	3006	4324	4662	2484	3723	4162
R-Squared	.11	.12	.12	.11	.12	.12

Notes: All columns include controls for child's decade of birth and race and parents' education. In columns (1)-(3), parent employment controls include dummies for 15 industries and 6 broad occupation categories, measured as mode over career. In columns (4)-(6), parent employment controls are replaced with the log of average real household income over the 2-4 years prior to child's reference age, defined as the age at which their parent was laid off or a randomly assigned age based on the distribution of ages at parent layoff. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In order to evaluate the importance of this difference, I use the trade-off estimated in section 2 between occupation risk and return. A $1 increase in occupation risk was associated with a $1.4 increase in expected return. Using the means in tables 2.6 and 2.7, the estimated elasticities, and this relationship, I find that sorting into less risky occupations can explain at most 13% of the earnings loss for either parent being laid off (3% under the specification with alternative controls) or at most 17% of the earnings loss for fathers being laid off.

2.5.3 Robustness and discussion

My results presented so far provide some evidence that negative parent experiences lead children to sort into less risky occupations, explaining some of the earnings gap in adulthood. However, the magnitude varies with the two sets of parent controls. Another concern could be that even with both sets of controls, layoffs are correlated with unobservable factors that could affect children's earnings potential. I repeat the same specifications for children whose parents are displaced by plant or firm closure. I am still finding that these children sort into less risky occupations, as seen in table B.2, but the estimated effects on earnings are imprecisely estimated and close to zero, as seen in table B.1. Since the number of displacements is quite small, it is hard to draw strong conclusions from these results.

Overall, I interpret these results to suggest that occupation choices are affected by negative parental experiences. Given the sensitivity to choice of controls and layoffs versus displacements, I complement this exercise with a second parent experience, described in section 2.6.

2.6. Macroeconomic exposure

The goal of this section is to explore how children's exposure to negative macroeconomic conditions affects the occupation choices they make. If I naively look at children who grew up during recessions or booms, I will simply be measuring cohort effects. To the extent that cohorts face different job markets, I may be mistaking different occupation vacancies on the labor demand side for different occupation choices on the labor supply side. Instead, I use variation in both birth year and parent's primary industry of employment to construct a measure of relative exposure to macroeconomic growth. By using within-cohort variation, I can take a cohort's labor demand as fixed and focus on differences in supply decisions.

In particular, I define $\tilde{g}_{kt} = g_{kt} - \bar{g}_t$ as the growth rate of output in industry k in year t relative to the aggregate growth rate of output. I define

$$\eta_{knt} = -\frac{1}{n}\sum_{l=0}^{n-1} \tilde{g}_{k,t-l}, \tag{2.6.1}$$

where k is the parent's primary industry of employment, n is the number of years considered, and t is the ending year. I use the negative sign to allow the interpretation that η_{knt} is exposure to relatively worse macroeconomic conditions. In my baseline specification, I choose $n = 18$ and t as the year in which the child turns 18. η_{knt} is thus the average relative macroeconomic growth from birth to age 18 in the parent's industry of employment. I measure growth using percent growth in chain-type quantity indexes for gross output by industry from the BEA, which is available from 1943-2019.

There are two main benefits of using parent's modal industry rather than letting it change over time. The first practical reason is that I do not observe all parents over the entire childhood so I would have to impute missing years for some children or focus on a stable panel. As argued in the previous section, I believe this would eliminate some important variation if macroeconomic exposure leads to changes in family structure. The second benefit of using modal industry is that I will capture fewer endogenous industry changes. If there is a downturn in one industry, some workers may shift to a different industry in response. I may still capture some of these shifts if they end up working in the new industry for a longer period of time, but I shouldn't have year-to-year switching.

I use this measure to study the effect of exposure to negative macroeconomic conditions on the riskiness of children's occupation choice. I estimate the reduced form model,

$$z_i = \gamma\eta_{knt} + \iota_t + u_i, \tag{2.6.2}$$

where η_{knt} is constructed as above, ι_t are birth cohort fixed effects, and z_i is either average real earnings in adulthood or occupation risk. I standardize z_i and η_{knt} so that γ may be interpreted as the standard deviation increase in outcome z_i associated with a one standard deviation decrease in relative macroeconomic growth. My prior is that γ will be negative for both outcomes, meaning that children with more negative exposure earn less as adults and sort into less risky occupations. I include birth cohort fixed effects so that γ reflects within-cohort effects, holding fixed labor market conditions when these children reach adulthood.

Table 2.8: Effect of exposure to negative macroeconomic conditions on adult earnings and occupation risk

	Income y_i		Risk σ_j	
	(1)	(2)	(3)	(4)
Father	-0.0657*		-0.116***	
	(0.0340)		(0.0291)	
Mother		-0.127***		-0.110***
		(0.0333)		(0.0283)
Mean($)	18121	16803	8133	7936
SD($)	12186	11873	2016	1948
Obs.	2455	3413	2976	4174
R-Squared	.08	.08	.04	.04

Notes: Regressions include fixed effects for child's birth year. Coefficients reported are on average relative macroeconomic growth of parent's industry from birth to age 18. Outcome variables and macroeconomic exposure are standardized so the estimated coefficients can be interpreted as the standard deviation increase in income or risk associated with a one standard deviation decrease in relative macroeconomic conditions. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2.8 reports the results of estimating (2.6.2) for income and occupation risk. A one standard deviation decrease in relative economic performance of the father's industry is associated with a .07 standard deviation decrease in adult earnings and .12 standard deviation decrease in occupation risk. For mother's exposure, the estimated effect on earnings is larger. The relative magnitude of the effect on risk is larger for this shock than the parent's layoff. Using the relationship between risk and return, the decrease in occupation risk accounts for 40% of the decrease in earnings through father's exposure and 20% of the decrease through mother's exposure.

Table 2.9: Effect of exposure to negative macroeconomic conditions on adult earnings and occupation risk, conditional on parent education

	Income y_i		Risk σ_j	
	(1)	(2)	(3)	(4)
Father	-0.0118		-0.0395	
	(0.0349)		(0.0291)	
Mother		-0.0734**		-0.0443
		(0.0327)		(0.0280)
Mean($)	18121	16803	8133	7936
SD($)	12186	11873	2016	1948
Obs.	2455	3413	2976	4174
R-Squared	.11	.11	.10	.10

Notes: Regressions include fixed effects for child's birth year and parent's education. Coefficients reported are on average relative macroeconomic growth of parent's industry from birth to age 18. Outcome variables and macroeconomic exposure are standardized so the estimated coefficients can be interpreted as the standard deviation increase in income or risk associated with a one standard deviation decrease in relative macroeconomic conditions. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

One concern with this specification is that relative performance of a parent's industry is not truly random within cohorts. There could be simultaneity bias, in which parents with more education and higher skills are able to sort into high-performing industries, and this is what causes the difference in children's adult outcomes. To address this possibility, I modify the regression framework in (2.6.2) to include controls for the parent's education. The results are reported in table 2.9. Though the magnitudes of both effects are smaller, they are both still negative. The magnitude of the decrease in occupation risk is still larger than the decrease in earnings for father's exposure.

Previous research has shown that experiences before age five can have substantial long-term impacts on children's long-term outcomes (Currie and Almond (2011)). To that end, I construct a second measure of childhood exposure with n and t corresponding to age five rather than age eighteen. The results are reported in appendix tables B.3 and B.4. I still see a negative effect of early childhood exposure on earnings and occupation risk, though smaller in magnitude than over full childhood. The difference in risk accounts for about 23% of the earnings gap for fathers and 5-9% of the gap for mothers.

2.7. Conclusion

This paper studies the effect of childhood experiences on the riskiness of the career paths that children go on to choose in early adulthood. I focus on the choice of first occupation after completing school, which I argue can be characterized by the return and risk relative to predicted lifetime earnings. Using parental layoffs and parent's exposure to relative macroeconomic growth as two childhood experiences, I find that children with negative parental experiences go on to earn less as adults and sort into less risky starting occupations.

In constructing measures of risk and return, I have taken starting occupation as given, not accounting for differences in taste, abilities, and labor market conditions that surely affect occupation choices. Thus, caution should be applied when interpreting my results. I do see children with negative parental experience sorting into less risky occupations, but I cannot disentangle the mechanism for this change. It could be that their investments in human capital across occupations are changing, or that they are more liquidity-constrained as a result of parents' income loss, or that their risk tolerance has changed. Teasing out these mechanisms will be important for understanding the consequences for intergenerational effects of labor market policies.

CHAPTER III

External Crises and Devaluations: A Heterogeneous-Firm Perspective (with Matias Moretti, Pablo Ottonello, and Diego J. Perez)

3.0 Abstract

This paper studies the transmission of external crises through the microlevel patterns of firms' adjustments. The first section develops an open-economy model with heterogeneous firms that finance their investment using debt subject to default risk and face fluctuations in the risk premium required by foreign investors. The model reveals that the differential responses of firms by default risk is informative about the channels through which global risk premium fluctuations affect the economy. Guided by the model's predictions, the next section uses firm-level data for a panel of emerging markets and show that while investment of risky firms contracts in response to increases in the global risk premium, that of risk-free firms expands. Combining the empirical evidence with the model, the findings imply that exchange rate depreciations play a stabilizing role during external crises for most firms in the economy, which helps them attenuate their adjustments, owing to more favorable prices. Devaluations are contractionary only for heavily indebted firms, for which the negative balance-sheet effects dominate the stabilizing effects of lower costs.

3.1. Introduction

Systemic crises in emerging economies tend to display a classic pattern. As external borrowing costs surge, firms reduce investments, economic activity declines, and currencies depreciate. Salient examples include the Latin American debt crises in the early 1980s, the

East Asian/Russian crisis in the late 1990s, and the Global Financial Crisis that started in 2008. Based on the recurrence of these patterns, an old adage among policymakers is that depreciations are contractionary.

In this paper, we study what firms' adjustments at the microlevel reveal about economic transmission during external crises. To do so, we combine new measurements of firms' responses to fluctuations in the global risk premium with a quantitative model of heterogeneous firms subject to default risk. Our analysis reveals two main findings. First, surges in the global risk premium during crises play a major role in driving the dynamics of external borrowing costs and firms' investment, particularly for firms exposed to default risk. Second, we find that exchange rate depreciations play a stabilizing role during debt crises for most firms in the economy, which helps them attenuate their adjustments through more favorable prices. Devaluations are contractionary only for heavily indebted firms, for which the negative balance-sheet effects dominate the stabilizing effects of lower costs. In this sense, the old adage only applies to a minority of firms.

The paper begins by formulating a heterogeneous-firms open-economy model to study the transmission of aggregate external shocks. Domestic firms face endogenous default risk and finance their investment with risky debt. Credit to firms is provided by foreign investors, who are risk averse and subject to exogenous fluctuations in their required premium for risk, or global risk premium. The rest of the model features classic forces studied in the analysis of currency depreciations in open economies. On the one hand, firms face currency mismatch that gives rise to a contractionary role of currency depreciations through balance-sheet effects. They produce a home good that is both exported and consumed domestically, and borrow in foreign currency. On the other hand, the economy is subject to nominal rigidities that give rise to a stabilizing role for currency depreciations.

In this framework, we study the transmission of increases in the global risk premium and the role of currency depreciations as a policy response. Shocks to the global risk premium constitute a central source of fluctuations that give rise to the global financial cycle (Rey, 2015; Maggiori, 2021), and are particularly relevant for determining business cycles in emerging economies (Neumeyer and Perri, 2005). Fluctuations in the global risk premium affect economic activity through two channels. One is a direct channel, by which changes in the global risk premium affect firms' financing costs and their investment. The other is an indirect channel, which stems from the feedback between firms' responses, domestic aggregate demand, and exchange rate policy. Our model analysis suggests a strategy to measure the relative strength of these channels based on the differential responses of firms: Since risk-free firms are not affected by direct channels—their borrowing costs remain invariant to changes in the risk premia—their response is primarily informative of the strength of indirect channels.

Guided by this model prediction, we estimate the heterogeneous responses of firms with different levels of default risk to changes in risk premia. For this, we begin by constructing a novel empirical measure of the global risk premium, which uses balance sheet and asset price data on publicly held firms in multiple emerging economies. Building on the methodology pioneered by Gilchrist and Zakrajšek (2012), we estimate time-series measures of the risk premium as the residuals from projecting firms' bond yields on their probabilities of default using **?**'s **?** model. Our empirical measure of the global risk premium captures major global financial turmoil as measured, for example, by the VIX and the US excess bond premium.

We combine our empirical measure of risk premia with firm-level data to estimate the effects of fluctuations in the global risk premium on firms' investment. Our estimates show that increases in the global risk premium are associated with heterogeneous responses for risk-free and risky firms. Risky firms experience large drops in investment following an increase in the risk premium. For instance, a one-standard-deviation increase in the global risk premium is associated with a 3% cumulative decline in the capital stock of risky firms, which peaks 6 quarters after the shock. Risk-free firms (those with a small default probability) exhibit positive responses to changes in risk premium. In particular, we show that the peak cumulative increase in capital for risk-free firms is about 2%. This positive response indicates the presence of expansionary indirect effects for risk-free firms, which provides an informative empirical moment to anchor our model analysis.

We then use our empirical estimates as well as other micro- and macroeconomic data to conduct a quantitative analysis of our model. The combination of risk-premium shocks and heterogeneous firms with default risk introduces nonlinearities at the aggregate and firm levels. We solve the model using global methods for both the aggregate and idiosyncratic blocks. The model matches the differential responses of risk-free and risky firms to shocks to the global risk premium. In the model, risk-free firms respond expansively to the global risk premium shock because real wages contract due to falling labor demand because of the adjustments of risky firms.

Lastly, we use our model as a laboratory to analyze how exchange-rate policy can stabilize/amplify fluctuations in the global risk premium. Floating exchange rate regimes endogenously lead to currency depreciations during these crisis episodes. A depreciation, in turn, has two effects that affect firms in opposite directions. First, because debt is denominated in foreign currency, depreciations give rise to a debt revaluation that increases the debt burden for firms. Second, a depreciation allows for an adjustment of real wages if nominal wages are sticky, and this allows firms to expand due to lower costs. Our model calibration, which is informed by the expansionary response of risk-free firms, suggests that the latter effect dominates and, hence, devaluations have a stabilizing effect on the economy.

Related literature Our paper contributes to various strands of the literature. First, our paper is related to the literature that studies the "global financial cycle" and imperfect international capital markets (see, e.g., Rey, 2015; Maggiori, 2021, and references therein). This literature has shown how international financial markets play a central role in determining exchange rate dynamics (Gabaix and Maggiori, 2015; Itskhoki and Mukhin, 2021), the allocation of credit to firms (Baskaya et al., 2017), and systemic debt crises (Morelli et al., 2022).[1] We contribute to this literature by studying the channels of transmission of fluctuations in the global risk premium and their implications for exchange rate policy.

Second, our paper contributes to the literature on international business cycles and sudden stops (see, for example, Backus et al., 1992; Aguiar and Gopinath, 2007; **?**). A strand of this literature analyzes the role of fluctuations in external borrowing costs on business cycles in open economies (see, for example, Neumeyer and Perri, 2005; **?**). We contribute to this literature by using a micro-to-macro approach that exploits cross-sectional firm heterogeneity to assess the aggregate implications of changes in the risk premium.

Third, our paper relates to the contractionary devaluation debate. The classic Mundellian view is that currency fluctuations act as shock stabilizers in open economies (see, for example, Galí and Monacelli, 2005; Schmitt-Grohé and Uribe, 2016) and play a stabilizing role in open economies. However, the literature motivated by emerging-market experiences has highlighted that depreciations can be contractionary in the presence of strong balance-sheet effects and real income channels (see, for example Aguiar, 2005; **?**; **?**; Auclert et al., 2021, among others). We contribute to this literature by showing how analyzing empirical evidence on the heterogeneous responses of firms to an external financial shock can shed light on this debate. In this sense, our findings are consistent with those from **?** that show that depreciations can be expansionary in a financially driven exchange rate model as in Gabaix and Maggiori (2015) and Itskhoki and Mukhin (2021).

Finally, a related literature has analyzed the role of firm dynamics in macroeconomic fluctuations (see, for example, Khan and Thomas, 2008; Ottonello and Winberry, 2020). In open economies, firm heterogeneity has been shown to play a central role during crises and sudden stops (examples include **?**Blaum, 2019; Ates and Saffie, 2021; **?**). Methodologically, our work is related to **?** and Aruoba et al. (2022) that analyze how heterogeneity in firms' leverage informs the channels of transmission of sovereign risk and monetary policy, respectively. We contribute to this literature by developing a heterogeneous-firm open-economy framework to study exchange rate regimes.

[1] A related literature in asset pricing studies the role of fluctuations in the risk premium (see **?**, for a survey). In the international macro literature, risk premium fluctuations have been relevant in explaining cross-sectional currency and country risk (see, for example, **?**Hassan et al., 2021; **?**).

3.2. The Model

We consider a world economy composed of a domestic small open economy and the rest of the world. Among these economies, there is trade of goods (home and foreign) and international lending. The domestic economy is the main focus of the model and is populated by a representative household, a set of heterogeneous firms, and a government. Firms produce the home good using capital and labor as inputs, and finance their investment by borrowing from investors in the rest of world subject to endogenous default risk. The global economy is subject to two sources of aggregate risk: productivity and global risk premium shocks. The latter capture fluctuations in the premium for risk required by global investors and is the main focus of our analysis.

In Subsection 3.2.1, we start by describing the heterogeneous firms' problem. In Subsection 3.2.2, we summarize the households' problem. Subsection 3.2.5 describes the rest of the world and characterizes the stochastic discount factor of the global investors, which allows us to introduce risk premia in the model. Lastly, Subsection 3.2.3 introduces nominal rigidities, which then allows us to study different exchange rate policies.

3.2.1 Heterogeneous Firms

There is a unit mass of heterogeneous firms, which are owned by households. Firms have access to a decreasing returns-to-scale technology to produce home goods (H) using capital and $\left(k_{i,t}, l_{i,t}\right)$ as inputs:

$$y_{i,t} = \left(A_t z_{i,t}\right)^{\varsigma} \left(k_{i,t}^{\alpha} l_{i,t}^{1-\alpha}\right)^{\chi} \tag{3.2.1}$$

where $\chi \in (0,1)$ governs the degree of decreasing returns; $\alpha \in (0,1)$ is the value-added share of capital; $\varsigma \equiv 1-(1-\alpha)\chi$; and $z_{i,t}$ and A_t denote idiosyncratic and global productivity, assumed to follow first-order autoregressive processes, $log(z_{i,t+1}) = (1-\rho_z)log(z^{\star})+\rho_z log(z_{i,t})+\sigma_z\epsilon^z_{i,t+1}$ and $log(A_{t+1}) = (1-\rho_A)log(A^{\star}) + \rho_A log(A_t) + \sigma_A\epsilon^A_{t+1}$, where $\epsilon^z_{i,t+1}$ and ϵ^A_t are standard Gaussian shocks. Firms have also access to a technology to accumulate capital by investing out of the final good subject to convex adjustment costs:

$$k_{i,t+1} = (1-\delta)k_{i,t} + I_{i,t} - \Psi(k_{i,t+1}, k_{i,t}) \tag{3.2.2}$$

where $I_{i,t}$ denotes investment expenditure in terms of the home good; $\delta \in (0,1)$ is the depreciation rate; and $\Psi_k(k_{i,t+1}, k_{i,t}) \equiv \frac{\psi_k}{2}\left(\frac{k_{i,t+1}-(1-\delta)k_{i,t}}{k_{i,t}}\right)^2 k_{i,t}$.

Firms sell their home-good output and hire labor inputs in competitive markets. For a given choice of labor, firms' real profits (in terms of the H-good) are given by $\pi_{i,t} = y_{i,t} - w_t l_{i,t}$, where $w_t \equiv W_t/P_{H,t}$ denotes the real wage. From the firms' static first-order condition with respect to $l_{i,t}$, the demand for labor is given by

$$l^d_{i,t} = A_t\, z_{i,t}\, \left(k_{i,t}\right)^{\frac{\alpha\chi}{\varsigma}} \left(\frac{1-\varsigma}{w_t}\right)^{\frac{1}{\varsigma}}. \tag{3.2.3}$$

After replacing $l^d_{i,t}$ in the profit function, we get that real profits are given by $\pi_{i,t} = A_t\, z_{i,t}\, k_{i,t}^{\frac{\alpha\chi}{\varsigma}}\, \iota_t$, where $\iota_t \equiv \varsigma \left(\frac{1-\varsigma}{w_t}\right)^{\frac{1-\varsigma}{\varsigma}}$. Since $\varsigma \in (0,1)$, profits are increasing in the capital input $k_{i,t}$ and decreasing in the real wage w_t.

To finance investment, firms can issue bonds denominated in foreign currency subject to endogenous default risk. Following Chatterjee and Eyigungor (2012), we consider long-term debt contracts that mature probabilistically. Each bond matures in the next period with probability m and, if it does not mature, the firm pays a constant coupon υ. Let $q^\star_t(k_{i,t+1}, b_{i,t+1}, z_{i,t})$ denote the unit foreign-currency price of a bond for a firm with productivity $z_{i,t}$ and whose next-period stock of capital and debt is $(k_{i,t+1}, b_{i,t+1})$. Let $\Delta B^\star_t\left(b_{i,t+1}, b_{i,t}\right)$ denote the foreign-currency proceeds from issuing new debt, net of debt payments that are due today.[2] It is given by

$$\Delta B^\star_t\left(b_{i,t+1}, b_{i,t}\right) = q^\star_t(.)\left[b_{i,t+1} - (1-m)b_{i,t}\right] - \left[(1-m)\upsilon + m\right] b - \Psi_b\left(b_{i,t+1}, b_{i,t}\right), \tag{3.2.4}$$

where the term $q^\star_t\,(.)\left[b_{i,t+1} - (1-m)b_{i,t}\right]$ denotes the proceeds from issuing new bonds and $\left[(1-m)\,\upsilon + m\right] b_{i,t}$ denotes current debt services. The $\Psi_b\left(b_{i,t+1}, b_{i,t}\right)$ function captures debt adjustment costs, which are defined as $\Psi_b(b_{i,t+1}, b_{i,t}) \equiv \frac{\psi_b}{2}\left(\frac{b_{i,t+1}-(1-m)b_{i,t}}{b_{i,t}}\right)^2 b_{i,t}$. As an alternative source of finance, firms can raise equity, which features a cost $\mathcal{C}(d_{it}) = -\mathbb{I}_{\{d_{it}<0\}}\varphi d_{it}$, where d_{it} denote dividends paid by firms (as in Cooley and Quadrini, 2001; **?**).

Firms' Recursive Problem

The firm's state space can be written as the n-tuple $(k, b, z, \boldsymbol{S})$, where $\boldsymbol{S}$ denotes the aggregate state, which includes the firm distribution, Ω, and all other aggregate states. Conditional on repaying, the equity value of a firm solves the following Bellman equation:

$$V^r\left(k, b, z, \boldsymbol{S}\right) = \max_{k',b'}\; d + \mathbb{E}_{\left(z',\boldsymbol{S}',\epsilon'^d\right)|(z,\boldsymbol{S})}\left[\Lambda\left(\boldsymbol{S}, \boldsymbol{S'}\right) \times V\left(k', b', z', \boldsymbol{S}', \epsilon'^d\right)\right] \tag{3.2.5}$$
$$\text{s.t. } d(1-\mathcal{C}(d)) = (1-\tau)\,\pi(k, z, \boldsymbol{S}) - I\left(k', k\right) + \xi/P_H(\boldsymbol{S}) \times \Delta B^\star(b', b, \boldsymbol{S})$$
$$\boldsymbol{S}' = \Upsilon\left(\boldsymbol{S}\right),$$

[2] $B_t\left(b_{i,t+1}, b_{i,t}\right)$ is also a function of $k_{i,t+1}$ and $z_{i,t}$, since they affect the pricing kernel $q^\star_t$. We omit that dependency for easiness of exposure.

where $I(k', k) \equiv k' - (1-\delta)k + \Psi(k', k)$ denotes investment expenditure; $\Lambda(\boldsymbol{S}, \boldsymbol{S'})$ households' stochastic discount factor; and d firms' dividends; τ is a fixed tax rate on firms' profit; $\xi/P_H(\boldsymbol{S})$ is the real exchange rate; $\Upsilon(\boldsymbol{S})$ denotes the conjectured law of motion for all the aggregates and for the firm distribution, Ω; and $V\left(k, b, z, \boldsymbol{S}, \epsilon^d\right) = \max\left\{V^r(k, b, z, \boldsymbol{S}), V^d(\epsilon^d)\right\}$, where $V^d(\epsilon^d)$ is the value of default and $\epsilon^d_{i,t} \sim_{iid} N(0, \sigma^d)$ is a shock to the value of default.[3] By integrating across the ϵ^d shock, we can obtain the exante default probability:

$$h(k, b, z, \boldsymbol{S}) = \int_{V^r(k,b,z,\boldsymbol{S})}^{\infty} \mathrm{d}\Phi_{(0,\sigma^d)}(\epsilon^d) = 1 - \Phi_{(0,\sigma^d)} V^r(k, b, z, \boldsymbol{S}), \tag{3.2.6}$$

where $\Phi_{(0,\sigma^d)}(\epsilon^d)$ is the cumulative density function of a normal distribution with zero mean and standard deviation σ^d. In the case of a default, the firm liquidates all of its assets and permanently exits the economy (after production takes place). The recovery rate, per unit of bond, is given by

$$\mathbb{R}^d_f(k, z, \boldsymbol{S}) = \lambda \, \frac{\pi(k, z, \boldsymbol{S}) + (1-\delta)k}{b} \, \frac{1}{\xi/P_H(\boldsymbol{S})}, \tag{3.2.7}$$

where $1 - \lambda$ captures the share of resources lost upon a default. Firms that exit are explaced by an equal mass of new entrants. The initial stocks of capital, debt, and productivity for all entrants are drawn from a uniform distribution with supports $\{\underline{x}, \bar{x}\}$ for $x = \{k, b, z\}$.

Firms' debt is priced by global investors. Let $\Lambda^\star_F(\boldsymbol{S}, \boldsymbol{S'})$ be the global investors' stochastic discount factor (further described below). Given a firm's current choice of k' and b', the debt price schedule faced by firms is given by

$$q^\star\left(k', b', z, \boldsymbol{S}\right) = \mathbb{E}_{\left(z', \boldsymbol{S'}\right)|(z,\boldsymbol{S})}\left[\Lambda^\star_F(\boldsymbol{S}, \boldsymbol{S'}) \mathbb{R}_f\left(k', b', z', \boldsymbol{S'}\right)\right], \tag{3.2.8}$$

where $\mathbb{R}_f\left(k', b', z', \boldsymbol{S'}\right)$ is the next-period firm's repayment, given by

$$\mathbb{R}_f\left(k', b', z', \boldsymbol{S'}\right) \equiv \left[1 - h\left(k', b', z', \boldsymbol{S'}\right)\right] \times \mathbb{R}^r_f\left(k', b', z', \boldsymbol{S'}\right) + h\left(k', b', z', \boldsymbol{S'}\right) \times \mathbb{R}^d_f\left(k', b', z', \boldsymbol{S'}\right),$$

with $\mathbb{R}^r_f(k', b', z', \boldsymbol{S'}) \equiv (1-m)\left(\upsilon + q\left(k'', b'', z', \boldsymbol{S'}\right)\right) + m$, and $k'' \equiv k'(k', b', z', \boldsymbol{S'})$ and $b'' \equiv b'(k', b', z', \boldsymbol{S'})$ denote the next-period firm's optimal policy functions.

[3]Introduction of the ϵ^d shock allows us to smooth the default decision, which helps with the convergence of our algorithm. It also allows us to target the observed credit spreads.

3.2.2 Households

We assume a representative household with preferences over consumption (c) and labor (l) described by the lifetime utility function:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u\left(c_t, l_t\right), \tag{3.2.9}$$

where $\beta \in (0,1)$ denote the subjetive discount factor; $u(c_t, l_t) = c - \psi_l \frac{l^{1+\theta}}{1+\theta}$, where θ is the inverse of the Frisch elasticity; and the consumption good is a composite of home and foreign goods, with a constant elasticity of substitution aggregation technology

$$c_t = \mathbb{C}\left(c_{H,t}, c_{F,t}\right) = \left[\omega_H^{1/\eta}\left(c_{H,t}\right)^{1-1/\eta} + \left(1-\omega_H\right)^{1/\eta}\left(c_{F,t}\right)^{1-1/\eta}\right]^{\frac{\eta}{\eta-1}}, \tag{3.2.10}$$

where $c_{H,t}$ and $c_{F,t}$ denote consumption of home and foreign goods; $\eta > 0$ is the elasticity of substitution; and ω_H measures the home bias. For tractability, we assume that households do not have direct access to international lending. Their budget constraint (in terms of the H-good) is given by

$$\frac{P_t}{P_{H,t}} c_t = w_t l_t + d_t + t_t, \tag{3.2.11}$$

where $w_t l_t$ is the households' labor income and $d_t = \int_i d_{i,t}$ is the aggregate dividend paid by the heterogeneous firms (net of equity issuance). The term t_t denotes the government's lump-sum transfers.

Under our assumption on preferences, the optimal allocation of expenditures between domestic and foreign goods can be expressed as

$$c_{H,t} = \omega_H \left(\frac{P_{H,t}}{P_t}\right)^{-\eta} c_t \tag{3.2.12}$$

$$c_{F,t} = \left(1-\omega_H\right)\left(\frac{P_{F,t}}{P_t}\right)^{-\eta} c_t, \tag{3.2.13}$$

where $P_{H,t}$ and $P_{F,t}$ are the prices of the home and foreign goods denominated in local currency. Let $P_t c_t = P_{H,t} c_{H,t} + P_{F,t} c_{F,t}$, where P_t is the price aggregator given by $P_t = \left[\omega_H P_{H,t}^{1-\eta} + \left(1-\omega_H\right) P_{F,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}$. Households' labor supply, in turn, is given by

$$l_t^S = \left(\frac{1}{\psi_l} w_t \frac{P_{H,t}}{P_t}\right)^{\frac{1}{\theta}}. \tag{3.2.14}$$

3.2.3 Nominal Rigidities

We assume that the labor market is characterized by nominal wage rigidities, which give rise to involuntary unemployment and a Mundellian role for exchange rate stabilization. We follow a formulation similar to that of Schmitt-Grohé and Uribe (2016) by assuming that nominal wage face downward rigidity i.e., $W_t \geq \alpha_W \bar{W}$ where $\alpha_W \geq 0$ captures the degree of nominal rigidities and $\bar{W}$ is the equilibrium wage in the stationary equilibrium (which we normalize to one). A higher α_W implies that nominal wages have a smaller margin to adjust in the event of a negative shock, which may lead to involuntary unemployment.

From equation (3.2.3), we can integrate across firms to compute the aggregate demand for labor, which is given by

$$l_t^d \equiv \int_i l_{i,t}^d = A_t \, \tilde{K}_t \left(\frac{1-\varsigma}{w_t} \right)^{\frac{1}{\varsigma}}, \tag{3.2.15}$$

where $\tilde{K}_t \equiv \int_i z_{i,t} \, \left(k_{i,t} \right)^{\frac{\alpha \chi}{\varsigma}}$ captures the productive capacity of the economy. In any equilibrium, it must be the case that $l_t^d \leq l_t^s$. Because of the presence of rigid nominal wages, the labor market may not clear. At any point in time, wages and employment must thus satisfy the following slackness condition:

$$\left(l_t^s - l_t^d \right) \left(W_t - \alpha_W \bar{W} \right) = 0. \tag{3.2.16}$$

That is, in periods of unemployment, it must be the case that the wage constraint is binding. If the constraint does not bind, then it must be the case that the economy is in full employment. Combining equations (3.2.14) and (3.2.15), the full-employment (FE) real wage can be expressed as

$$w_t^{FE} = \left((1-\varsigma) \, A_t \tilde{K}_t \right)^{\frac{\theta \varsigma}{\varsigma + \theta}} \left(\psi_l \frac{P_t}{P_{H,t}} \right)^{\frac{\varsigma}{\varsigma+\theta}}, \tag{3.2.17}$$

where $\frac{P_t}{P_{H,t}} = \left[\omega_H + (1-\omega_H) \left(\varepsilon_t \right)^{1-\eta} \right]^{\frac{1}{1-\eta}}$ and $\varepsilon_t \equiv \xi_t / P_{H,t}$ is the equilibrium real exchange rate (i.e., the exchange rate at which the H-good market clears). Under wage rigidities, the full-employment real wage may not be attained. Instead, for a given nominal exchange rate ξ_t, the economy's real wage is given by

$$\frac{W_t}{P_{H,t}} = max \left\{ w_t^{FE}, \frac{\alpha_W \bar{W}}{\xi_t} \times \varepsilon_t \right\}. \tag{3.2.18}$$

3.2.4 Government

The government collects taxes on firms and gives those proceeds as lump-sum transfers to households. For simplicity, we assume that it does not have debt. Its (static) budget constraint is thus $t_t = \tau \times \int_i \pi_{i,t}$. In addition, the government chooses the path for the nominal exchange rate, $\{\xi_t\}$. For the quantitative analysis, we consider two types of policy intervention. For our baseline case, we consider a "flexible" exchange rate regime, in which the policymaker chooses ξ_t to ensure full employment in every period t. From equation (3.2.18), this is given by: $\xi_t = \frac{1}{w_t^{FE}} \alpha_W \bar{W} \varepsilon_t$. We then consider a case in which the government is constrained to stick to a currency peg, in which $\xi_t = 1$ for all t.

3.2.5 Rest of the World

The rest of the world provides a perfectly elastic supply of the foreign good at a fixed price in terms of foreign currency ($P_F^\star$) and downward-sloping foreign demand of the home good given by

$$C_{H,t}^\star = \left(\frac{P_{H,t}^\star}{P_F^\star} \right)^{-\eta} \mathbb{C}^\star(\boldsymbol{S}_t), \tag{3.2.19}$$

where $\mathbb{C}^\star(\boldsymbol{S})$ denotes consumption by the rest of the world in state $\boldsymbol{S}$, and $P_{x,t}^\star$ is the foreign-currency price of good $x = \{H, F\}$. We assume a constant price for the foreign good $P_F^\star$, which we normalize to one. Both the home and foreign good satisfy the law of one price, i.e., $P_{F,t} = P_F^\star \xi_t$ and $P_{H,t}^\star = P_{H,t}/\xi_t$.

The rest of the world also provides a perfectly elastic supply of international credit to domestic firms. To study fluctuations in the risk premium of global investors, we parameterize their stochastic discount factor as

$$\Lambda_{F,(t,t+1)}^\star = \beta^\star \times \exp\left(-\kappa_t \, \epsilon_{t+1}^A - \frac{1}{2} \kappa_t^2 \, \sigma_A^2 \right), \tag{3.2.20}$$

where $\beta^\star$ is the rest of the world's discount factor; κ_t is a stochastic exogenous variable that captures the market price of risk; and ϵ_{t+1}^A are the innovations of the global productivity process. This type of formulation of foreign investors' stochastic discount factor has been used in the sovereign debt literature (Arellano and Ramanarayanan, 2012; Bianchi et al., 2018) to provide a tractable representation that captures changes in the global risk premium. Under this formulation, global investors value bond payoffs more in states in which firms are more likely to default. To see this, after replacing equation (3.2.20) in the bond pricing kernel of equation (3.2.8) and based on a first-order Taylor approximation, we can rewrite the pricing kernel as

$$q^{\star}\left(k', b', z, \boldsymbol{S}\right) = \mathbb{E}_{\left(z', \boldsymbol{S'}\right)|(z,\boldsymbol{S})}\left[\beta^{\star}\,\mathbb{R}_f\left(k', b', z', \boldsymbol{S'}\right)\right] - \beta^{\star}\,\kappa\,\mathbb{C}ov_{\left(z', \boldsymbol{S'}\right)|(z,\boldsymbol{S})}\left[\epsilon'_A, \mathbb{R}_f\left(k', b', z', \boldsymbol{S'}\right)\right]. \tag{3.2.21}$$

For risky firms, the covariance term is negative since these firms are more likely to default in bad times (i.e., in states in which the aggregate productivity shocks ϵ_{t+1}^{A} are smaller). Whenever $\kappa > 0$, lenders thus require a premium in excess of the default risk, which implies higher borrowing costs for risky firms. For risk-free firms, on the other hand, the covariance term is zero, which implies that they are not (directly) affected by changes in κ.

3.2.6 Equilibrium

***Definition* 1.** Let $\boldsymbol{S} = (A, \kappa, \Omega)$ denote the aggregate state, where A is the global TFP component, κ is the market price of risk, and Ω is the distribution of firms across the idiosyncratic states (k, b, z). Given a nominal exchange rate policy $\xi\left(\boldsymbol{S}\right)$, a recursive competitive equilibrium is a set of

1. Value functions for firms $\{V(k, b, z, \boldsymbol{S}), V^r(k, b, z, \boldsymbol{S})\}$,
2. Policy functions $\{k'(k, b, z, \boldsymbol{S}), b'(k, b, z, \boldsymbol{S}), h(k, b, z, \boldsymbol{S}), l^d(k, b, z, \boldsymbol{S}), l^s(\boldsymbol{S}), c(\boldsymbol{S})\}$,
3. A bond pricing kernel $q^{\star}\left(., \boldsymbol{S}\right)$,
4. A real wage $w\left(\boldsymbol{S}\right) = W/P_H\left(\boldsymbol{S}\right)$ and a real exchange rate $\varepsilon\left(\boldsymbol{S}\right) = \xi/P_H\left(\boldsymbol{S}\right)$, and
5. A conjectured law of motion for the aggregates $\varUpsilon\left(\boldsymbol{S}\right)$,

such that:

- Given prices and the perceived $\varUpsilon\left(\boldsymbol{S}\right)$, $l^d\left(., \boldsymbol{S}\right)$ is given by Equation (3.2.3), the policies $\{k'\left(., \boldsymbol{S}\right), b'\left(., \boldsymbol{S}\right), h\left(., \boldsymbol{S}\right)\}$ solve the maximization problem in Equation (3.2.5), and $V\left(., \boldsymbol{S}\right), V^r\left(., \boldsymbol{S}\right)$ are the associated value functions.
- Given firms' optimal policies, the bond pricing kernel $q^{\star}(., \boldsymbol{S})$ satisfies Equation (3.2.8).
- Given prices and $\varUpsilon\left(\boldsymbol{S}\right)$, $c\left(\boldsymbol{S}\right), l^s\left(\boldsymbol{S}\right)$ solve the households' problem, as defined in Equations (3.2.9)-(3.2.14).
- The conjectured law of motion $\varUpsilon\left(\boldsymbol{S}\right)$ is consistent with agents' policies.

- The H-good market clears:

$$\int \left[y\left(.,\boldsymbol{S}\right)-I\left(.,\boldsymbol{S}\right)\right]\, d\Omega\left(.,\boldsymbol{S}\right)=c_H\left(\boldsymbol{S}\right)+c_H^{\star}\left(\boldsymbol{S}\right),$$

  where $y\left(.,\boldsymbol{S}\right)$ is defined in Equation (3.2.1), $I\left(.,\boldsymbol{S}\right)$ is defined in Equation (3.2.2), and $c_H\left(\boldsymbol{S}\right)$ and $c_H^{\star}\left(\boldsymbol{S}\right)$ are defined in Equations (3.2.12) and (3.2.19), respectively.

- The balance of payment (BOP) is satisfied:

$$\int \left[y\left(.,\boldsymbol{S}\right)-I\left(.,\boldsymbol{S}\right)\right]\, d\Omega\left(.,\boldsymbol{S}\right)-P/P_H\left(\boldsymbol{S}\right)\, c\left(\boldsymbol{S}\right)+\xi/P_H\left(\boldsymbol{S}\right)\int \Delta B^{\star}\left(.,\boldsymbol{S}\right) d\Omega\left(.,\boldsymbol{S}\right)=0$$

  where $\Delta B^{\star}\left(.,\boldsymbol{S}\right)$ is defined in Equation (3.2.4).

- The condition $l^d\left(\boldsymbol{S}\right)\leq l^s\left(\boldsymbol{S}\right)$ and the slackness condition of Equation (3.2.16) are both satisfied.

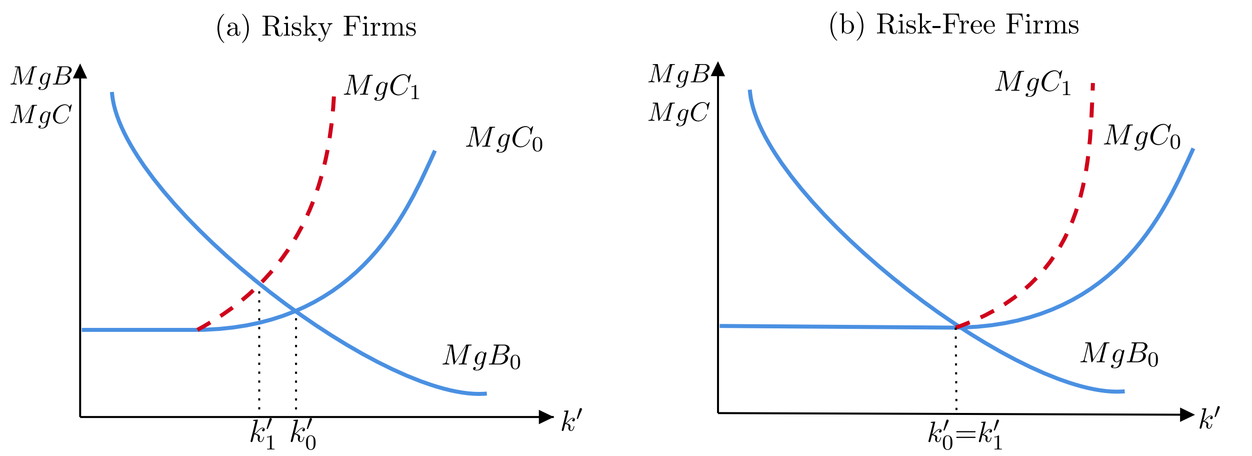
3.2.7 Effects of a Risk-Premium Shock: Illustration of the Mechanisms

In the model, there are two channels through which changes in global risk premia affect economic activity. One is a direct channel, by which fluctuations in risk premia affect firms' financing costs and their investment. The other is an indirect (or general equilibrium) channel, which stems from the feedback between changes in firms' optimal policies and the aggregate demand. In particular, through their effects on firms' investment, labor demand, and dividends, fluctuations in risk premia affect households' income, which ends up affecting the demand for the domestic good and the real exchange rate.

To characterize these channels more formally, assume there are no capital or debt adjustment costs. For a firm in which the dividend constraint is not binding, the optimal choice of investment k' and borrowing b' must satisfy the following condition:

$$\begin{aligned}
&\mathbb{E}_{z',\boldsymbol{S'}|\boldsymbol{z},\boldsymbol{S}}\left(\Lambda\left(\boldsymbol{S},\boldsymbol{S'}\right)\times MRPK(k',z',\boldsymbol{S'})\times\left(\Phi\left(.\right)+\Xi\left(.\right)\right)\right)=\\
&\frac{1}{q^{\star}(k',b',z,\boldsymbol{S})}\mathbb{E}_{z',\boldsymbol{S'}|\boldsymbol{z},\boldsymbol{S}}\left(\Lambda\left(\boldsymbol{S},\boldsymbol{S'}\right)\times\Delta\varepsilon\left(\boldsymbol{S},\boldsymbol{S'}\right)\times\mathbb{R}_f^r(k',b',z',\boldsymbol{S'})\times\left(\Phi\left(.\right)+\Xi\left(.\right)\right)\right)+\\
&\mid\eta_{b'}^q\mid-\eta_{k'}^q\times\frac{\varepsilon\left(\boldsymbol{S}\right)q^{\star}(k',b',z,\boldsymbol{S})\left(b'-\left(1-m\right)b\right)}{k'}
\end{aligned}\tag{3.2.22}$$

Figure 3.1: Effects of a Risk Premium Shock: Direct Channel



where $MRPK(k', z', \boldsymbol{S'}) = \pi_k(k, z) + (1 - \delta)$ is the next-period marginal product of capital, $\Phi(.) \equiv \Phi_{(0,\sigma^d)}\left(V^r\left(k', b', z', \boldsymbol{S'}\right)\right)$ is the probability that the firm will not default next period and $\Xi(.) \equiv V^r\left(k', b', z', \boldsymbol{S'}\right)\left[\frac{\partial\Phi(.)}{\partial V^r(.)} - \Phi(.)\right]$ captures the effect of a unit increase in the firm's valuation on its continuation value (net of the outside option).[4] The term $\Delta\varepsilon(\boldsymbol{S}, \boldsymbol{S'})$ is the change in the real exchange rate and $\mathbb{R}^r_f(k', b', z', \boldsymbol{S'})$ denotes the repayment to bondholders in case the firm does not default, as defined in equation (3.2.8). Lastly, the terms $\eta_{q,b'} < 0$ and $\eta_{q,k'} > 0$ are the elasticities of the bond pricing kernel with respect to b' and k', respectively.

The left-hand-side of the previous equation describes the marginal benefit of capital. The term $MRPK(k', z', \boldsymbol{S'}) \times \Phi(.)$ is the next-period marginal product of capital, weighted by the non-default probability. The $MRPK(k', z', \boldsymbol{S'}) \times \Xi(.)$ component captures how an additional unit of capital affects the next-period valuation of the firm and, therefore, its continuation value.

The right-hand-side describes the marginal cost of capital. The first line shows the additional debt repayment that the firm has to incur next period (conditional on not defaulting) plus the effects of that additional repayment burden on the firm's continuation value. The second line shows the effect of an additional unit of borrowing on the firm's current borrowing costs, which depends on how sensitive the pricing kernel is to changes in b' and k'.

How do changes in risk premia affect firms' investment? From equation (3.2.21), an increase in κ decreases the bond pricing kernel $q^\star(k', b', z, \boldsymbol{S})$ for risky firms (i.e., those with a positive $\mathbb{C}ov(.)$ term), which raises a firm's borrowing costs and the marginal cost of capital.

[4]Given $\left(k', b', z', \boldsymbol{S'}\right)$, then from equation (3.2.6), notice that $\Phi(.)$ is just a function of the outside option shock, ϵ'_d.

For a given marginal benefit, the larger marginal cost leads to a reduction in the firm's optimal investment level. For risk-free firms, however, the marginal cost of capital is unaffected, since $q^{\star}(.)$ is not affected by κ. Thus, these firms should not exhibit a decrease in their investment. Figure 3.1 provides a graphical illustration of this direct channel.

Upon a risk-premium shock, other prices in the economy adjust and this ultimately affects the marginal benefits and costs of investment. For instance, a decrease in real wages affects the marginal benefit through the $MRPK(k', z', \boldsymbol{S'})$ term. A real depreciation affects the marginal cost, since it increases the local-currency repayment burden, $\Delta\varepsilon\left(\boldsymbol{S}, \boldsymbol{S'}\right) \times \mathbb{R}^r_f(k', b', z', \boldsymbol{S'})$. A third mechanism operates through the effects of relative prices on firms' SDF, $\Lambda\left(\boldsymbol{S}, \boldsymbol{S'}\right) = \beta\, P_H/P\left(\boldsymbol{S'}\right)\, P/P_H\left(\boldsymbol{S}\right)$. We refer to all these adjustment as an indirect channel. The sign and magnitude of this indirect channel depends on how the aggregate economy responds to the risk-premium shock. In particular, it is a function of the degree of nominal rigidities and the exchange rate policy of the government. Importantly, even risk-free firms are affected by these indirect mechanisms, and thus riskless firms should also react to a risk-premium shock.

The main takeaway from our model is that we can exploit the heterogeneity in firms' default risk to identify direct and indirect channels of the transmission of a risk-premium shock. In the next section, we begin our analysis by providing empirical evidence on the differential responses of risky and risk-free firms.

3.3. Empirical Analysis

3.3.1 Measurement and Data

Our empirical strategy relies on using micro-data to measure the heterogeneous responses of firms' investment to changes in global borrowing costs. This section describes our measurement of firm risk, investment, and the global risk premium.

3.3.1.1 Firm-level Default Risk and Investment

We estimate the default risk for each firm in each time period using the measure of distance-to-default proposed by **?**, defined as

$$\mathrm{dd}_{jkt} = \frac{\log\left(\frac{V_{jkt}}{D_{jkt}}\right) + \left(\mu_{jt} - 0.5\sigma^2_{jkt}\right)}{\sigma_{jkt}}, \tag{3.3.1}$$

where V_{jkt} denotes the total value of firm j from country k in period t, μ_{jkt} the firm's annual expected return, σ_{jkt} the annual volatility of its value, and D_{jkt} the firm's debt. The interpretation of this measure is the number of standard deviations by which $\log V_{jkt}$ must deviate from its mean for the firm to default (assuming the firm defaults when $V_{jkt} < D_{jkt}$).

Measuring distance-to-default with equation (3.3.1) requires two ingredients: the firm's debt and the firm's value. To measure debt, we use data from Compustat Global, which contains balance-sheet information on publicly traded firms. Appendix C.1.1.1 describes the Compustat Global dataset and variable construction. To measure a firm's value, we follow **?** and use daily stock-price data, based on the idea that the equity of a firm can be seen as a call option on the firm's value with a strike price equal to the value of the firm's debt. We use an iterative procedure described in C.1.1.2 to back out the value of the firm.

We combine the distance to default data with other balance sheet data from Global Compustat to measure investment, sales growth, and other firm-level variables, as described in Appendix C.1.1.1. Appendix Table C.1 describes these variables for our sample of Latin American firms. We use distance to default to construct a time-varying measure of "risky" and "risk-free" firms, as described in Appendix C.1.1.2. Appendix Table C.2 reports summary statistics for each group. Risky firms tend to have higher leverage and slightly lower sales growth and investment, and are comparable in size. To give a fuller picture of our sample, Appendix Table C.3 reports summary statistics by country.

As an alternative to measuring firms' risk with distance to default, we use firms' credit ratings from S&P and Moody's. Appendix C.1.1.1 describes the data. Appendix Figure C.1 shows the distribution of ratings. We use the credit ratings and firms' leverage to construct additional measures of firms' risk. For credit ratings, we define risk-free firms as those with A- or higher ratings or those with investment grade or higher ratings (BBB-). For leverage, we define risk-free firms as those with leverage below the 10th percentile of the distribution, to mimic the classification for distance to default. We also construct a measure of risk-free firms that encompasses all of these criteria. Appendix Tables C.4 and C.5 report the number of observations that meet these criteria and the correlations across risk-free measures.

3.3.1.2 Risk Premium

We measure the global risk premium by building on the methodology of Gilchrist and Zakrajšek (2012), whose method is widely used to measure risk premia in the United States. We extend this measurement globally to provide a decomposition of the risk premium into systemic and country components.

This methodology for measuring the risk premium combines the measures of distance to default described in the previous section with data on corporate-bond spreads. We collected data from Bloomberg on individual corporate bond prices and their characteristics (i.e., maturity, coupon structure, cross-default clauses, face value, and market of issuance). Appendix Table C.6 describes the coverage of our sample and Appendix Tables C.7 and C.8

present summary statistics regarding various characteristics of the bonds for the full sample and the Latin America subsample, respectively. Finally, we merge the data on bond spreads with the data on firm characteristics and distance to default. Appendix C.1.1.3 describes the spread construction, sample selection, and merging process.

To estimate time-varying, firm-specific risk premia, we follow Gilchrist and Zakrajšek (2012) by residualizing bond spreads on bond-specific characteristics and firm measures of distance to default. In particular, we estimate the following regression:

$$\log S_{ijkt} = \beta \mathrm{dd}_{jkt} + \gamma' \boldsymbol{Z}_{it} + \epsilon_{ijkt}, \tag{3.3.2}$$

where S_{ijkt} is the spread of bond i for firm j from country k in period t; $\boldsymbol{Z}_{it}$ is the vector of bond-level characteristics; and ϵ_{ijkt} denotes a random error term. The logic behind this approach is to extract the component of bond spreads due to default risk in order to obtain fluctuations in the component due to the risk premium. Appendix Table C.9 reports the regression estimates. As expected, firms with larger distance to default have lower bond spreads. However, there is significant variation in bond spreads that is not explained by these covariates; the R^2 of the regression is 36%. We use these estimates to construct the bond-specific risk premium as

$$\hat{RP}_{ijkt} = S_{ijkt} - exp\left(\hat{\beta} dd_{jkt} + \hat{\gamma}' Z_{ijkt} + \frac{\hat{\sigma}^2}{2}\right), \tag{3.3.3}$$

where $\hat{\sigma}$ is the mean-squared error of the estimated ϵ_{ijkt} shocks.

Finally, we decompose fluctuations in the risk premium into systemic and idiosyncratic components. We estimate

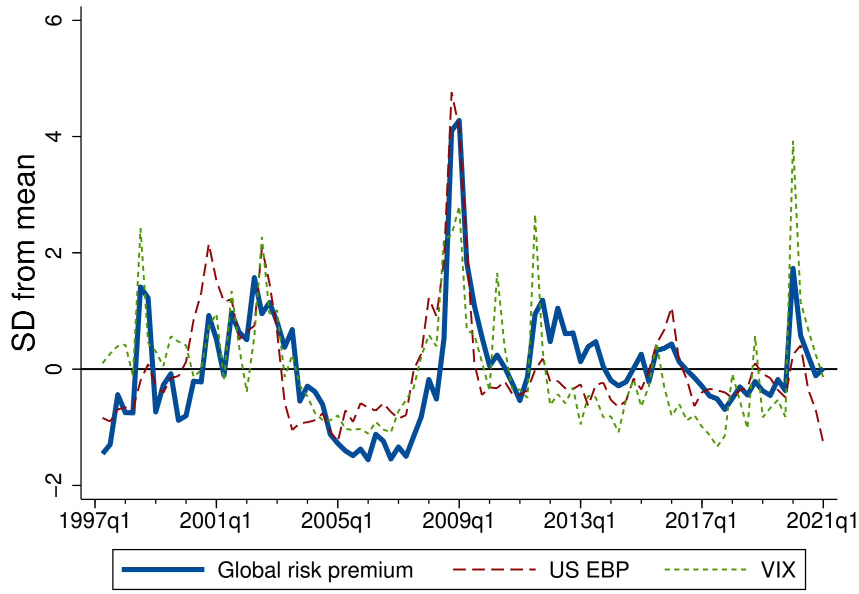
$$\hat{RP}_{ijkt} = \rho_k + \rho_t + v_{ijkt}, \tag{3.3.4}$$

where ρ_k and ρ_t denote country and time fixed effects.[5] We refer to ρ_t as the systemic component of the risk premium and to v_{ijkt} as the idiosyncratic component of the risk premium. Appendix Table C.10 reports the country averages of risk premia.

Figure 3.2 depicts our measure of the global risk premium since the late 1990s. Increases in the risk premium coincide with widely studied periods of global financial turbulence, including the dot-com crash, Lehman bankruptcy, European debt crisis, and Covid pandemic. As shown in Figure 3.2, our measure of the global risk premium exhibits a strong comovement with the

[5] We also estimate a version in which we first extract time-varying country risk premia and then estimate the systemic risk premium in a second stage. We prefer the one-step measure because it puts more weight on the number of individual observations within periods, rather than the number of countries. We report country-specific estimates and the two-step estimate of the systemic risk premium in Appendix C.1.1.4.

Figure 3.2: Global Risk Premium



Note: The figure compares our measure of the global risk premium (ρ_t) to the U.S. excess bond premium (EBP) and the VIX. Units are standard deviations from the mean. The measures are highly correlated, with 0.73 correlation between the global risk premium and the U.S. EBP. The global risk premium and the U.S. EBP have correlations of 0.66 and 0.59 with the VIX, respectively.

U.S. excess bond premium (EBP), which uses the methodology of Gilchrist and Zakrajšek (2012) for U.S. corporate bonds and is regularly updated by the Federal Reserve. The correlation of these two series is 0.73, which is indicative of the high level of synchronization of risk premia across markets. The global risk premium also comoves with the VIX, which is a common measure used in the empirical literature to capture fluctuations in the global financial cycle. The correlations between the VIX and both the global risk premium and the U.S. EBP are also high, at 0.66 and 0.59, respectively.

Because we are focusing on Latin America, we also estimate the Latin America risk premium by estimating equation (3.3.4) using only that sample of countries. Appendix Figure C.2 shows the risk premium estimates for the full sample as well as for the Latin America and Asia subsamples. Table C.11 reports the correlation matrix for the three samples as well as the U.S. excess bond premium and the VIX. To understand variation by country, Appendix Figure C.3 plots the Latin America risk premium with country-specific risk premia for the three biggest countries in our sample. Appendix Figure C.4 shows that our risk premia estimates are similar if we use an alternative two-step estimation procedure that estimates these country-specific risk premia in a first step.

3.3.2 Empirical Results

We provide evidence on how changes in the systemic risk premium transmit to the macroeconomy using a micro-to-macro approach, which estimates micro-level heterogeneous responses to changes in the risk premium.[6] In particular, we use our measure of risk premia to study how nonfinancial firms with different risk profiles respond to changes in the risk premium demanded by lenders.

We consider the following Jordà (2005) local projection:

$$\Delta_h log(k_{jt+1+h}) = \alpha_{hj} + \underbrace{\beta_h^R \times \rho_t \times \mathbb{I}_{j\in\mathcal{R}_{t-1}}}_{\text{Risky Firms}} + \underbrace{\beta_h^F \times \rho_t \times \mathbb{I}_{j\in\mathcal{R}^f_{t-1}}}_{\text{Risk-Free Firms}} + \gamma_h \mathbb{I}_{j\in\mathcal{R}_t} \ + \ \omega_h' Z_{jt-1} + \epsilon_{jth}, \tag{3.3.5}$$

where $\Delta_h \log\left(k_{jt+1+h}\right) \equiv \log\left(k_{jt+1+h}\right) - \log\left(k_{jt}\right)$ denotes period t log cumulative change for h quarters in firm j's capital; α_{hj} denotes firm fixed effects; $\mathcal{R}_t$ denotes the set of risky firms and $\mathcal{R}_t^f$ the set of risk-free firms; ρ_t measures the systemic risk premium in period t; and Z_{jt} is a vector of firm-level covariates, which includes dummy variables for firms' risk ($\mathbb{I}_{j\in\mathcal{R}_t}$ and $\mathbb{I}_{j\in\mathcal{R}^f_{t-1}}$), firms' size (measured as log total assets), lagged capital growth, sales growth, fiscal quarter, and current assets relative to total assets. Standard errors are clustered by firm and by year. The coefficients of interest are β_h^R and β_h^F. The first captures the effects of changes in the systemic risk premium for the average "risky" firm. The latter captures the effects for the average "risk-free" firm, which, through the lens of our model, are particularly informative about indirect channels.

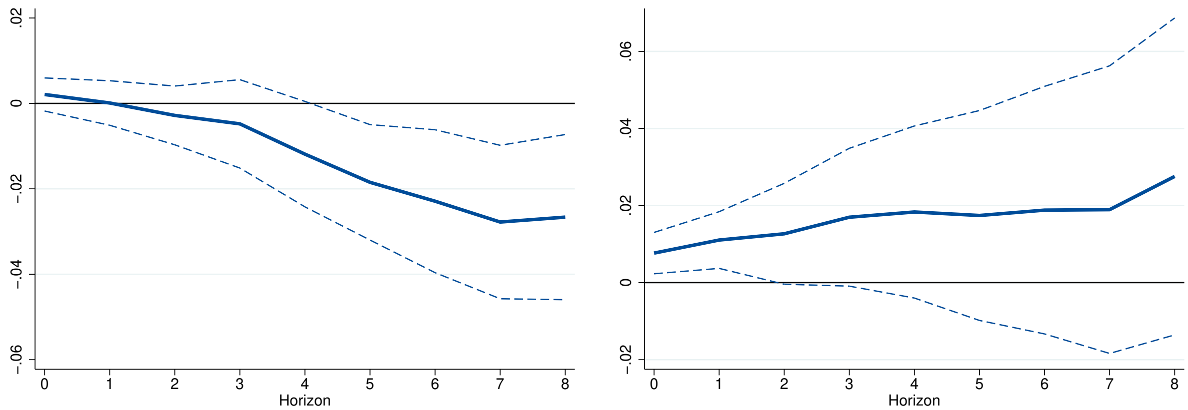
Figure 3.3 reports the results from estimating equation (3.3.5) and highlights two main results in particular. First, Panel (a) shows that increases in the systemic risk premium are associated with an average contraction in risky firms' investment, which is large and persistent: A one-standard-deviation increase in the systemic risk premium is associated with a 2.5% cumulative decline in the capital stock, which peaks 7 quarters after the shock. Second, Panel (b) shows that increases in the systemic risk premium are not associated with declines in investment for risk-free firms. A one-standard-deviation increase in the systemic risk premium is associated with a 2% cumulative increase in the capital stock–which also peaks 2 years after the shock, though the effects are statistically indistinguishable from zero at later horizons.

The finding that the negative effects of the systemic risk premium shock on investment are concentrated among risky firms is robust to alternative specifications. Notably, it is consistent across measures of risk-free firms using credit ratings or leverage rather than distance to

[6] As we are focusing on Latin America, we will use the Latin America risk premium, as shown in Appendix Figure C.2 as our measure of the systemic risk premium, ρ_t.

Figure 3.3: Dynamics of Responses to Movements in the Systemic Risk Premium

(a) Risky firms (b) Risk-free firms



Note: The figure shows the estimated β_h^R (left panel) and β_h^F (right panel) coefficients of equation (3.3.5), which correspond to the cumulative (log) change in capital stock in response to the systemic risk premium (ρ_t) for risky and risk-free firms. The variable ρ_t is standardized so that the units are standard deviations. The x-axes show the horizon h (quarterly frequency). The vector of controls includes firms' sales growth, investment, fiscal quarter, size, and share of current assets. All controls are standardized. Standard errors are clustered by firm and year. Dashed lines represent 90% confidence intervals.

default, as shown in Appendix Figure C.5. This is interesting because our baseline risk-free measure has approximately zero correlation with the credit ratings measures, as reported in Appendix Table C.5, suggesting they are measuring different aspects of firms' risk.

Appendix Figure C.6 adds time by country fixed effects to show that cumulative investment falls for risky relative to risk-free firms within the same country and quarter. Appendix Figures C.7 and C.8 use a continuous interaction term with distance to default, rather than our risky and risk-free categories, to show that firms with one standard deviation higher distance to default have higher cumulative growth in capital stock at each horizon, with and without the inclusion of country by time fixed effects. Appendix Figure C.9 shows that our results are robust to adding additional interactions with the systemic risk premium. Appendix Figure C.10 shows that our results are stable across sectors, while Appendix Figures C.11 and C.12 show that our results are stable across varying subsets of countries. Appendix C.1.2 describes each of these exercises in more detail.

3.4. Quantitative Analysis

This section builds a quantitative version of the model, consistent with the empirical evidence presented in the previous section, to study the transmission of the global risk premium and implications for exchange rate policies. Section 3.4.1 describes the parameterization of the model. Section 3.4.2 compares model predictions to their empirical counterparts. Section 3.4.3 uses the parameterized model to analyze the channels of tranmission of the global risk premium and compares the dynamics of alternative exchange rate regimes.

3.4.1 Parameterization

We calibrate the model to a prototypical emerging market economy. In our calibration, we target both macro and micro moments to capture the heterogeneity across domestic firms. The calibration is done at quarterly frequency. Appendix C.2.2 summarizes the computational algorithm used to solve the model.

We calibrate the model in three steps. First, we fix a subset of parameters to standard values in the literature. These are reported in Table 3.1. Panel 1 shows the parameters that govern domestic firms' problem. The value-added share of capital α is set to 0.30 and the decreasing returns-to-scale parameter χ to 0.85, as in **?**. The quarterly depreciation rate δ is set to 0.025. We fix tax parameter τ to target a corporate tax rate of 27.5%. Regarding firms' bonds structure, we set m to match the median average maturity of the nonfinancial firms in our sample. We set υ to target the (annualized) observed coupon yield. We fix θ, the inverse of the Frisch elasticity, to 0.5, which is a common value in the literature. Lastly, we consider a home bias of 0.66 and a trade elasticity of 4. Lastly, we fix the wage rigidity parameter α_W to 1. For foreign lenders (Panel 2), we fix the discount factor $\beta^{\star}$ to target a 3% annual risk-free rate. We also fix foreign lenders' Markov transition matrix, Π_{κ}, to capture a quarterly probability of a global crisis of 2.5% and a crisis duration of 5 quarters.

In the second step, we calibrate the parameters that govern a set of firms' cross-sectional moments (Table 3.2, Panel 1). We set firms' discount factor β and the volatility of the outside option, σ^d, to match the average leverage and credit spread observed in the data. We calibrate the debt adjustment cost parameter, ψ_b, to match the cross-sectional volatility of leverage. The recovery value parameter, λ, targets an average recovery value of 33%. Parameters related to the idiosyncratic productivity processes, ρ_z and σ_z, are calibrated to match the dispersion of the firm size distribution. In particular, they are set to target the ratios between the 25th and 50th and 50th and 75th percentiles for firms' stock of capital. We set the capital adjustment cost parameter, ψ_k, to match the cross-sectional volatility of investment. Lastly, we calibrate the equity issuance cost parameter to target the annual share of firms that tap equity markets.

In the third step, we calibrate the parameters related to aggregate responses (Table 3.2, Panel 2). For productivity, we fix the autocorrelation to ρ_A to 0.97 and set σ_A to match the volatility of a typical emerging country's GDP (Neumeyer and Perri, 2005). For the global risk premium, we assume a two-state Markov process, with values $\kappa_L = 0$ and $\kappa_H > 0$, with a

Table 3.1: Fixed Parameters

Parameter	Description	Value
Panel 1. Domestic Economy		
α	Capital share	0.3
χ	Dec. returns to scale	0.85
δ	Depreciation rate	0.028
τ	Corporate tax rate	0.275
m	Bond maturity	0.052
c	Bond coupon	0.018
$\bar{d}$	Dividend constraint	0.0
θ	Frisch elasticity	0.5
ω_H	Home bias	0.66
η	Trade elasticity	4.0
Panel 2. Rest of the World		
$\tilde{\beta}$	Lenders' discount factor	0.992
$\Pi_\kappa(\kappa_L, \kappa_H)$	Probability of global crisis	0.025
$\Pi_\kappa(\kappa_H, \kappa_L)$	Duration of global crisis	0.2

Note: This table shows the set of parameters that are fixed in our calibration. Panel 1 shows the set of parameters for domestic firms. Panel 2 shows the parameters relevant to foreign lenders.

transition matrix Π_κ. We set κ_H to target an (on-impact) increase in the risk premium during a global crisis (i.e., when moving from $\kappa_{t-1} = \kappa_L$ to $\kappa_t = \kappa_H$) of 190 basis points, which corresponds to a one-standard-deviation increase in the data. We describe in the quantitative appendix the steps used to compute our model-implied measure of risk premium.

3.4.2 Targeted and Untargeted Moments

To analyze the model's fit, we compute the model-implied targeted moments under a flexible exchange rate scenario. Table 3.3 shows that the model is able to match all of the targeted cross-sectional and aggregate moments reasonably well.

Our calibrated model is also consistent with key untargeted moments. Table 3.4 shows that the model is able to capture the observed quarterly-to-profits ratio of nonfinancial firms and the cross-sectional volatility of spreads. It also captures the observed negative correlation between corporate spreads and investment and GDP.

3.4.3 Implications of a Global Risk-premium Shock

We now quantify the effects of changes in risk premia on firms' optimal policies and aggregates variables. We first analyze aggregate responses and then explore the differential effects across firms with different levels of default risk. We consider two exchange rate regimes.

Table 3.2: Calibrated Parameters

Parameter	Description	Value
Panel 1. Parameters governing cross-sectional moments		
β	Firms' discount factor	0.966
ρ_z	Idiosyncratic TFP, persistence	0.96
σ_z	Idiosyncratic TFP, volatility	0.085
ψ_k	Capital adjustment costs	0.25
ψ_b	Debt adjustment costs	3.5
λ	Recovery rate	0.08
σ_d	Exit value	2.0
φ	Share firms issuing equity	0.5
Panel 2. Parameters governing aggregate moments		
ρ_A	Aggregate TFP, persistence	0.97
σ_A	Aggregate TFP, volatility	0.028
κ_H	Lenders' risk aversion	200.0

Note: This table shows the set of calibrated parameters. Panel 1 shows parameters for domestic firms that govern the targeted cross-sectional moments. Panel 2 shows parameters that govern aggregate responses.

Table 3.3: Targeted Moments

Targeted Moments	Data/Target	Model
Panel 1. Cross-sectional moments		
Credit Spread (avg)	3.0%	3.1%
Leverage (avg)	28.0%	37.27%
Leverage (cs std)	20.0%	21.29%
Recovery Value	33.0%	36.13%
log(k): 25th/50th percentile	0.85	0.88
log(k): 75th/50th percentile	1.15	1.17
Investment/k (cs std)	7.0%	4.91%
Share firms issuing equity	15.0%	11.0%
Panel 2. Aggregate moments		
GDP (std)	3.0%	3.58%
Δ Risk premium (pp)	1.79	1.25

Note: This table shows the targeted moments. Panel 1 shows targeted cross-sectional moments. Panel 2 shows the set of targeted aggregate moments.

Table 3.4: Untargeted Moments

Untargeted Moments	Data	Model
Quarterly Profits-to-Capital	10.0%	54.0%
Spreads (cs std)	2.1%	4.0%
Correlation Spreads, GDP	−0.63	−0.48
Correlation Spreads, Investment	−0.59	−0.37

Note: The table shows a set of untargeted moments. Panel 1 shows untargeted cross-sectional moments. Panel 2 shows untargeted aggregate moments. The data moments of Panel 2 are based on Neumeyer and Perri (2005).

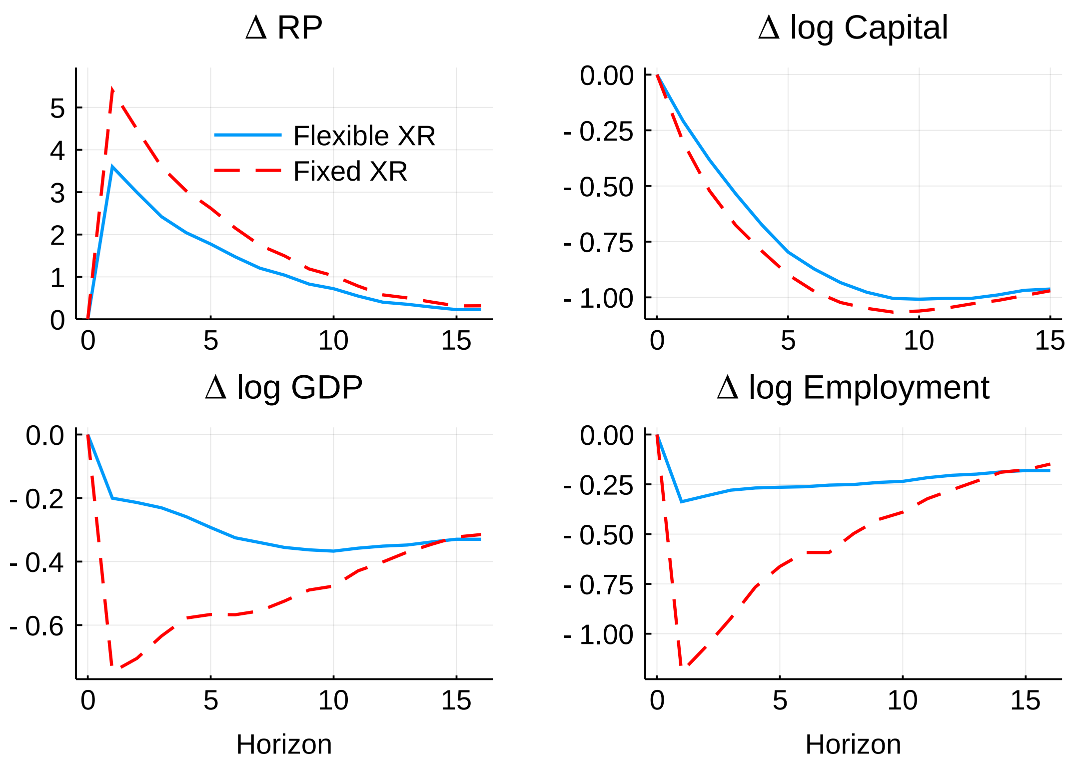
The baseline scenario, a flexible regime, is one in which the policymaker chooses ξ_t to ensure full employment in every period t. We compare this case with an alternative scenario in which the government is constrained to stick to a currency peg with $\xi_t = 1$ for all t.

Figure 3.4 shows the impulse response to a risk-premium shock. We assume that at time $t = 1$ there is an increase in global risk aversion ($\kappa_1 = \kappa_H$), and then the $\{\kappa_t\}$ process evolves according to its Markov matrix. The blue (red) lines show the results for the flexible (fixed) nominal exchange rate. The figure shows that the effects of an increase in the risk premium are significant and long lived. More importantly, the fixed exchange rate scenario significantly amplifies the magnitude of the crisis: Employment and GDP decrease more than 3 times more than under a flexible rate.

The larger drop in GDP and employment under a currency peg is explained by the different adjustment of prices and wages (Figure 3.5). Under a fixed exchange rate policy, P_H has to decrease significantly more so that the H-good market clears. Since W is downwardly rigid, this leads to a much larger (although temporary) increase in real wages, which further decreases labor demand. Aggregate capital also contracts more under a currency peg. The difference with respect to the flexible exchange rate scenario is smaller because investment decisions are forward-looking and the differential adjustment of prices only lasts for 2 years.

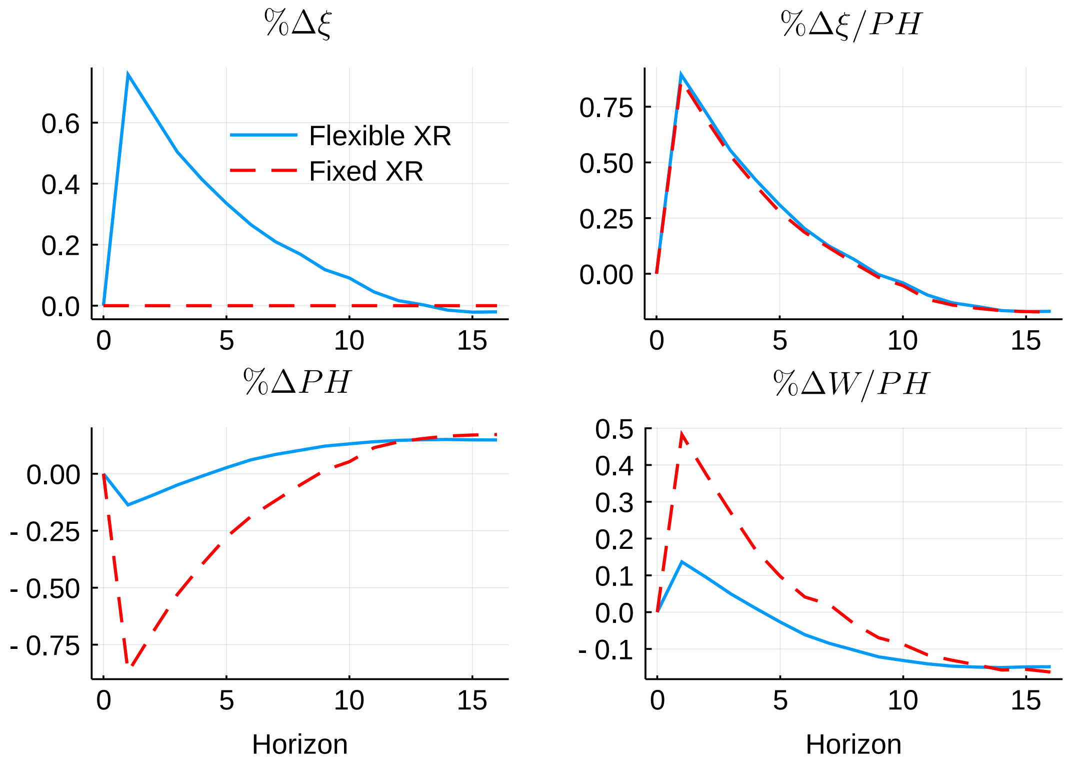
In Figure 3.6, we analyze the heterogeneous effects of a risk-premium shock. We sort firms into deciles based on their pre-shock default probability and study the effects of an increase in the risk premium in terms of $\Delta_h log(k_{t+1+h})$ for a fixed horizon of 4 quarters. There are important asymmetries in the transmission of global risk premia. In line with our empirical estimates, riskier firms are significantly more affected by a risk-premium shock: Their borrowing costs increase more and they reduce their investment more than the median firm. Firms in the first deciles of the distribution display an expansion in their investment. Since risk-free firms are not directly affected by the risk-premium shock, the increase in $log(k)$ is purely accounted for by the indirect channel.

Figure 3.4: Risk-premium Shock: Impulse Response — Macroeconomic Variables



Note: Impulse response to a risk-premium shock ($\Delta\kappa > 0$). Solid blue lines show the economy's aggregate responses when the government follows a flexible exchange rate regime that ensures full employment. Dashed red lines show the same aggregate responses when the nominal exchange rate is fixed.

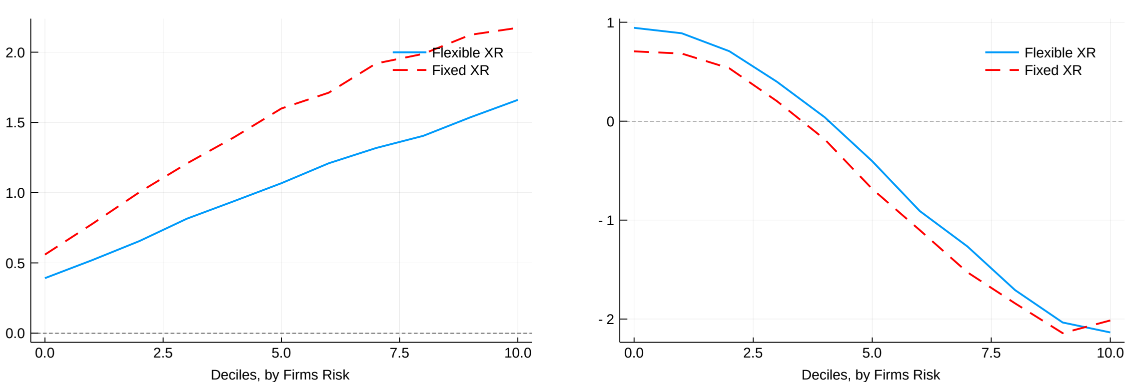
Figure 3.5: Risk-premium Shock: Impulse Response — Prices



Note: Impulse response to a risk-premium shock ($\Delta\kappa > 0$). Solid blue lines show the response of prices when the government follows a flexible exchange rate regime that ensures full employment. Dashed red lines show a case in which the nominal exchange rate is fixed.

Figure 3.6: Risk-premium Shock: Heterogeneous Effects

(a) ΔRP (b) $\Delta \log(k)$



Note: Impulse response to a risk-premium shock ($\Delta\kappa > 0$) by firm risk. The time horizon is fixed at 4 quarters. Firms are sorted into deciles based on their pre-shock default probability. The left panel shows the change in firms' risk premium. The right panel shows the change in firms' capital. Solid blue lines show the firms' responses when the government follows a flexible exchange rate regime that leads to full employment. Dashed red lines show the same responses when the nominal exchange rate is fixed.

3.5. Conclusion

In this paper, we studied the macroeconomic transmission of fluctuations in global risk premia to open economies. We combined a new measurement of firms' responses to fluctuations in the global risk premium with an open-economy general-equilibrium model of heterogeneous firms subject to default risk. We described two channels through which the global risk premium affects economic activity. One is a direct channel through which changes in the global risk premium affect firms' financing costs and their investment. The other is an indirect channel, which stems from the feedback between firms' investment policies, domestic aggregate demand, and adjustment of the real exchange rate.

Our model analysis suggests a strategy for measuring the relative strength of these channels based on the differential responses of firms: Since risk-free firms are not affected by the direct channel—their borrowing costs remain invariant to changes in risk premia—their response is primarily informative of the strength of indirect channels. We estimate the response for these risk-free firms in the data and use the estimates to discipline our model. We then use the calibrated model to disentangle the direct and indirect channels and to study implications for exchange rate policy.

APPENDICES

APPENDIX A

Appendix to Chapter 1

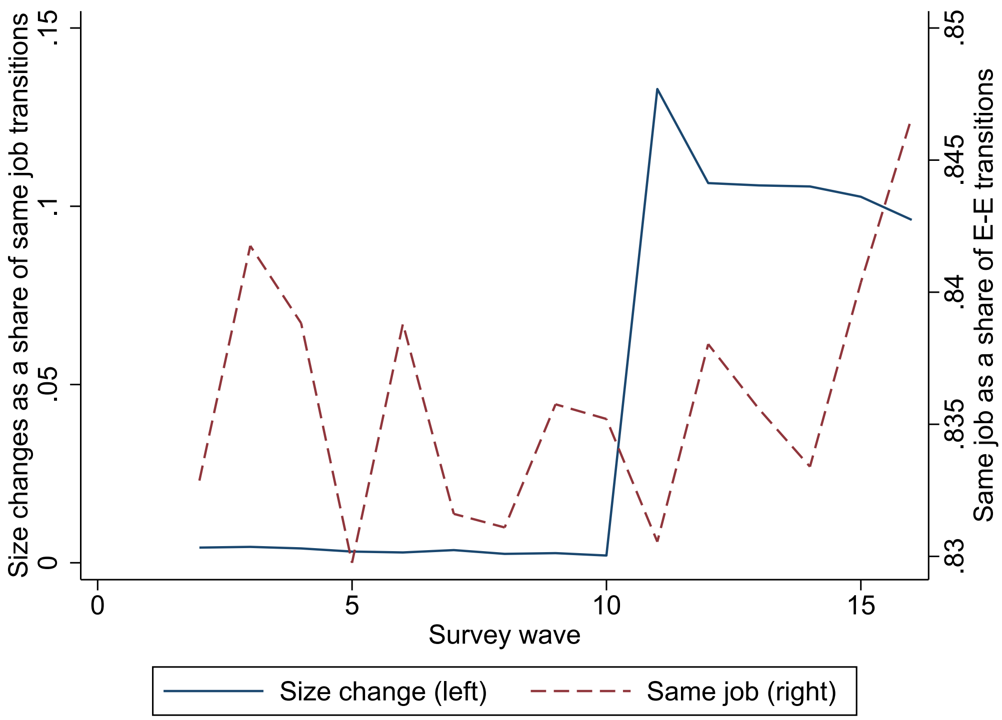
A.1. Additional information on background empirical facts

A.1.1 Firm size measurement in the SIPP

I construct a measure of firm size using three survey questions: "About how many persons are employed by ...'s employer at the location where ... works?" (tempsiz), "Does ...'s employer operate in more than one location?" (eemploc), and "About how many persons were employed by ...'s employer at ALL LOCATIONS together" (tempall). I choose 100 employees as the cutoff for large firms because it is available across waves even though the bins change over time. For all panels before 2008, there were three bins for both establishment and firm size with the largest being 100 or more. These bins were used in the 2008 panel as well until the 11th wave, when the bins were expanded to include eight bins for establishment size (three with 100 or fewer) and six bins for firm size (two with 100 or fewer). This causes discontinuities in the data for two reasons. First, if households report their firm size precisely, employers with exactly 100 employees would be reclassified from large to small between waves 10 and 11. Second, more choices may lead workers to reconsider their estimates of firm/establishment sizes. The former explanation would manifest as a temporary increase in the number of reclassifications of the same employer from large to small between waves 10 and 11 but we would expect the share of reclassifications to return to its pre-change level between waves 11 and 12.

The solid line in figure (A.1) plots the share of workers who have the same employer across adjacent months over survey waves but report their employer size differently across waves. The number of employer size changes spikes in wave 11, consistent with the switch to the new classification system. It dips slightly in wave 12 but remains significantly elevated relative to its pre-change trend. Thus, although some of the change may have been due to reclassification of 100-employee firms, the vast majority seems to be inconsistencies in how workers report their employer size. One might worry that some other change happened between waves 10 and 11 that caused workers to be more likely to report changing employers. Thus the share of reclassifications could look elevated if the denominator is smaller. The dashed line in figure (A.1) shows that this does not appear to be the case, as the share of workers who stay with the same employer is similar across waves.

Figure A.1: Reclassifications of firm size by survey wave.



Workers are classified as having the same job if they report working for the same employer number in reference month 4 of wave $t-1$ and reference month 1 of wave t. Of those who have the same job, size changes are defined as workers who classify employer x as a small firm in wave $t-1$ and a large firm in wave t or vice versa.

A.1.2 Additional background information

To evaluate how much of the employment gaps by race are attributable to worker characteristics, I fit the following linear probability model,

$$E_{irt} = \alpha_{rt} + \beta_{rt} X_{irt} + \epsilon_{irt}, \tag{A.1}$$

where E_{irt} is an indicator equal to 1 if person i of race r in month t is employed, α_{rt} are race by time fixed effects, X_{irt} includes a quadratic in age interacted with gender, martial status interacted with gender, typical occupation, typical industry, state, and metro area size. The coefficients on worker characteristics, β_{rt}, are estimated separately by race and time.

Using these estimates, I predict the employment rate for each race with respect to the white population as in a Oaxaca-Blinder decomposition,

$$\hat{E}_{irt} = \hat{\alpha}_{wt} + \hat{\beta}_{wt} X_{irt}. \tag{A.2}$$

Then, I construct the raw and conditional gaps,

$$\text{gap}_{rt}^{raw} = \frac{1}{N_r} \sum_{i}^{N_r} E_{irt} - \frac{1}{N_w} \sum_{i}^{N_w} E_{iwt}, \tag{A.3}$$

$$\text{gap}_{rt}^{cond} = \frac{1}{N_r} \sum_{i}^{N_r} E_{irt} - \hat{E}_{irt}. \tag{A.4}$$

For the estimation and constructing the gaps, I use the sample weights provided by the CPS. If the Black-white employment gap were fully explained by differences in industry exposure, age, geography, etc., then the conditional gap should be zero. Figure 1.1 shows that this is not the case. Table A.1 reports the means, standard deviations, and correlations with the headline unemployment rate for each series.

Next, I perform the same analysis by gender, where I estimate equations (A.1)-(A.4) separately for men and women. Figure A.2 reports the same series separately by gender. Again, Table A.1 reports summary statistics. The raw employment gaps are quite different across groups. Black men face persistently lower employment relative to white men, whereas Hispanic men have persistently higher employment. Black women tend to have higher employment than white women on average, although notably this pattern tends to reverse around recessions. Hispanic women generally have lower employment than white women. Across all groups, the mean conditional gap, reported in Table A.1 is negative, indicating that even for the groups with positive average employment gaps, these gaps should be even more positive after adjusting for worker characteristics, industries, and occupations. Across all

Table A.1: Employment gap summary statistics

	Raw gap			**Conditional gap**		
	Mean	SD	Corr w/ UR	Mean	SD	Corr w/ UR
Both genders						
Black	-0.039	0.016	-0.799	-0.031	0.009	-0.813
Hispanic	0.010	0.024	-0.455	-0.009	0.007	-0.498
Men						
Black	-0.080	0.018	-0.801	-0.036	0.011	-0.815
Hispanic	0.053	0.027	-0.512	-0.007	0.011	-0.427
Women						
Black	0.004	0.017	-0.648	-0.026	0.008	-0.681
Hispanic	-0.038	0.024	-0.285	-0.011	0.006	-0.427

Source: CPS.

The table reports the mean, standard deviation, and correlation with the headline unemployment rate for the raw and conditional gaps in employment to population ratios relative to the white population, as defined in equations (A.3)-(A.4).

groups, both the raw gap and the conditional gap are negatively correlated with the headline unemployment. The gaps for Black men are the most strongly correlated.

I also report results in logs for each race and race by gender group,

$$\log \text{gap}_{rt}^{raw} = \log\left(\frac{1}{N_r}\sum_{i}^{N_r} E_{irt}\right) - \log\left(\frac{1}{N_w}\sum_{i}^{N_w} E_{iwt}\right), \tag{A.5}$$

$$\log \text{gap}_{rt}^{cond} = \log\left(\frac{1}{N_r}\sum_{i}^{N_r} E_{irt}\right) - \log\left(\frac{1}{N_r}\sum_{i}^{N_r} \hat{E}_{irt}\right). \tag{A.6}$$

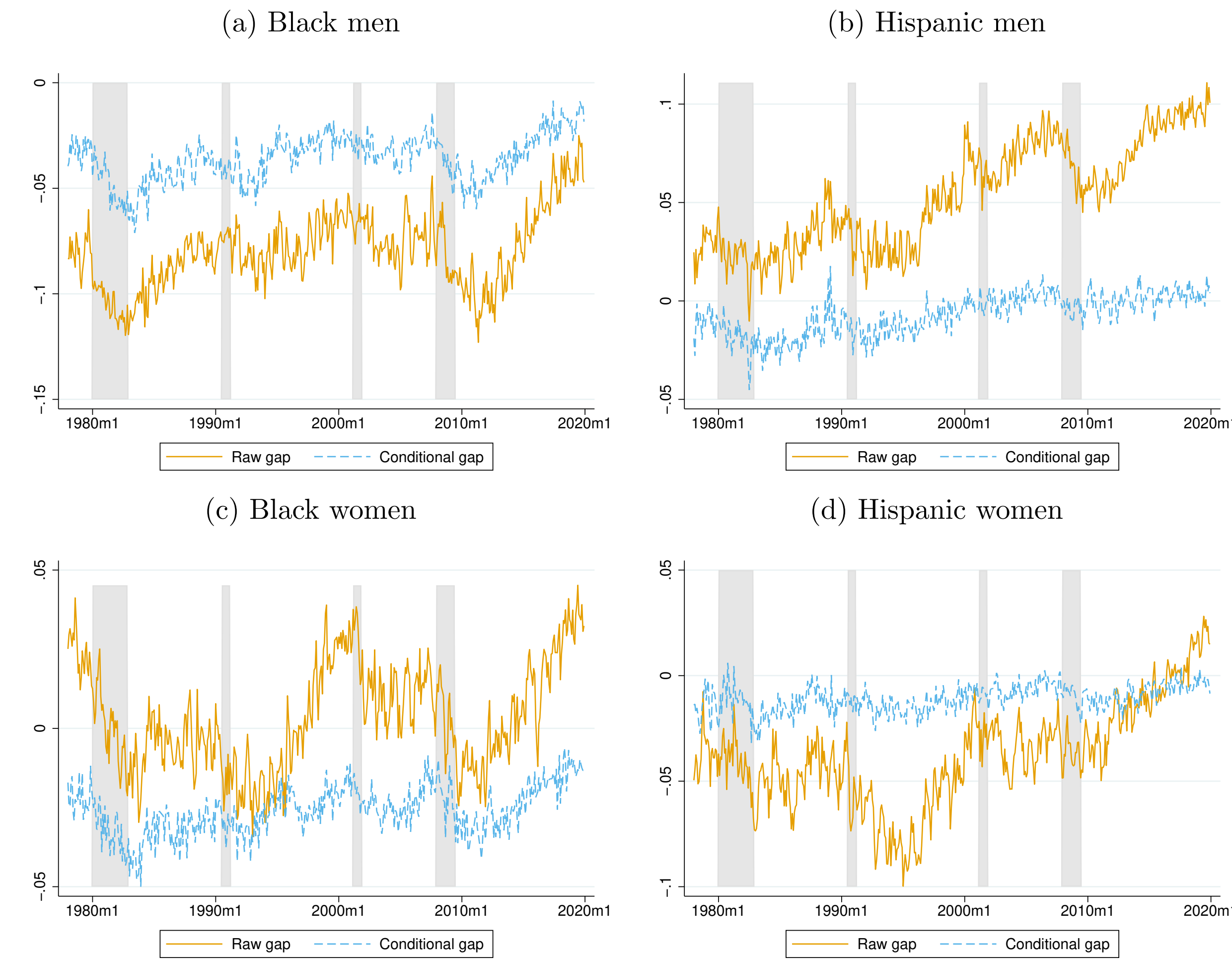
The results are shown in Figures A.3 and A.4, with summary statistics in Table A.2. The patterns are similar in both levels and logs.

Table A.2: Log employment gap summary statistics

	Raw gap			**Conditional gap**		
	Mean	SD	Corr w/ UR	Mean	SD	Corr w/ UR
Both genders						
Black	-0.065	0.027	-0.863	-0.051	0.016	-0.861
Hispanic	0.016	0.038	-0.497	-0.014	0.012	-0.541
Men						
Black	-0.118	0.028	-0.847	-0.055	0.018	-0.854
Hispanic	0.071	0.037	-0.518	-0.009	0.014	-0.461
Women						
Black	0.006	0.030	-0.670	-0.046	0.016	-0.745
Hispanic	-0.073	0.047	-0.384	-0.022	0.014	-0.464

Source: CPS.
The table reports the mean, standard deviation, and correlation with the headline unemployment rate for the raw and conditional gaps in employment to population ratios relative to the white population, as defined in equations (A.5)-(A.6).

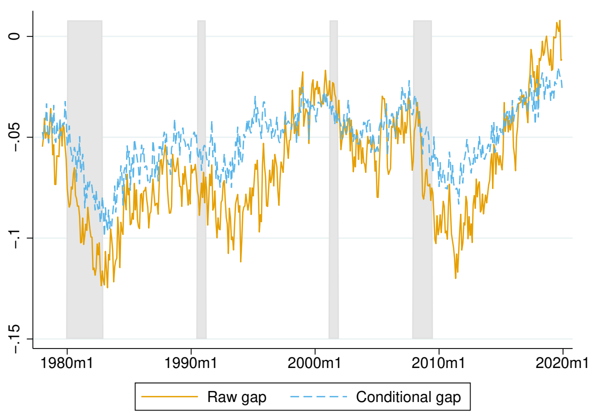
Figure A.2: Employment to population gap relative to white population



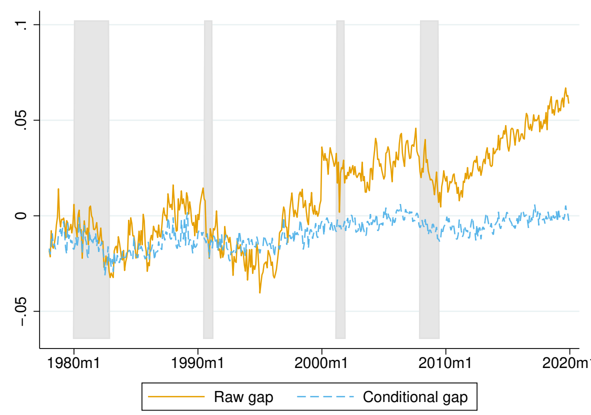
Source: CPS.
The solid (Raw gap) lines plot the gap in the employment to population ratio for the Black and Hispanic populations relative to the white population, separately by gender. Panels (a) and (b) compare Black and Hispanic men to white men. Panels (c) and (d) compare Black and Hispanic women to white women. The dashed (Conditional gap) line plots the within-month employment gap, conditional on an age quadratic, marital status, occupation, industry, state, and metro area size. Table A.1 reports the means, standard deviations, and correlations with the headline unemployment rate for each series.

Figure A.3: Employment to population gap relative to white

(a) Black

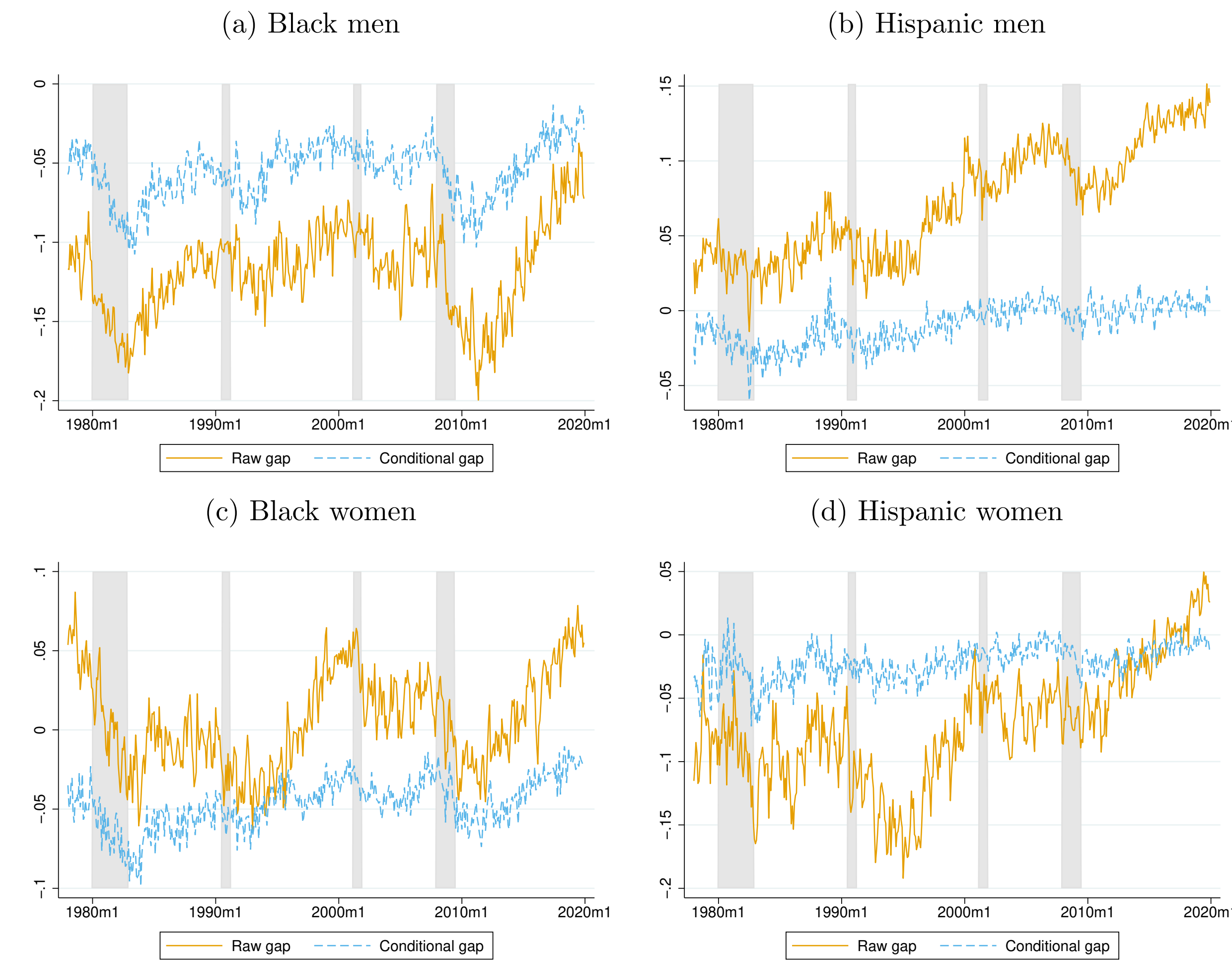


(b) Hispanic



Source: CPS.
The solid (Raw gap) line plots the gap in the employment to population ratio for the Black and Hispanic populations relative to the white population in logs. The dashed (Conditional gap) line plots the within-month employment gap, conditional on an age quadratic by gender, marital status by gender, occupation, industry, state, and metro area size. Means, standard deviations, and correlations with the headline unemployment rate are reported in Table A.2.

Figure A.4: Employment to population gap relative to white population



Source: CPS.
The solid (Raw gap) lines plot the log gap in the employment to population ratios, defined in equation A.5, for the Black and Hispanic populations relative to the white population, separately by gender. Panels (a) and (b) compare Black and Hispanic men to white men. Panels (c) and (d) compare Black and Hispanic women to white women. The dashed (Conditional gap) line plots the within-month employment gap, defined in equation A.6, conditional on an age quadratic, marital status, occupation, industry, state, and metro area size. Table A.2 reports the means, standard deviations, and correlations with the headline unemployment rate for each series.

Table A.3 shows that the patterns over employer composition are broadly consistent between the SIPP and the CPS and across different definitions of firm size. Panel (a) reports the raw and conditional gaps in the probability of working for a large firm, relative to white workers. Black workers are 8 percentage points more likely to work for a large firm as measured by the SIPP, 6.8 percentage points measured by the CPS and 6.2 percentage points when the threshold is raised to 500 or more employees. The estimates are reasonably similar across sources, with the SIPP tending to overestimate the propensity of Black workers to sort to large firms and underestimate the propensity for Hispanic workers to sort to small firms, relative to the CPS.

Table A.3: Employer composition comparison across sources

	Raw gap			Conditional gap		
	SIPP	CPS	CPS	SIPP	CPS	CPS
(a) Large	100+	100+	500+	100+	100+	500+
Black	8.015	6.782	6.237	7.061	6.690	6.196
	(0.390)	(0.120)	(0.117)	(0.0721)	(0.122)	(0.120)
Hispanic	-0.780	-3.066	-3.905	-0.392	-1.435	-1.951
	(0.392)	(0.0989)	(0.0920)	(0.0799)	(0.114)	(0.108)
(b) Small						
Black	-7.400	-5.664	-5.119	-8.544	-6.943	-6.448
	(0.301)	(0.104)	(0.116)	(0.0630)	(0.109)	(0.120)
Hispanic	9.065	11.63	12.47	0.911	3.383	3.899
	(0.367)	(0.0973)	(0.0997)	(0.0762)	(0.111)	(0.115)

A.2. Additional empirical results

A.2.1 Results by gender

Table 1.2 reports the baseline results for how employer type-specific separation and job-finding rates vary by race and with aggregate conditions. Tables A.4 and A.5 report the results for men and women, respectively. Comparing Panel (a) across the two tables, the increase in separations during high unemployment months is particularly strong for men. The increase in separation rates during these months is similar for Black and white men. Comparing Panel (b) across the two tables, both genders experience a strong decrease in job-finding rates during high unemployment months. The result that Black workers in particular face lower job-finding rates and that this is driven by large firms is stronger among women than men.

A.2.2 Alternative measures of aggregate conditions

The results reported in Section 1.3 compare the transition rates of Black and white workers in high unemployment periods, defined as months in which the gap between the headline unemployment rate and its time-varying noncyclical rate are in the top tercile of all months. Table A.8 shows that the results are similar using the continuous unemployment gap rather than the indicator for high unemployment months. Table A.9 shows similar results with the continuous state-level unemployment rate.

A.3. Wage setting details

A.3.1 Bargaining with groups

Suppose the firm can observe the worker's group (g) and new hire status at the time of bargaining. The firm's value at the time of bargaining is given by

$$
\begin{aligned}
D_t(\{\tilde{n}_g\},\{h_g\},\{\hat{x}_g\},z) =& a_t z(n')^\alpha - \sum_g \Big(\tilde{n}_g w^n(n',z,g) + h_g w^h(x_g,n',z,g)\Big) + \beta \mathbb{E}_t J_{t+1}(n'_B,n'_W,z) \\
&\text{s.t.} \\
&n' = \sum_g n'_g \\
&n'_g = \tilde{n}_g + \hat{x}_g h_g
\end{aligned}
$$

where $\tilde{n}_g = (1-\delta)n_g$ is the number of non-separated workers from group g from the previous period and $h_g = \frac{u_{gt}}{u_t} v q(\theta_t)(1-F(x_g|p(g,z)))$ is the number of hires from group g. The last line shows the mapping back to the law of motion in equation (1.4.4).

To relate the firm value at bargaining back to the firm's problem from the main text, notice that vacancies can be rewritten as[1]

$$
v = \sum_g \frac{h_g}{q(\theta_t)(1-F(x_g|p(g,z)))}
$$

Then using this expression, the firm's problem from equation (1.4.2) can be equivalently expressed as

$$
J_t(n_B,n_W,z) = \max_{h_B,h_W,x_B,x_W} -\sum_g \frac{c_v h_g}{q(\theta_t)(1-F(x_g|p(g,z)))} + D_t(\{(1-\delta)n_g\},\{h_g\},\{\hat{x}_g(x_g)\},z)
$$

[1]The omitted step is $v = \frac{h_g}{\frac{u_{gt}}{u_t} q(\theta_t)(1-F(x_g|p(g,z)))} = \frac{u_{Bt}}{u_t}\frac{h_B}{\frac{u_{Bt}}{u_t} q(\theta_t)(1-F(x_B|p(B,z)))} + \frac{u_{Wt}}{u_t}\frac{h_W}{\frac{u_{Wt}}{u_t} q(\theta_t)(1-F(x_W|p(W,z)))}$

where the first term comes the expression for vacancies from the law of motion for productive hires.

To solve the wage problem, we need the marginal surplus for each group, $D_{t,\tilde{n}_g}$ and D_{t,h_g}, where the arguments of $D()$ are omitted to ease notation.

$$\begin{aligned}
D_{t,\tilde{n}_g} =& \alpha a_t z(n')^{\alpha-1} - w^n(n',z,g) - \sum_k \Big(\tilde{n}_k w^n_{n'}(n',z,k) + h_k w^h_{n'}(\hat{x}_k,n',z,k)\Big) \\
&+ \beta(1-\delta)\mathbb{E}_t D_{t+1,\tilde{n}_g} \\
D_{t,h_g} =& \hat{x}_g \alpha a_t z(n')^{\alpha-1} - w^h(x_g,n',z,g) - \hat{x}_g \sum_k \Big(\tilde{n}_k w^n_{n'}(n',z,k) + h_k w^h_{n'}(\hat{x}_k,n',z,k)\Big) \\
&+ \beta(1-\delta)\hat{x}_g \mathbb{E}_t D_{t+1,\tilde{n}_g}
\end{aligned}$$

The marginal surplus from the worker's side is given by

$$\begin{aligned}
V^n_t(g,z) - V^u_t(g) =& w^n_t(n',z,g) - (b+\Omega_t(g)) + \beta(1-\delta)\mathbb{E}_t\left[V^n_{t+1}(g,z) - V^u_{t+1}(g)\right] \\
V^h_t(g,z) - V^u_t(g) =& w^h_t(\hat{x}_g,n',z,g) - (b+\Omega_t(g)) + \beta(1-\delta)\hat{x}_g(z)\mathbb{E}_t\left[V^n_{t+1}(g,z) - V^u_{t+1}(g)\right]
\end{aligned}$$

Using the bargaining rules defined in equations (1.4.15) and (1.4.16),

$$\begin{aligned}
w^n(n',z,g) =& \phi\alpha a_t z(n')^{\alpha-1} - \phi\sum_k \Big(\tilde{n}_k w^n_{n'}(n',z,k) + h_k w^h_{n'}(\hat{x}_k,n',z,k)\Big) + (1-\phi)(b+\Omega_t(g)) \\
w^h(\hat{x}_g,n',z,g) =& \hat{x}_g\phi\alpha a_t z(n')^{\alpha-1} \\
&- \hat{x}_g\phi\sum_k \Big(\tilde{n}_k w^n_{n'}(n',z,k) + h_k w^h_{n'}(\hat{x}_k,n',z,k)\Big) + (1-\phi)(b+\Omega_t(g))
\end{aligned}$$

Notice that the relationship between new hire wages and existing worker wages is given by

$$w^h(\hat{x}_g,n',z,g) = \hat{x}_g w^n(n',z,g) + \big(1-\hat{x}_g\big)(1-\phi)(b+\Omega_t(g))$$

which implies

$$w^h_{n'}(x_g,n',z,g) = \hat{x}_g w^n_{n'}(n',z,g)$$

Next, the wage gap between existing workers from the two groups is given by

$$w^n(n',z,B) - w^n(n',z,W) = (1-\phi)(\Omega_t(W) - \Omega_t(B))$$

which doesn't depend on the size of the firm, and so $w_{n'}(n',z,B) = w_{n'}(n',z,W)$. Using these observations, we can simplify the differential equation for $w^n(n', z, g)$,

$$w^n(n', z, g) = \phi a_t z(n')^{\alpha-1} - \phi n' w^n_{n'}(n', z, g) + (1-\phi)(b + \Omega_t(g))$$

Solving this differential equation gives the following equilibrium wages

$$\begin{aligned} w^n(n', z, g) =& \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z(n')^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) \\ w^h(\hat{x}_g, n', z, g) =& \hat{x}_g \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z(n')^{\alpha-1} + (1-\phi)(b + \Omega_t(g)) \end{aligned}$$

A.3.2 Bargaining without observing groups

Now suppose the firm cannot observe the group of the individual workers they are bargaining with, but they do know the relative shares and hiring thresholds. The firm's value at the time of bargaining is given by

$$\begin{aligned} D_t(\tilde{n}, h, \{x_g\}, \lambda^n_g, \lambda^h_g, z) =& a_t z(n')^{\alpha} - \tilde{n} w^n(n', z) - h w^h(\hat{x}, n', z) + \beta \mathbb{E}_t J_{t+1}(\lambda'_B n', \lambda'_W n', z) \\ & \text{s.t.} \\ & n' = \tilde{n} + h\hat{x} \\ & \lambda'_g n' = \underbrace{\lambda^n_g \tilde{n}}_{\text{composition existing}} + \underbrace{\lambda^h_g h \hat{x}(x_g, p(g, z))}_{\text{composition new hires}} \end{aligned}$$

where λ^n_g is the share of workers from group g that continued from the previous period and λ^h_g is the share of new hires from group g.

As before, we can relate the firm value at bargaining back to the firm's problem,

$$\begin{aligned} J_t(\lambda_B n, \lambda_W n, z) = \max_{h, \lambda_h, x_B, x_W} & - \sum_g \frac{c_v \lambda_h h}{q(\theta_t)(1 - F(x_g | p(g, z)))} \\ & + D_t((1-\delta)n, h, \hat{x}(x_B, x_W), \lambda^n_g, \lambda^h_g(x_B, x_W), z) \end{aligned}$$

where

$$J_{t,n}(n_B, n_W, z) = \lambda_B J_{t,n_B}(n_B, n_W, z) + \lambda_W J_{t,n_W}(n_B, n_W, z) = (1-\delta) D_{t,\tilde{n}}(\tilde{n}, h, \hat{x}, \lambda^n_g, \lambda^h_g, z)$$

Taking the marginal surplus with respect to a continuing worker ($\tilde{n}$) or a new hire (h),

$$\begin{aligned}
D_{t,\tilde{n}} =& a_t z(n')^{\alpha-1} - w^n(n',z) - \left(\tilde{n} w^n_{n'}(n',z) + h w^h_{n'}(\hat{x},n',z)\right) + \beta(1-\delta)\mathbb{E}_t D_{t+1,\tilde{n}} \\
D_{t,h} =& \hat{x} a_t z(n')^{\alpha-1} - w^h(\hat{x},n',z) - \hat{x}\left(\tilde{n} w^n_{n'}(n',z) + h w^h_{n'}(\hat{x},n',z)\right) + \hat{x}\beta(1-\delta)\mathbb{E}_t D_{t+1,\tilde{n}}
\end{aligned}$$

The marginal surplus on the worker's side depends on the composition of workers the firm is bargaining with,

$$\begin{aligned}
\sum_g \lambda^n_g \Big(V^n_t(g,z) - V^u_t(g)\Big) =& w^n_t(n',z) - \sum_g \lambda^n_g \Big((b+\Omega_t(g)) + \beta(1-\delta)\mathbb{E}_t\left[V^e_{t+1}(g,z) - V^u_{t+1}(g)\right]\Big) \\
\sum_g \lambda^h_g \Big(V^h_t(g,z) - V^u_t(g)\Big) =& w^h_t(\hat{x},n',z) \\
& - \sum_g \lambda^h_g \Big((b+\Omega_t(g)) + \beta(1-\delta)\hat{x}(x_g,p(g,z))\mathbb{E}_t\left[V^e_{t+1}(g,z) - V^u_{t+1}(g)\right]\Big)
\end{aligned}$$

Using the bargaining rules defined in equations (1.4.15) and (1.4.16),

$$\begin{aligned}
w^n(n',z) =& \phi a_t z(n')^{\alpha-1} - \phi\left(\tilde{n} w^n_{n'}(n',z) + h w^h_{n'}(\hat{x},n',z)\right) + (1-\phi)\left(b + \sum_g \lambda^n_g \Omega_t(g)\right) \\
w^h(\hat{x},n',z) =& \hat{x}\phi a_t z(n')^{\alpha-1} - \hat{x}\phi\left(\tilde{n} w^n_{n'}(n',z) + h w^h_{n'}(\hat{x},n',z)\right) + (1-\phi)\left(b + \sum_g \lambda^h_g \Omega_t(g)\right)
\end{aligned}$$

and we get the following wage equations

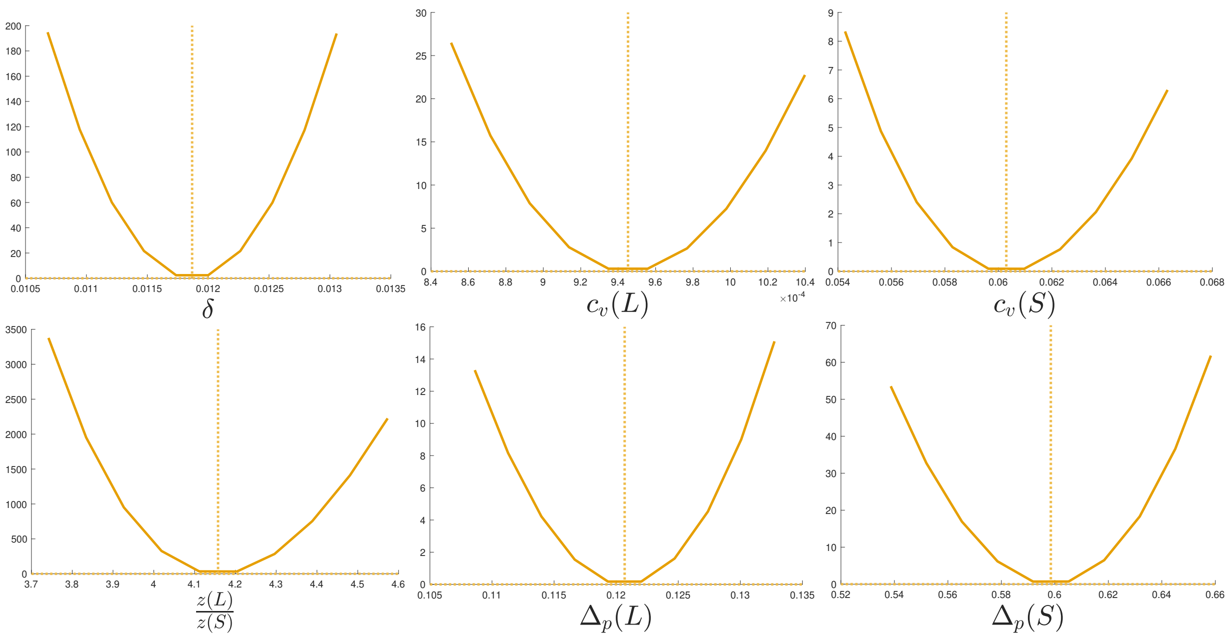
$$\begin{aligned}
w^n(n',z,\lambda^n) =& \frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z(n')^{\alpha-1} + (1-\phi)\left(b + \sum_g \lambda^n_g \Omega_t(g)\right) \\
w^h(\hat{x}_g,n',z,\lambda^h) =& \left(\sum_g \lambda^h_g \hat{x}(x_g,p(g,z))\right)\frac{\alpha\phi}{1-\phi+\alpha\phi} a_t z(n')^{\alpha-1} + (1-\phi)\left(b + \sum_g \lambda^h_g \Omega_t(g)\right)
\end{aligned}$$

From the perspective of the firm, the wage bill is the same whether they can observe the group of the worker or not, as long as the wages satisfy the participation constraint for all groups. However, in this case the distribution of wages across workers changes and this will have consequences for the workers' outside options, $\Omega_t(g)$.

A.4. Identification

Section 1.5 describes the intuition for the identification of the six estimated parameters. Figure A.5 shows that the objective function reaches a local minimum around each parameter value. The objective function uses the inverse of the variance-covariance matrix obtained from the block bootstrap described in Section 1.3.5 with 1,000 iterations.

Figure A.5: Objective function minimization



The figure plots the objection function for the GMM procedure around each of the estimated parameters. The weight matrix is the inverse of the variance covariance matrix obtained with a block bootstrap by individual within each SIPP panel.

Table A.4: Transition rates by race and aggregate unemployment, men

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.08	0.06	0.31	-0.28	-0.02
	(0.04)	(0.06)	(0.10)	(0.06)	(0.08)
High UR	0.14	0.12	0.28	0.17	0.03
	(0.05)	(0.06)	(0.09)	(0.07)	(0.04)
Black × High UR	0.01	0.12	-0.25	0.07	0.28
	(0.07)	(0.10)	(0.22)	(0.13)	(0.16)
N	1,900,483	1,900,483			
R^2	0.01	0.01			
Black mean	1.52	1.55	2.19	0.71	0.65
White mean	1.17	1.14	1.75	0.79	0.35

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-1.30	-0.33	-0.84	-0.00	-0.11
	(0.09)	(0.06)	(0.05)	(0.02)	(0.02)
High UR	-0.77	-0.33	-0.28	-0.02	-0.06
	(0.11)	(0.05)	(0.05)	(0.02)	(0.01)
Black × High UR	-0.10	-0.11	0.04	-0.04	0.03
	(0.14)	(0.10)	(0.07)	(0.04)	(0.03)
N	837,928	837,928	837,928	837,928	837,928
R^2	0.05	0.02	0.02	0.00	0.00
Black mean	2.81	1.45	0.85	0.23	0.12
White mean	3.01	1.31	1.17	0.23	0.17

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions for men. The units are percentage points. Panel (a) reports the estimates for aggregate separations rates from equation (1.3.1) in column (1) and the interacted coefficients with employer type from equation (1.3.3) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (1.3.2) in column (1) and the estimates for equation (1.3.4) with an outcome variable for each employer type in columns (2)-(5). All specifications include controls for age, age-squared, and marital status; education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table A.5: Transition rates by race and aggregate unemployment, women

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.08	0.25	0.21	-0.33	0.07
	(0.04)	(0.06)	(0.09)	(0.06)	(0.13)
High UR	-0.04	0.02	-0.08	-0.02	-0.09
	(0.04)	(0.05)	(0.06)	(0.10)	(0.06)
Black × High UR	-0.13	-0.28	-0.13	0.07	0.31
	(0.07)	(0.11)	(0.16)	(0.12)	(0.26)
N	1,800,752	1,800,752	1,800,752	1,800,752	1,800,752
R2	0.01	0.01	0.01	0.01	0.01
Black mean	1.66	1.81	2.20	0.88	1.09
White mean	1.44	1.42	1.83	1.09	0.70

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-0.36	0.12	-0.41	0.01	-0.06
	(0.07)	(0.05)	(0.03)	(0.02)	(0.01)
High UR	-0.53	-0.21	-0.18	-0.05	-0.03
	(0.07)	(0.03)	(0.03)	(0.02)	(0.01)
Black × High UR	-0.29	-0.31	0.05	-0.03	0.02
	(0.10)	(0.07)	(0.04)	(0.03)	(0.02)
N	1,388,861	1,388,861	1,388,861	1,388,861	1,388,861
R2	0.04	0.02	0.01	0.01	0.00
Black mean	2.53	1.40	0.66	0.31	0.07
White mean	2.01	0.85	0.68	0.27	0.10

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions for women. The units are percentage points. Panel (a) reports the estimates for aggregate separations rates from equation (1.3.1) in column (1) and the interacted coefficients with employer type from equation (1.3.3) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (1.3.2) in column (1) and the estimates for equation (1.3.4) with an outcome variable for each employer type in columns (2)-(5). All specifications include controls for age, age-squared, and marital status; education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table A.6: Separation rate heterogeneity, men

	(1) All	(2) Voluntary	(3) Involuntary
Large	-0.03	-0.02	-0.16
	(0.06)	(0.10)	(0.09)
Small × Black	-0.17	-0.93	0.36
	(0.18)	(0.25)	(0.24)
Large × Black	0.03	-0.42	0.38
	(0.07)	(0.12)	(0.09)
Small × HighUR	0.01	-0.88	1.21
	(0.10)	(0.14)	(0.15)
Large × HighUR	-0.22	-0.84	0.62
	(0.05)	(0.07)	(0.06)
Small × Black × HighUR	-0.13	-0.10	-0.11
	(0.31)	(0.40)	(0.49)
Large × Black × HighUR	-0.19	-0.26	-0.05
	(0.12)	(0.17)	(0.16)
N	1,276,825	1,269,010	1,269,010
R^2	0.02	0.02	0.02
Black mean	2.29	2.05	2.08
White mean	2.06	2.28	1.60

The table reports differences in size-specific and reason-specific separation rates by race and macroeconomic conditions given by equation (1.3.9) for men. The units are percentage points. The sample includes all workers who report a job at a large or small firm. The outcome variable in column (1) is an indicator equal to 1 if the worker reports the job ending that month. The outcome variables in columns (2)-(3) are indicators equal to 1 if the worker reports the job ending and gives an involuntary or voluntary reason for it, respectively. All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects; job tenure in years; log wage; hours; union membership; and industry. Standard errors are clustered by month.

Table A.7: Separation rate heterogeneity, women

	(1) All	(2) Voluntary	(3) Involuntary
Large	-0.12	-0.11	0.06
	(0.06)	(0.10)	(0.07)
Small × Black	0.09	-0.45	0.77
	(0.17)	(0.25)	(0.20)
Large × Black	-0.00	-0.46	0.36
	(0.07)	(0.12)	(0.09)
Small × HighUR	-0.53	-1.13	0.61
	(0.10)	(0.14)	(0.11)
Large × HighUR	-0.22	-0.83	0.61
	(0.05)	(0.07)	(0.06)
Small × Black × HighUR	-0.04	-0.05	0.01
	(0.27)	(0.39)	(0.38)
Large × Black × HighUR	-0.19	-0.26	-0.05
	(0.12)	(0.17)	(0.16)
N	1,295,415	1,287,197	1,287,197
R^2	0.02	0.02	0.01
Black mean	2.46	2.51	1.81
White mean	2.24	2.54	1.34

The table reports differences in size-specific and reason-specific separation rates by race and macroeconomic conditions given by equation (1.3.9) for women. The units are percentage points. The sample includes all workers who report a job at a large or small firm. The outcome variable in column (1) is an indicator equal to 1 if the worker reports the job ending that month. The outcome variables in columns (2)-(3) are indicators equal to 1 if the worker reports the job ending and gives an involuntary or voluntary reason for it, respectively. All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects; job tenure in years; log wage; hours; union membership; and industry. Standard errors are clustered by month.

Table A.8: Transition rates by race and unemployment deviations from trend

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.07	0.14	0.21	-0.29	0.10
	(0.02)	(0.04)	(0.06)	(0.04)	(0.06)
UR gap	0.02	0.02	0.03	0.03	0.00
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Black × UR gap	-0.02	-0.03	-0.04	0.01	0.08
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
N	3,701,235	3,701,235	3,701,235	3,701,235	3,701,235
R2	0.01	0.01	0.01	0.01	0.01
Black mean	1.60	1.69	2.20	0.82	0.82
White mean	1.30	1.27	1.79	0.96	0.47

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-0.82	-0.14	-0.58	-0.00	-0.07
	(0.05)	(0.03)	(0.03)	(0.01)	(0.01)
UR gap	-0.17	-0.07	-0.06	-0.01	-0.01
	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)
Black × UR gap	-0.05	-0.06	0.01	-0.01	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
N	2,226,789	2,226,789	2,226,789	2,226,789	2,226,789
R2	0.04	0.02	0.02	0.01	0.00
Black mean	2.65	1.42	0.74	0.28	0.09
White mean	2.39	1.03	0.87	0.26	0.13

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions. The units are percentage points. UR gap is the demeaned unemployment rate deviations from trend. Panel (a) reports the estimates for aggregate separations rates from equation (1.3.1) in column (1) and the interacted coefficients with employer type from equation (1.3.3) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (1.3.2) in column (1) and the estimates for equation (1.3.4) with an outcome variable for each employer type in columns (2)-(5). All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

Table A.9: Transition rates by race and state-level unemployment

(a) Separations: E to N	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	0.07	0.14	0.21	-0.29	0.09
	(0.02)	(0.04)	(0.06)	(0.04)	(0.06)
State UR	0.03	0.02	0.05	0.03	-0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Black × State UR	-0.01	-0.02	-0.04	0.00	0.06
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
N	3,701,235	3,701,235	3,701,235	3,701,235	3,701,235
R2	0.01	0.01	0.01	0.01	0.01
Black mean	1.60	1.69	2.20	0.82	0.82
White mean	1.30	1.27	1.79	0.96	0.47

(b) Job-finding: N to E	(1) All	(2) Large	(3) Small	(4) Government	(5) Self
Black	-0.79	-0.13	-0.57	0.00	-0.07
	(0.05)	(0.03)	(0.03)	(0.01)	(0.01)
State UR	-0.15	-0.07	-0.05	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Black × State UR	-0.05	-0.05	0.00	-0.01	0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
N	2,226,789	2,226,789	2,226,789	2,226,789	2,226,789
R2	0.04	0.02	0.02	0.01	0.00
Black mean	2.65	1.42	0.74	0.28	0.09
White mean	2.39	1.03	0.87	0.26	0.13

The table reports differences in employer-type specific separation and job-finding rates by race and macroeconomic conditions. The units are percentage points. State UR is the demeaned state-level unemployment rate. Panel (a) reports the estimates for aggregate separations rates from equation (1.3.1) in column (1) and the interacted coefficients with employer type from equation (1.3.3) in columns (2)-(5). Panel (b) reports the estimates for aggregate job-finding rates from equation (1.3.2) in column (1) and the estimates for equation (1.3.4) with an outcome variable for each employer type in columns (2)-(5). All specifications include controls for age, age-squared, and marital status interacted with gender; education; geographic region; metro area size; calendar month fixed effects. Panel (a) includes controls for industry; occupation; and length of employment spell in years. Panel (b) includes controls for length of nonemployment spell in years; indicator for new entrants; and indicator for unobserved full length of nonemployment spell. Standard errors are clustered by month.

APPENDIX B

Appendix to Chapter 2

B.1. Additional Empirical Results

Table B.1: Effect of parent's displacement on adult earnings

	(1)	(2)	(3)	(4)	(5)	(6)
Father	0.0210			-0.00633		
	(0.0884)			(0.0967)		
Mother		-0.111*			-0.00943	
		(0.0667)			(0.0706)	
Either parent			-0.0290			0.00572
			(0.0528)			(0.0561)
Family income				0.275***	0.259***	0.254***
				(0.0382)	(0.0322)	(0.0298)
Mean ($)	18121	16803	16864	17412	16656	16756
Mean (log $)	9.56	9.47	9.47	9.51	9.46	9.46
SD (log $)	.75	.79	.79	.76	.79	.79
Observations	2477	3516	3852	2009	3001	3406
R-Squared	.15	.15	.15	.13	.15	.14

Notes: All columns include controls for child's decade of birth and race and parents' education. In columns (1)-(3), parent employment controls include dummies for 15 industries and 6 broad occupation categories, measured as mode over career. In columns (4)-(6), parent employment controls are replaced with the log of average real household income over the 2-4 years prior to child's reference age, defined as the age at which their parent was laid off or a randomly assigned age based on the distribution of ages at parent layoff. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Effect of parent's displacement on occupation risk

	(1)	(2)	(3)	(4)	(5)	(6)
Father	-0.0443*			-0.0396		
	(0.0256)			(0.0277)		
Mother		-0.00540			0.00958	
		(0.0214)			(0.0207)	
Either parent			-0.0225			-0.0137
			(0.0164)			(0.0166)
Family income				0.0663***	0.0525***	0.0558***
				(0.0115)	(0.00842)	(0.00809)
Mean ($)	8133	7936	7921	8063	7908	7907
Mean (log $)	8.97	8.95	8.95	8.96	8.95	8.95
SD (log $)	.25	.24	.24	.25	.24	.24
Observations	3006	4324	4662	2484	3723	4162
R-Squared	.11	.117	.11	.11	.12	.12

Notes: All columns include controls for child's decade of birth and race and parents' education. In columns (1)-(3), parent employment controls include dummies for 15 industries and 6 broad occupation categories, measured as mode over career. In columns (4)-(6), parent employment controls are replaced with the log of average real household income over the 2-4 years prior to child's reference age, defined as the age at which their parent was laid off or a randomly assigned age based on the distribution of ages at parent layoff. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Effect of early childhood exposure to negative macroeconomic conditions on adult earnings and occupation risk

	Income y_i		Risk σ_j	
	(1)	(2)	(3)	(4)
Father	-0.0480*		-0.0468*	
	(0.0283)		(0.0248)	
Mother		-0.127***		-0.0507*
		(0.0309)		(0.0260)
Mean($)	18121	16803	8133	7936
SD($)	12186	11873	2016	1948
Obs.	2455	3413	2976	4174
R-Squared	.08	.08	.03	.02

Notes: Regressions include fixed effects for child's birth year. Coefficients reported are on average relative macroeconomic growth of parent's industry from birth to age 5. Outcome variables and macroeconomic exposure are standardized so the estimated coefficients can be interpreted as the standard deviation increase in income or risk associated with a one standard deviation decrease in relative macroeconomic conditions. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Effect of early childhood exposure to negative macroeconomic conditions on adult earnings and occupation risk, conditional on parent education

	Income y_i		Risk σ_j	
	(1)	(2)	(3)	(4)
Father	-0.0153		-0.0157	
	(0.0290)		(0.0255)	
Mother		-0.0948***		-0.0215
		(0.0302)		(0.0257)
Mean($)	18121	16803	8133	7936
SD($)	12186	11873	2016	1948
Obs.	2455	3413	2976	4174
R-Squared	.11	.11	.06	.05

Notes: Regressions include fixed effects for child's birth year and parent's education. Coefficients reported are on average relative macroeconomic growth of parent's industry from birth to age 5. Outcome variables and macroeconomic exposure are standardized so the estimated coefficients can be interpreted as the standard deviation increase in income or risk associated with a one standard deviation decrease in relative macroeconomic conditions. Regressions are weighted using the individual weight in the last year the individual is observed with a nonzero weight.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX C

Appendix to Chapter 3

C.1. Empirical Appendix

C.1.1 Data Description

For our empirical analysis, we combine firm-level data from Global Compustat with corporate bond data from Bloomberg. This section describes the process for cleaning the data and merging across sources.

C.1.1.1 Global Compustat

We get quarterly data on firms' balance-sheets from Global Compustat and construct variables using standard methodology in the literature, with some additional adjustments for currency. We keep only observations in which the reporting currency is either local currency or USD (99.8% of sample). For observations denominated in USD (8% of sample), we convert variables to local currency using average quarterly spot exchange rates. When considering changes in variables–e.g., sales growth or changes in the capital stock–we only compare observations reported in the same currency. For real variables, we deflate the nominal variables with GDP deflators from each country.

Variable Definitions

1. *Investment:* We define investment as $\Delta \log\bigl(k_{jt+1}\bigr)$, where k_{jt+1} is the stock of capital at firm j at the end of period t. We set the initial value k_{jt+1} to the level of gross plant, property, and equipment (ppegtq) in the first period in which this is available. We then compute the evolution of the capital stock using changes in net plant, property,

and equipment (ppentq). This variable measures investment net of depreciation with more observations than ppegtq. We linearly interpolate ppentq if there is one missing observation between two non-missing. We only interpolate between observations reported in the same currency.

2. *Leverage:* We define leverage as the ratio of total debt (dlcq + dlttq) to total assets (atq).

3. *Real sales growth:* We define real sales growth as the percent change in sales (saleq), deflated by the local GDP deflator. We exclude observations if a firm changes reporting currency between consecutive quarters ($< 0.1\%$ of observations).

4. *Size:* We define size as the log of total real assets, converted to USD for comparability across countries. We deflate total assets by the price deflator for the US.

5. *Liquidity:* We define liquidity as the ratio of cash and short-term investments (cheq) to total assets.

6. *Cash flow:* We define operating cash flow as the ratio of operating income before depreciation (oibdp) minus interest (xint) minus taxes (txt) to lagged total assets.

7. *Sector:* We identify firms in tradeable and non-tradeable sectors using 2-digit NAICS codes. Tradeable industries are agriculture (11), mining (21), manufacturing (31-33), wholesale trade (42), retail trade (44-45), and transportation and warehousing (48-49). Non-tradeable industries are information (51), professional, scientific, and technical services (54), administrative services (56), education (61), health and social services (62), arts (71), hospitality (72), and other services (81). We exclude the construction industry (23) and a small number of firms with unclassified industries from our sector definitions.

Sample Construction We restrict our final sample to exclude extreme outliers. We make the following sample restrictions, in this order.

1. We only include firms with balance sheets reported in local currency or USD.

2. We drop firms in the financial (SIC 6000-6799 or NAICS 52-53) and utilities (SIC 4900-4999 or NAICS 22) industries.

3. We exclude firm-quarter observations with negative capital or assets.

4. We exclude firm-quarter observations for which acquisitions are larger than 5% of assets.

Table C.1: Summary Statistics

	Mean	SD	p10	Med	p90	N
Investment	-0.12	5.92	-4.74	-0.90	4.85	29,383
Real sales growth	1.33	21.58	-20.77	0.82	24.29	29,140
Size	6.14	1.93	3.63	6.11	8.69	29,221
Tradeable sector	0.78	0.41	0.00	1.00	1.00	29,383
Book leverage	0.31	0.34	0.08	0.28	0.52	25,190
Distance to Default	6.57	5.11	1.08	5.38	13.78	17,451
Credit rating			B	BB+	BBB+	3,633
Risk-free measures						
–90th percentile DD	0.10	0.30	0.00	0.00	0.00	17,451
–A credit rating	0.01	0.09	0.00	0.00	0.00	29,383
–Investment grade rating	0.05	0.22	0.00	0.00	0.00	29,383
–10th percentile leverage	0.10	0.30	0.00	0.00	1.00	23,414

Note: The table reports summary statistics for firm investment and default risk data. The sample includes Argentina, Brazil, Chile, Colombia, Mexico, and Peru over the time period 1997q2 to 2019q4. Investment is defined as the log change in capital stock multiplied by 100. Real sales growth is measured in percentage points. Size is log real total assets, measured in USD. Tradeable and nontradeable sectors are defined in Appendix C.1.1.1. Credit ratings are long-term foreign issuer ratings from S&P and/or Moodys, obtained from Bloomberg. Where rating are available from both agencies, the lower rating is used.

5. We exclude firm-quarter observations if net current assets as a share of total assets is higher than 10 or below -10.

6. We exclude firm-quarter observations if leverage is higher than 10 or negative.

7. We exclude firm-quarter observations with negative real sales or liquidity.

8. We trim investment at the 1st and 99th percentiles.

Table C.1 reports summary statistics for the Latin America Global Compustat sample. We have 29,030 observations across Argentina, Brazil, Chile, Colombia, Mexico, and Peru over the time period 1997q2 to 2019q4, with considerable variation in investment, sales growth, size, and financial position.

C.1.1.2 Firm Risk

We measure firms' quarterly default risk using the measure of distance to default proposed by **?**, defined as $\mathrm{dd}_{jt} = \frac{\log\left(\frac{V_{jt}}{D_{jt}}\right)+(\mu_{jt}-0.5\sigma^2_{jt})}{\sigma_{jt}}$, where V_{jt} is the value of firm j in quarter t, D_{jt} is the firm's debt, μ_{jt} is the firm's annual expected return, and σ_{jt} is the annual volatility of the firm's value. We measure debt, D_{jt}, as the sum of short-term debt (dlcq) and one-half of long-term debt (dlttq). We follow an interative procedure based on Gilchrist and Zakrajšek (2012) to impute the firm's value, V_{jt}. The procedure is as follows:

1. We set an initial value of the firm equal to the sum of debt and equity, $V = D + E$. We measure equity as the firm's stock price times the number of shares, using Global Compustat Security Daily.

2. We estimate the mean (μ) and variance (σ) of the return on the firm's value over a 250-day moving window.

3. We estimate a new value of V using the Black-Scholes-Merton option-pricing framework $E = V\Phi(\delta_1) - e^{rT} D\Phi(\delta_2)$, where $\delta_1 \equiv \frac{\log\left(V/D\right)+(r+0.5\sigma^2)T}{\sigma^2\sqrt{T}}$ and $\delta_2 \equiv \delta_1 - \sigma\sqrt{T}$. Here, r is the daily 1-year constant maturity Treasury-yield and T is equal to 1 because the frequency is daily.

4. We repeat steps (a)-(c) until V converges.

Our methodology requires firms to have positive values for both debt and equity. To exclude extreme outliers, we trim distance to default at 1% and 99% of the global sample (-1.3 and 25.8). We are able to construct distance to default for about 60% of our Compustat sample. Table C.1 reports statistics for distance to default and the number of observations.

Using distance to default, we classify firm-by-quarter observations in our sample as either risky or risk-free, where risk-free firms are those with distance to default above the 90th percentile. Table C.2 summarizes the characteristics of each sample. Unsurprisingly, risky firms have higher leverage. They have slightly lower investment and sales growth, but are comparable in size. Table C.3 summarizes the sample by country. Because the threshold for the risk-free variable is uniform across countries, there is variation in the share of risk-free observations from each country, with Chile having the most risk-free observations and Brazil the fewest.

Table C.2: Summary Statistics by Firm Risk

	Mean	SD	p10	Med	p90	N
Risk-free						
Investment	0.37	5.44	-4.02	-0.35	4.63	1,744
Real sales growth	2.26	18.34	-15.85	1.23	22.45	1,735
Size	6.59	1.70	4.47	6.57	8.80	1,740
Book leverage	0.16	0.12	0.02	0.14	0.34	1,507
Distance to Default	17.60	2.99	14.22	16.94	22.16	1,744
Implied one-year default prob.	0.00	0.01	0.00	0.00	0.00	1,744
Credit rating			B+	BBB	A-	152
Tradeable sector	0.76	0.43	0.00	1.00	1.00	1,744
Nontradeable sector	0.19	0.39	0.00	0.00	1.00	1,744
Risky						
Investment	-0.28	5.68	-4.98	-0.98	4.64	15,697
Real sales growth	1.37	19.98	-19.16	0.87	22.41	15,550
Size	6.61	1.82	4.22	6.56	9.04	15,652
Book leverage	0.31	0.24	0.10	0.28	0.51	14,722
Distance to Default	5.36	3.61	0.97	4.82	10.75	15,697
Implied one-year default prob.	0.05	0.14	0.00	0.00	0.16	15,697
Credit rating			B	BB+	BBB+	2,568
Tradeable sector	0.77	0.42	0.00	1.00	1.00	15,697
Nontradeable sector	0.15	0.35	0.00	0.00	1.00	15,697

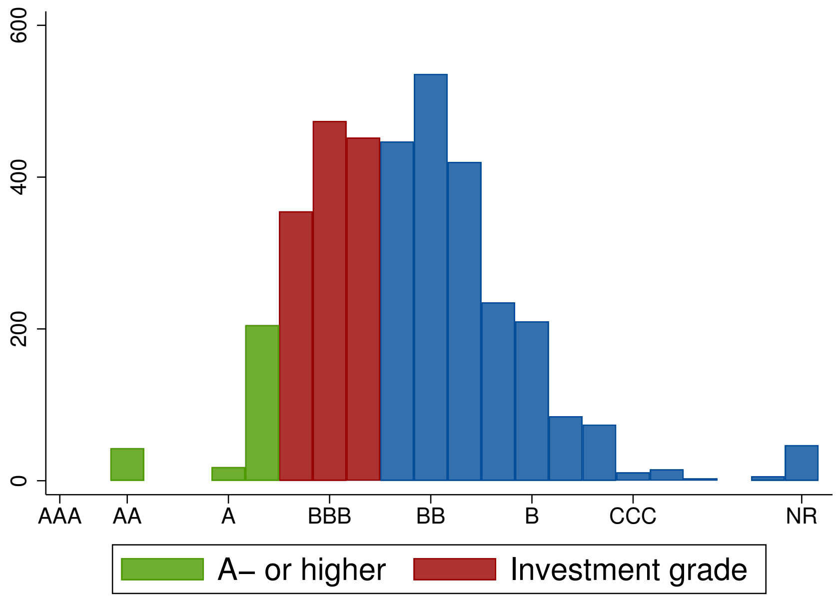
Note: The table reports summary statistics for firm investment and default risk data for risky and risk-free firms. Risk-free firms are those with distance to default above the 90th percentile. Investment is defined as the log change in capital stock multiplied by 100. Real sales growth is measured in percentage points. Size is log real total assets, measured in USD. Tradeable and nontradeable sectors are defined in Appendix C.1.1.1. Credit ratings are long-term foreign issuer ratings from S&P and/or Moodys, obtained from Bloomberg. Where rating are available from both agencies, the lower rating is used.

Table C.3: Summary Statistics by Country

	Observations	Firms	DD	Risk-free	Investment	Leverage	Tradeable	Non-tradeable
Argentina	1,664	55	6.56	0.08	-3.28	0.24	0.75	0.13
Brazil	7,108	260	5.25	0.07	-0.18	0.33	0.81	0.14
Chile	2,974	103	8.48	0.17	0.16	0.29	0.74	0.15
Colombia	497	24	8.16	0.14	0.71	0.21	0.83	0.08
Mexico	3,452	105	8.05	0.12	0.32	0.28	0.67	0.22
Peru	1,746	64	5.45	0.08	0.66	0.24	0.86	0.08

Note: The table reports summary statistics for the sample of Latin American firms with non-missing distance to default (DD). The sample period is 1997q2 to 2019q4. DD, risk-free, leverage, tradeable, and non-tradeable are means by country. Risk-free indicates observations with distance to default above the 90th percentile. Leverage is book leverage.

Figure C.1: Credit Ratings



Note: The figure reports the distribution of credit ratings from S&P and/or Moody's. Where both ratings are available, the lower rating is used. y-axis reports the number of firm-by-quarter observations.

We also measure firm risk using credit ratings from S&P and/or Moodys. For each of the firms in our sample, we use crosswalks between Compustat ID (gvkey) and ticker symbols to find the firm on Bloomberg and extract long-term foreign issuer ratings and the date at which they took effect. We obtain historical ratings for 15% of firms in our sample. We use a crosswalk from the BIS to put the ratings on the same scale and construct an aggregate rating using the worse rating of the two where both are available. S&P and Moody's ratings coincide for 91% of observations and are within 2 steps for 80% of the remaining observations. Figure C.1 shows the distribution of ratings. Table C.1 reports the number of firm-by-quarter observations. Table C.2 shows that there is variation in ratings within risky and risk-free firms, as defined by distance to default, but risk-free firms are about a step higher in ratings at each percentile reported.

We construct additional measures of risky and risk-free firms to be used for robustness checks. First, we define risk-free firms as those with a rating of A- or higher and those with an investment grade rating or higher (BBB-). We classify firms with no rating as risky in these measures. Next, we define risk-free firms as those with book leverage below the 10th percentile of the distribution. Finally, we construct a measure that combines all three and classifies a firm as risk-free if it has an investment grade rating, leverage below the 10th percentile, or distance to default above the 90th percentile. Table C.4 reports the number of

Table C.4: Number of Observations across Samples

	(1) Firms	(2) h=0	(3) h=4	(4) h=8
A Rating	8	255	222	200
Investment grade	55	1,488	1,305	1,183
90pct dd	257	1,745	1,286	1,144
10pct leverage	277	2,342	1,855	1,680
Any above	418	5,213	4,203	3,772
Any Rating	106	3,577	3,066	2,718
Bond data	63	3,128	2,718	2,505
All observations	736	29,383	24,223	21,728

Note: The table reports the number of observations that meet each criteria. Column (1) reports the number of firms. Columns (2)-(4) report the number of firm-by-quarter observations measured h quarters into the future. A rating and investment grade are based on S&P or Moody's credit ratings. 90pct dd indicates distance to default above the 90th percentile. 10pct leverage indicates leverage below the 10th percentile. Any above includes observations that meet any of the four criteria above. Any rating includes all observations with a rating by S&P or Moody's. Bond data indicates that the firm is matched to bond-level data as described in Section C.1.1.3.

firms and number of firm-by-quarter observations that meet each of these criteria. Table C.5 shows the correlations across measures. The measures based on credit ratings show little or negative correlation with the measures based on distance to default or leverage, suggesting these are picking up different aspects of firm risk. The measures based on distance to default and leverage are positively correlated.

Table C.5: Correlation of Risk-free Measures

	A Rating	Inv Grade	DD	Leverage	Any Above
A Rating	1.000	.	.	.	.
Inv Grade	0.405	1.000	.	.	.
90th Pct DD	0.002	-0.014	1.000	.	.
10th Pct Leverage	-0.015	-0.070	0.243	1.000	.
Any Above	0.201	0.497	0.617	0.655	1.000

Note: The table reports correlations across risk-free criteria. A rating and investment grade are based on S&P or Moody's credit ratings. 90pct dd indicates distance to default above the 90th percentile. 10pct leverage indicates leverage below the 10th percentile. Any above includes observations that meet any of the four criteria above.

C.1.1.3 Corporate Bond Data

We collect corporate bond data from Bloomberg and then match it to firm-level data using crosswalks to connect identifiers across the datasets. Firms in Compustat are uniquely identified by the gvkey variable. Bonds in Bloomberg are uniquely identified by a Bloomberg ID (bbgid) but are attached to firm identifiers–ISIN, CUSIP, and ticker. We use WRDS Capital IQ to create crosswalks between the Compustat gvkey and the other identifiers available from Bloomberg. Due to limits imposed by Bloomberg on the amount of data that can be downloaded from the terminal each month, we collect the data in stages to minimize unnecessary data collection.

1. For each country, except the United States, we download a list of corporate bonds that meet the following criteria: denominated in USD, fixed or zero coupon, and have some firm identifier data. We do this by country as a natural way to break the large download into smaller pieces. We exclude local currency bonds because we do not want to capture currency risk in our spreads relative to US treasury yields.

2. For each bond on the list, we match to Compustat gvkey first using ISIN, then CUSIP, then ticker, so we have one firm attached to each bond.

3. For bonds that are successfully matched to firms, we return to the Bloomberg terminal and download end-of-quarter price data (px_last).

4. For bonds that have non-missing price data, we download additional descriptive variables, including coupon rate, coupon frequency, call options, etc.

In addition to the criteria listed in step 1, we limit our sample to bonds with a term to maturity of at least 1 year and no more than 30 years (890 observations). We drop firms in the financial (SIC 6000-6799) and utilities (SIC 4900-4999) industries (2,156 observations). We drop observations that are missing any data on duration, market value of issue, coupon, date of issue, maturity type (i.e. callable), or industry (517 observations). We start our sample in 1997q2 (65 observations). Finally, we drop countries with fewer than 100 observations (619 observations). Table C.6 describes the coverage of our dataset. We have data from 12 countries in total, covering 561 bonds issued by 221 firms. Almost half of our sample is from Latin America.

Using price data and bond characteristics, we construct a spread for each corporate bond relative to a risk-free security that accounts for the coupon structure of the bond and its maturity. We follow the methodology of Gilchrist and Zakrajšek (2012) to price a synthetic

Table C.6: Sample Composition

	Observations	Bonds	Firms	Min year
Argentina*	681	46	10	1997
Brazil*	590	38	15	1997
Chile*	553	33	7	1998
Colombia*	180	11	2	2005
India†	1,319	101	42	2002
Korea†	1,455	113	31	1997
Mexico*	1,357	95	23	1997
Peru*	301	15	7	2012
Philippines†	494	29	7	1997
Thailand†	468	34	16	1997
Turkey	563	38	12	2002
Ukraine	115	8	1	2009
Total	8,076	561	173	.

* Indicates countries in the Latin America subsample.

† Indicates countries in the Asia subsample.

risk-free security with the same coupon structure and maturity as the corporate bond,

$$P_{it}^f = \sum_{s=1}^{S} C_i(s) D(t+s) \tag{C.1}$$

where P_{it}^f is the price of the risk-free security that corresponds to bond i in quarter t, $C_i(s)$ is the cash flow from the coupon and principal repayment in that quarter, and $D(t) = e^{-r_t t}$ is the discount function in period t. We implement this equation using the continuously compounded zero-coupon Treasury yields estimated by **?**. Finally, we construct the spread, $S_{ijt} = y_{ijt} - y_{it}^f$, where y_{ijt} is the yield of corporate bond i issued by firm j in quarter t and y_{it}^f is the yield of the corresponding synthetic risk-free bond with the same cash flow structure.

We drop observations with spreads less than 5 basis points or more than 3,500 basis points. Table C.7 provides descriptive statistics for the bonds in our full sample, and table C.8 describes the Latin America subsample. Characteristics are relatively similar across the samples.

C.1.1.4 Global risk premium

Table C.9 reports results from the first stage of the risk premium estimation across three samples of countries, given by Equation 3.3.2. The coefficient on distance to default is negative across all three samples, though the magnitude varies, with Asia exhibiting the

Table C.7: Summary Statistics of Corporate Bond Characteristics

	mean	sd	min	p50	max
Number of bonds per firm/quarter	2.31	2.28	1.00	2.00	23.00
Market value of issue (usd mil., 2000)	394	267	5	363	1779
Maturity at issue (years)	10.58	6.97	1.00	10.00	50.00
Term to maturity (years)	6.27	5.10	1.00	5.00	30.00
Duration (years)	5.03	3.11	0.97	4.49	20.36
Callable (pct.)	0.28	0.45			
Credit rating (Bloomberg)			CCC-	BBB-	AA
Coupon rate (pct.)	6.16	2.40	0.25	5.75	13.00
Nominal effective yield (pct.)	5.90	3.70	0.49	5.05	37.18
Credit spread (basis points)	381	353	5	281	3406

The table reports summary statistics for 561 bonds issued by 173 firms across 12 countries over 1997q2 to 2021q1. Callable includes bonds with a maturity type of "CALLABLE," "CALL/PUT," or "CALL/SINK." The Bloomberg composite credit rating is measured at time of data download and is only available for 184 bonds. The countries are Argentina, Brazil, Chile, Colombia, India, Korea, Mexico, Peru, Philippines, Thailand, Turkey, and Ukraine.

largest sensitivity and Latin America the smallest.

Because we are focusing on the Latin America sample of countries in our results, we also construct the systemic risk premium for this subset of countries. We use the estimates from Table C.9 to predict spreads, as in Equation 3.3.3, and then estimate Equation 3.3.4 for each subsample. Country-specific risk premia (ρ_k) are reported in Table C.10 with respect to Argentina (columns (1)-(2)) or India (column (3)) as the omitted country. Argentina has the highest risk premium in Latin America, with an average risk premium that is 233-266 basis points higher than Chile. Figure C.2 shows the global risk premium, estimated on the full sample of countries, Latin America sample, and Asia sample.

Our baseline results simultaneously estimate time-invariant country-specific risk premia (ρ_k) and time-varying systemic risk premia (ρ_t), as given by C.9. This implicitly places more weight on the number of observations within each quarter, rather than the number of countries represented within each quarter. We also perform an additional specification in which we first estimate a time-varying risk premium for each country,

$$\hat{RP}_{ijkt} = \alpha_{kt} + u_{ijkt}, \tag{C.2}$$

and then extract the systemic component in a second step,

$$\alpha_{kt} = \rho_k + \rho_t + v_{kt}. \tag{C.3}$$

Table C.8: Summary Statistics of Corporate Bond Characteristics, Latin America

	mean	sd	min	p50	max
Number of bonds per firm/quarter	2.36	1.99	1.00	2.00	13.00
Market value of issue (usd mil., 2000)	456	325	7	363	1779
Maturity at issue (years)	10.16	5.19	1.00	10.00	40.00
Term to maturity (years)	6.37	4.97	1.00	5.50	30.00
Duration (years)	5.08	2.96	0.97	4.74	19.85
Callable (pct.)	0.43	0.49			
Credit rating (Bloomberg)			CCC-	BBB-	A-
Coupon rate (pct.)	7.02	2.23	1.48	6.75	12.75
Nominal effective yield (pct.)	6.72	3.63	0.81	5.94	36.83
Credit spread (basis points)	448	357	6	350	3406

The table reports summary statistics for 238 bonds issued by 64 firms across 6 countries over 1997q2 to 2021q1. Callable includes bonds with a maturity type of "CALLABLE," "CALL/PUT," or "CALL/SINK." The Bloomberg composite credit rating is measured at time of data download and is only available for 184 bonds. The countries are Argentina, Brazil, Chile, Colombia, Mexico, and Peru.

Figure C.3 shows the time-varying country risk premia for the three largest Latin American countries in our sample. Figure C.4 compares estimates of the global risk premium and the Latin America risk premium obtained by each method. The correlation between the two series is 0.93 for the global risk premium and 0.95 for Latin America. The differences between the series are less pronounced in the later part of the sample, where coverage across all countries is better and therefore the distinction between weighting observations rather than countries matters less.

Table C.9: Credit Spreads and Distance to Default

	(1) EMEs	(2) Latin America	(3) Asia
Distance to default	-0.041**	-0.023*	-0.107***
	(0.018)	(0.013)	(0.013)
log(Duration)	-0.047	0.052	0.028
	(0.049)	(0.060)	(0.039)
log(Amount issued)	-0.072	-0.023	-0.132*
	(0.051)	(0.065)	(0.067)
log(Coupon rate)	0.740***	1.075***	0.475***
	(0.108)	(0.155)	(0.105)
log(Age of issue)	-0.076***	-0.036	0.012
	(0.025)	(0.031)	(0.027)
Callable	0.364***	0.313***	0.219*
	(0.065)	(0.072)	(0.120)
Observations	8,076	3,662	3,736
R^2	0.361	0.442	0.381
Root MSE	0.581	0.507	0.570
Number of firms	173	64	96
Number of bonds	561	238	277

Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Note: Sample period: 1997q2-2021q1. The table shows the estimated coefficients of Equation (3.3.2) for different samples of countries, as defined in Table C.6. The dependent variable is $\log S_{ijkt}$, the log of the corporate bond spread for bond i issued by firm j in country k and quarter t. Standard errors are clustered by firm and quarter.

Table C.10: Country Risk Premia

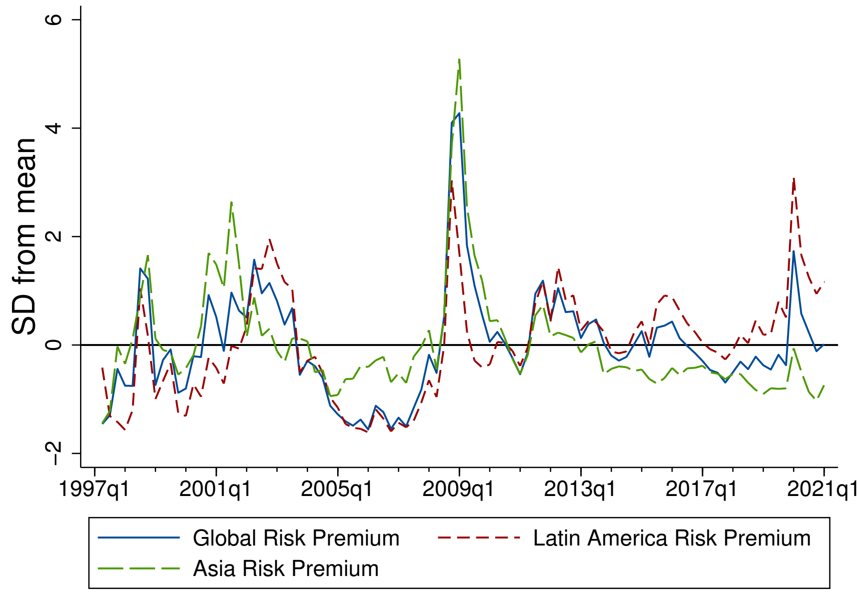
	(1) EME	(2) Latin America	(3) Asia
Argentina	0	0	
	(.)	(.)	
Brazil	-215***	-192***	
	(15.4)	(13.9)	
Chile	-233***	-266***	
	(16.0)	(14.8)	
Colombia	-210***	-264***	
	(23.1)	(20.9)	
Mexico	-191***	-147***	
	(13.1)	(12.2)	
Peru	-198***	-189***	
	(19.2)	(17.6)	
India	-149***		0
	(13.2)		(.)
Korea	-257***		-140***
	(12.7)		(10.7)
Philippines	-214***		-108***
	(16.2)		(15.6)
Thailand	-198***		-61***
	(16.5)		(14.9)
Turkey	-131***		
	(16.0)		
Ukraine	124***		
	(27.7)		
Observations	8,076	3,662	3,736
R^2	0.23	0.35	0.23
R^2- Just time FE	0.17	0.27	0.19
R^2- Just country FE	0.06	0.05	0.03

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table reports ρ_k estimates from $\hat{RP}_{ijkt} = \rho_k + \rho_t + \nu_{ijkt}$, where $\hat{RP}_{ijkt} = S_{ijkt} - \exp\Big(\beta dd_{jkt} + \gamma' \mathbf{Z}_{ijkt} + \frac{\hat{\sigma}^2}{2}\Big)$. Units can be interpreted as basis points relative to the omitted country, Argentina or India.

Figure C.2: Global Risk Premium by Region



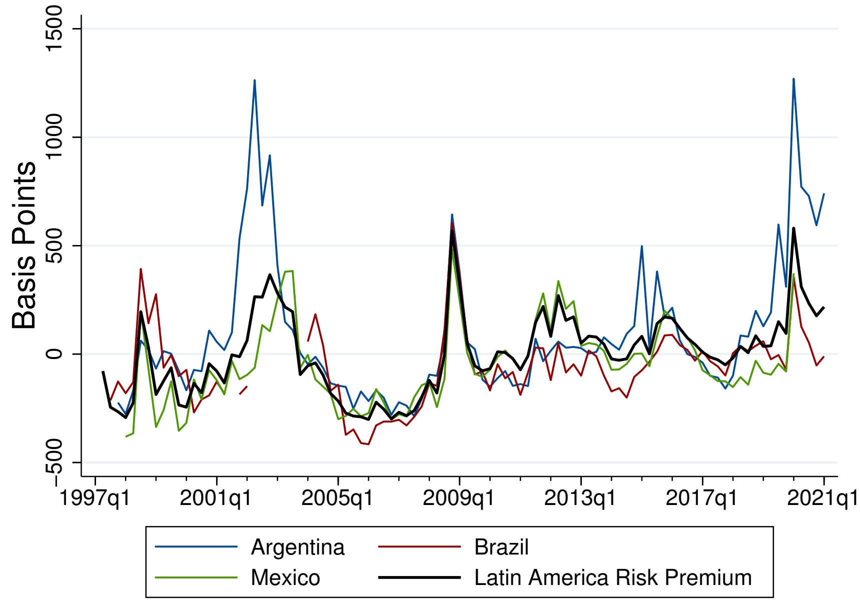
Note: The figure reports systemic risk premium (ρ_t) estimates from Equation 3.3.4 for the full sample of countries (blue solid line), Latin America sample (red short dashed line), and Asia sample (green long dashed line). Table C.11 *reports the correlations across samples and with risk measures from the U.S.*

Table C.11: Risk Premia Correlations

	GRP	Latin America RP	Asia RP	U.S. EBP	VIX
Global Risk Premium	1.000	.	.	.	.
Latin America Risk Premium	0.797	1.000	.	.	.
Asia Risk Premium	0.786	0.297	1.000	.	.
U.S. Excess Bond Premium	0.734	0.422	0.747	1.000	.
VIX	0.659	0.485	0.555	0.594	1.000

Note: The table reports correlations between the systemic risk premium (ρ_t) estimates from Equation 3.3.4 across subsamples of countres (as defined in Table C.6*), as well as the U.S. Excess Bond Premium and the VIX.*

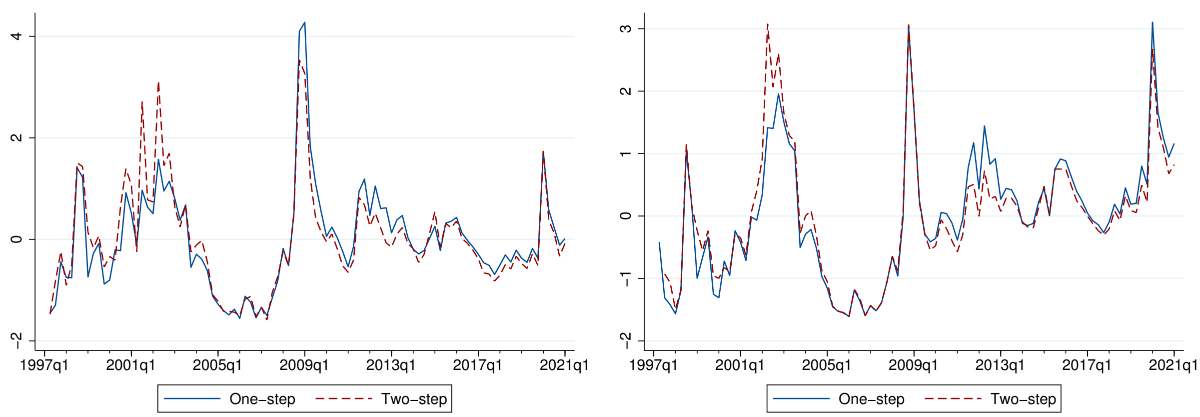
Figure C.3: Time-varying Country Risk Premia



Note: The figure shows time-varying country risk premia (α_{kt}) from Equation C.2 and the Latin America risk premium given by ρ_t in Equation 3.3.4 for the Latin America sample.

Figure C.4: Alternative Estimation of Risk Premia

(a) Global Risk Premium (b) Latin America Risk Premium



Note: The figure shows the systemic risk premium (ρ_t) estimates for the full sample of countries in Panel (a) and the Latin America subsample in Panel (b). The one-step procedure is the baseline procedure described in Equation 3.3.4 of the main text, which extracts time-invariant country and time-varying systemic risk premia. The two-step procedure follows Appendix Equations C.2 and C.3 to estimate time-varying country risk premia before extracting systemic risk premia. The correlation between the series is 0.93 in Panel (a) and 0.95 in Panel (b).

C.1.2 Additional Results

Our results are robust to a number of alternative specifications. First, we show that the expansionary effects of the systemic risk premium on risk-free firms are broadly consistent across several measures of risk, at least in the initial quarters after the shock. Figure C.5 shows results using credit ratings, leverage, and a measure that encompasses the baseline and any others. Tables C.4 and C.5 report the number of observations that meet the criteria and the correlations across measures.

Next, we introduce time-by-country fixed effects to capture any country-specific trends that could be affecting firms' investment with changes in the risk premium,

$$\Delta_h log(k_{jkt}) = \alpha_{hj} + \alpha_{hkt} + \underbrace{\beta_h^R \times \rho_t \times \mathbb{I}_{j\in\mathcal{R}_t}}_{\text{Risky Firms}} + \gamma_h \mathbb{I}_{j\in\mathcal{R}_t} \; + \; \omega_h' Z_{jt-1} + \epsilon_{jkth}, \tag{C.4}$$

where the coefficient of interest is β_h^R, which captures the cumulative change in capital stock for risky firms relative to risk-free, holding fixed conditions in country k in quarter t. Note that the inclusion of time fixed effects means we can only isolate these relative effects for risky firms, rather than the average effects for each group. Results are shown in Figure C.6. Risky firms have lower cumulative change in capital at all horizons relative to risk-free firms, peaking at 5.4% lower after 2 years.

Our baseline specification classifies firms as either risky or risk-free by the quantile of distance to default. We also estimate an interactive model in which we estimate a level effect and an interaction term with distance to default,

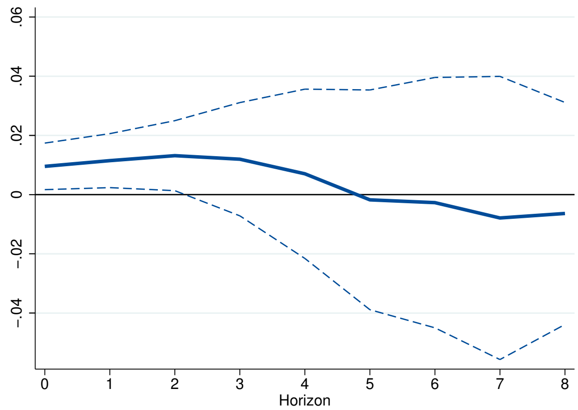
$$\Delta_h log(k_{jt}) = \alpha_{hj} + \beta_h \times \rho_t \; + \beta_h^D \times \rho_t \times \mathrm{dd}_{jt-1} + \gamma_h \mathrm{dd}_{jt-1} \; + \; \omega_h' Z_{jt-1} + \epsilon_{jkth}, \tag{C.5}$$

where β_h captures the average cumulative (log) change in capital stock and β_h^D captures the additional change for firms with one-standard-deviation higher distance to default (less risky). Results are shown in Figure C.7. Consistent with our other baseline, firms with higher distance to default have higher cumulative capital growth. The mean risky firm, as defined in our baseline, has a distance to default of -0.2 standard deviations, relative to 2.2 standard deviations for the mean risk-free firm. Results are similar when we include country-by-time fixed effects, as shown in Figure C.8.

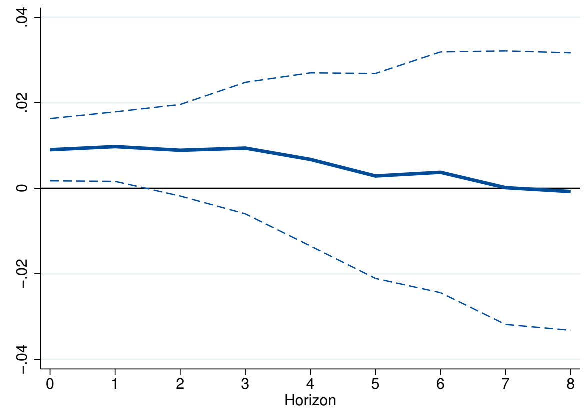
To ensure that we are not picking up differences in other firm characteristics and attributing them to firms' risk, we conduct multiple specifications in which we introduce interactions

Figure C.5: Risk-free Firms' Investment Responses Across Definitions

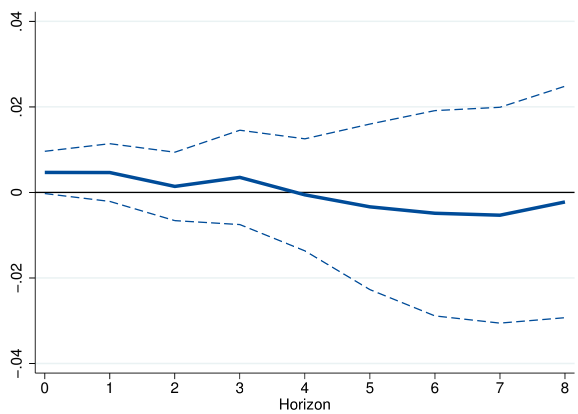
(a) A- rating or higher



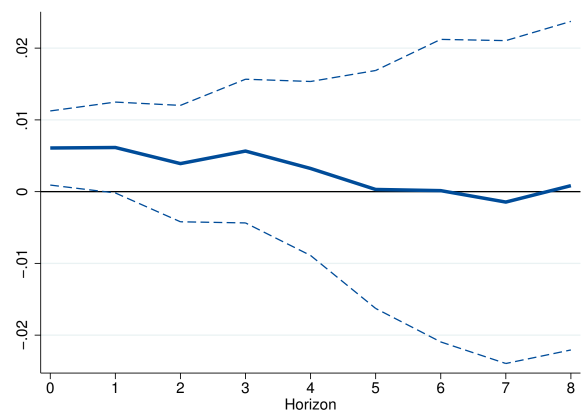
(b) Investment grade rating or higher



(c) 10th percentile leverage

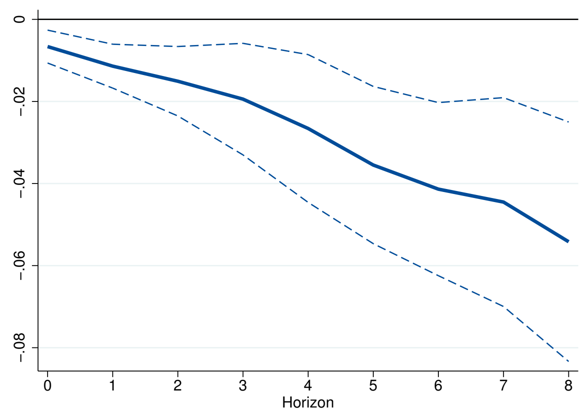


(d) Any criteria



Note: The figure shows coefficient estimates from Equation (3.3.5) with alternative definitions of risk-free firms. Panels (a) and (b) define risk-free observations based on credit ratings. Panel (c) defines risk-free observations as those with leverage below the 10th percentile of the distribution. Panel (d) defines risk-free observations as those with distance to default above the 90th percentile or that meet the criteria in Panels (a)-(c). x-axes show horizon h (quarterly frequency). The vector of controls includes firms' sales growth, investment, fiscal quarter, size, and share of current assets. All controls are standardized. Standard errors are clustered by firm and year. Dashed lines represent 90% confidence intervals.

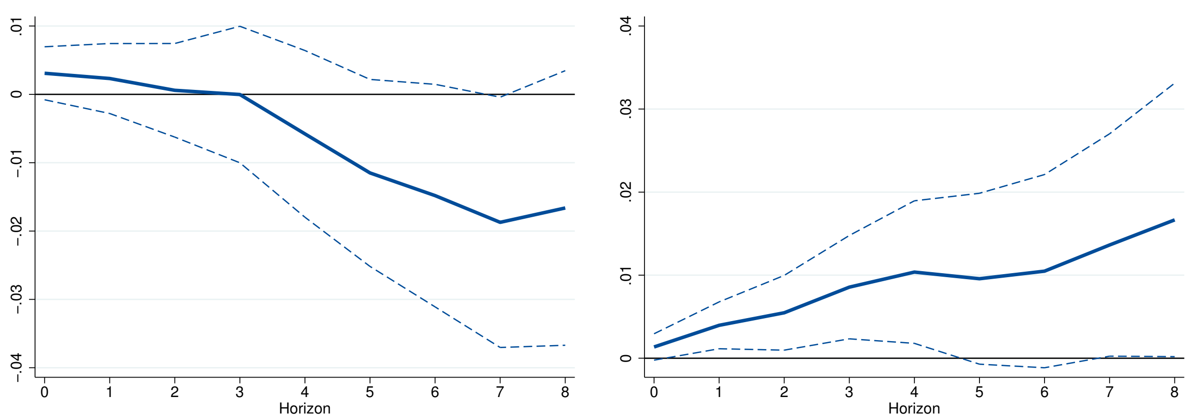
Figure C.6: Risky Firms' Responses to the Systemic Risk Premium, within Country × Time



Note: The figure shows the estimated β_h^R coefficients of Equation (C.4), which correspond to the cumulative (log) change in capital stock in response to the systemic risk premium (ρ_t) for risky relative to risk-free firms. The variable ρ_t is standardized so the units are standard deviations. The x-axes show the horizon h (quarterly frequency). The vector of controls includes firms' sales growth, investment, fiscal quarter, size, and share of current assets. All controls are standardized. Standard errors are clustered by firm and year. Dashed lines represent 90% confidence intervals.

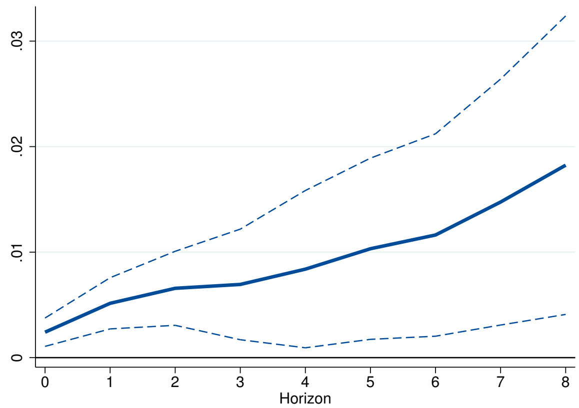
Figure C.7: Heterogeneous Responses to Movements in the Systemic Risk Premium, Continuous Measure

(a) Aggregate effect (b) Interaction with Distance to Default



Note: The figure shows the estimated β_h (left panel) and β_h^D (right panel) coefficients of Equation (C.5). The first is the cumulative average (log) change in capital stock in response to the systemic risk premium (ρ_t). The variable ρ_t is standardized so the units are standard deviations. The second is the interaction term with distance to default, which is standardized, so the coefficients can be interpreted as the additional cumulative (log) change in capital stock for firms with one-standard-deviation higher distance to default (i.e., less risky). x-axes show horizon h (quarterly frequency). The vector of controls includes firms' sales growth, investment, fiscal quarter, size, and share of current assets. All controls are standardized. Standard errors are clustered by firm and year. Dashed lines represent 90% confidence intervals.

Figure C.8: Hegerogeneous Responses to Movements in the Systemic Risk Premium, within Country × Time, Continuous Measure



Note: The figure shows the estimated β_h^D *(right panel) coefficients of Equation (C.5) with the addition of country-by-time fixed effects. This can be interpreted as the additional cumulative (log) change in capital stock for firms with one-standard-deviation higher distance to default (i.e., less risky), within countries in each period. x-axes show horizon h (quarterly frequency). The vector of controls includes firms' sales growth, investment, fiscal quarter, size, and share of current assets. All controls are standardized. Standard errors are clustered by firm and year. Dashed lines represent 90% confidence intervals.*

between firms' characteristics and systemic risk premium ρ_t,

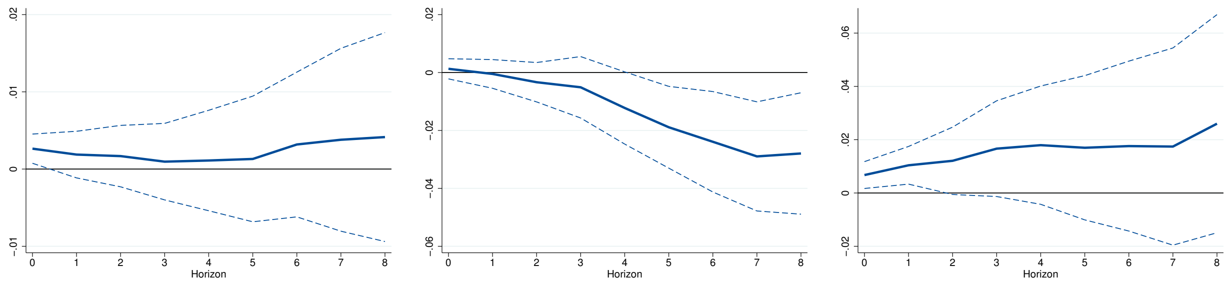
$$\Delta_h log(k_{jt}) = \alpha_{hj} + \beta_h^z \times \rho_t \times z_{jt-1} + \underbrace{\beta_h^R \times \rho_t \times \mathbb{I}_{j\in\mathcal{R}_t}}_{\text{Risky Firms}} + \underbrace{\beta_h^F \times \rho_t \times \mathbb{I}_{j\in\mathcal{R}_t^f}}_{\text{Risk-Free Firms}} + \gamma_h \mathbb{I}_{j\in\mathcal{R}_t} + \omega_h' Z_{jt-1} + \epsilon_{jth}, \tag{C.6}$$

where β_h^R and β_h^F are the coefficients of interest as before, but we add the interaction between variable z_{jt-1} and the systemic risk premium. Results are reported in Figure C.9 for several choices of z_{jt-1}. Estimated coefficients β_h^R and β_h^F in Panels (a)-(c) are remarkably similar with added controls for size, sales growth, and liquidity. The results in Panel (d) are noisier because the age variable is missing for many observations, but the pattern is nonetheless qualitatively similar, even in this selected sample.

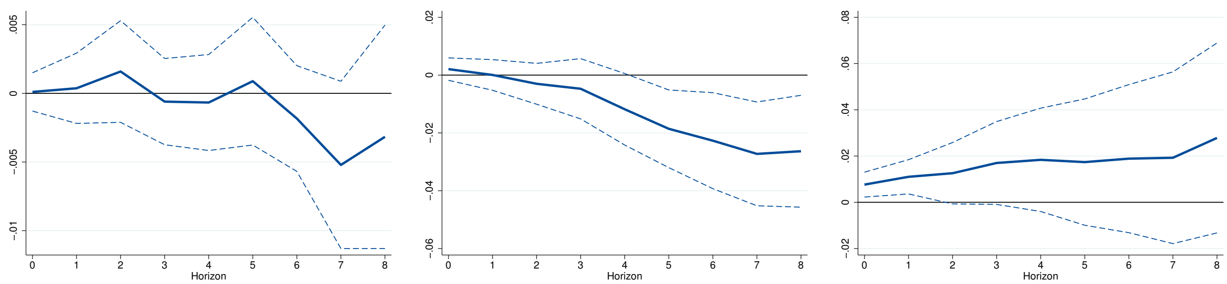
Next, we show that our results are not highly sensitive to subsamples of industries or countries. Figure C.10 introduces interactions between risky and risk-free indicators with tradeable and non-tradeable sectors (defined in Appendix C.1.1.1). The results are noisier but show that the negative effects of the systemic risk premium shock are concentrated among risky firms across both sectors. To address concerns about whether our results are being driven by particular countries, we re-estimate Equation 3.3.5 on a subsample that drops one country at a time. Results are shown in Figures C.11 and C.12. The negative results for risky firms are persistent across all subsamples. The results for risk-free firms are unsurprisingly

Figure C.9: Heterogeneous Responses to Movements in the Systemic Risk Premium with Interactions

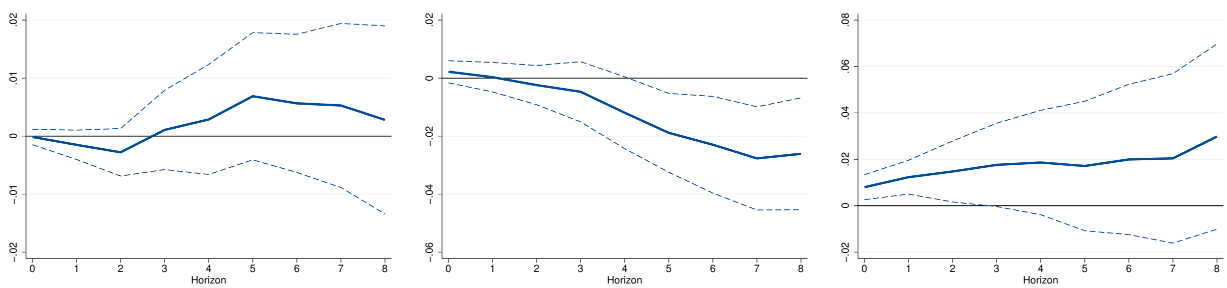
(a) Size | Risky | Risk-free



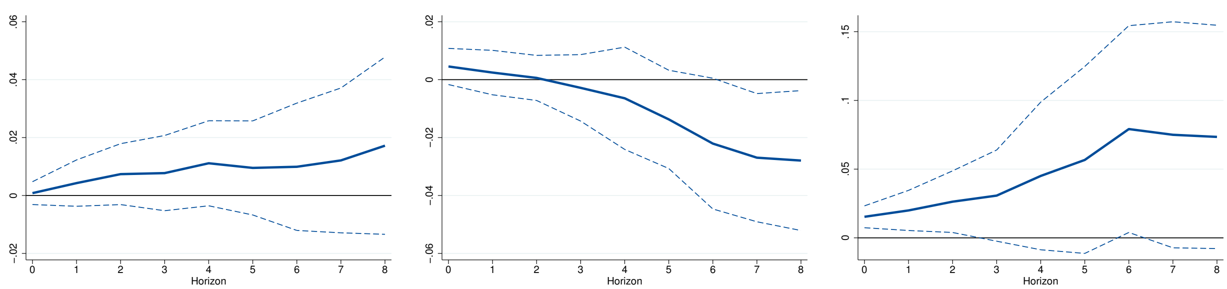
(b) Sales | Risky | Risk-free



(c) Liquidity | Risky | Risk-free



(d) Age | Risky | Risk-free

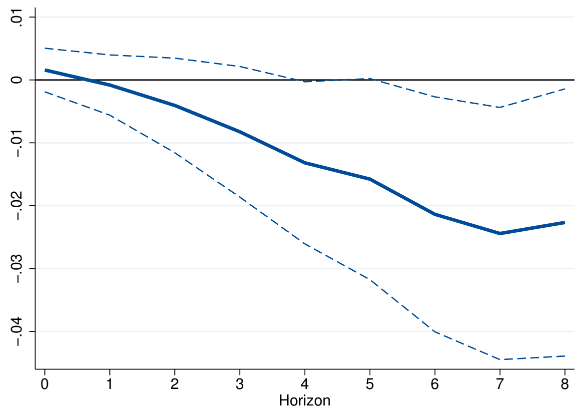


Note: The figure shows coefficient estimates from Equation (C.6). The left panel shows the coefficient β_h^z, from interacting the systemic risk premium (ρ_t) with the variable labeled, and the middle and right panels report coefficients β_h^R and β_h^F, respectively. Coefficients in the left panel can be interpreted as the effect of a one-standard-deviation higher level of each variable. All controls are standardized; size is log real total assets in USD; sales is real sales growth; liquidity is net current assets as a share of total; and age is relative to IPO date. Note that there are considerably fewer observations for the specification with age.

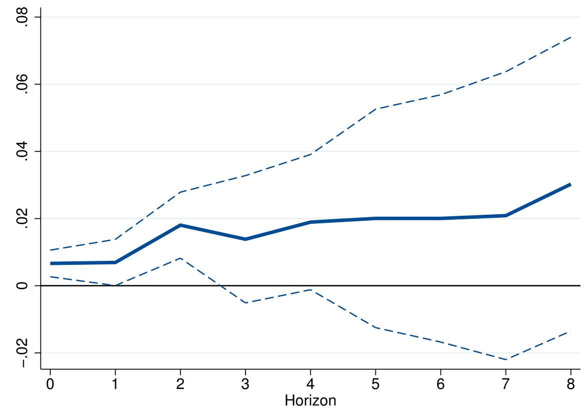
much noisier but are generally positive, with the exception of the latter horizons when we drop Brazil, which makes up 37% of our total sample. We do not estimate effects separately by country due to the low power of our sample size.

Figure C.10: Heterogeneous Responses to Movements in the Systemic Risk Premium by Sector

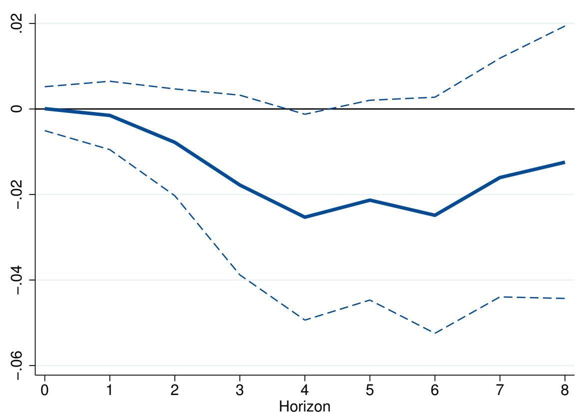
(a) Risky × Tradeable



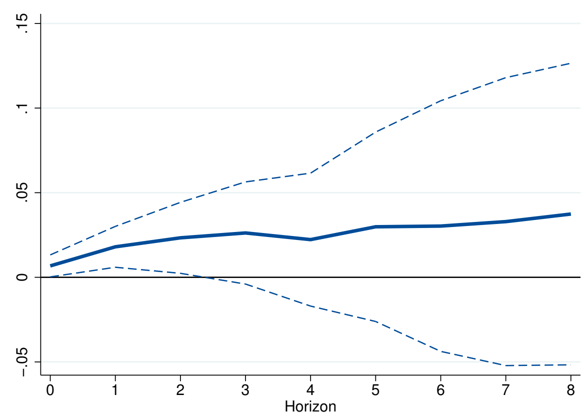
(b) Risk-free × Tradeable



(c) Risky × Non-tradeable



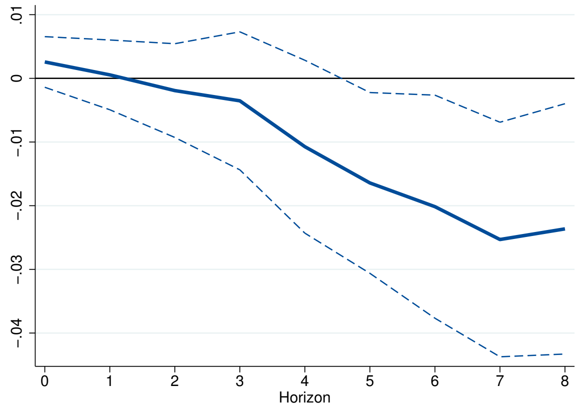
(d) Risk-free × Non-tradeable



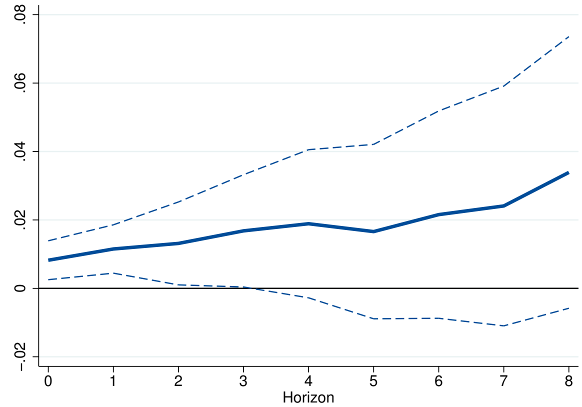
Note: The figure shows coefficient estimates from Equation (3.3.5) with additional interactions between tradeable and non-tradeable sectors. x-axes show horizon h (quarterly frequency). The vector of controls includes firms' sales growth, investment, fiscal quarter, size, and share of current assets. All controls are standardized. Standard errors are clustered by firm and year. Dashed lines represent 90% confidence intervals.

Figure C.11: Sensitivity by Country

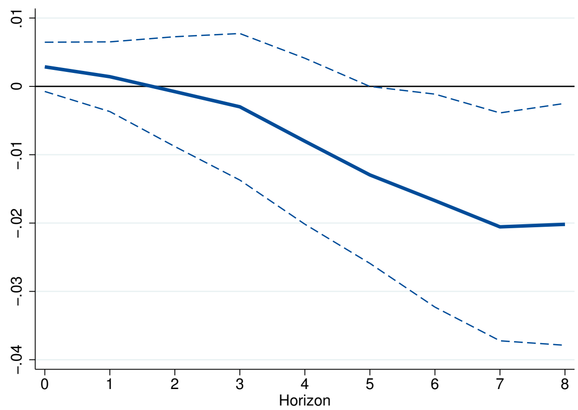
(a) Risky, ex. Argentina



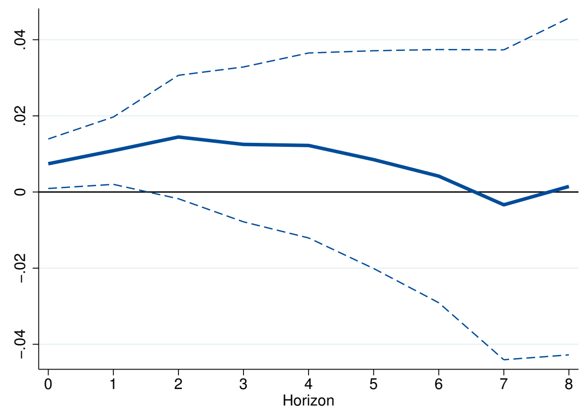
(b) Risk-free, ex. Argentina



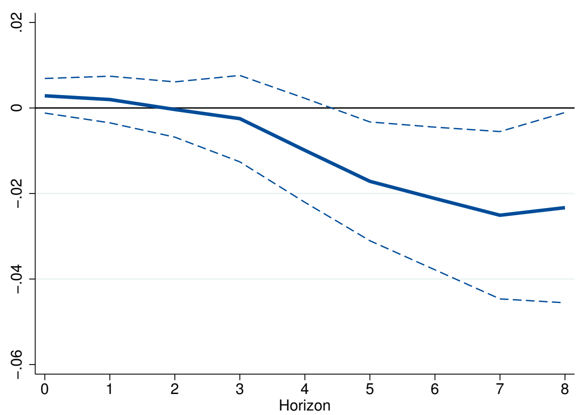
(c) Risky, ex. Brazil



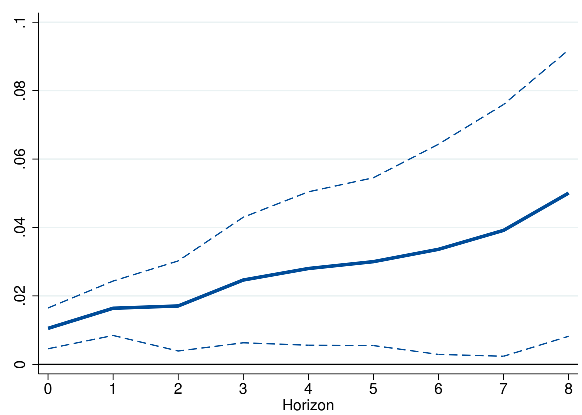
(d) Risk-free, ex. Brazil



(e) Risky, ex. Chile



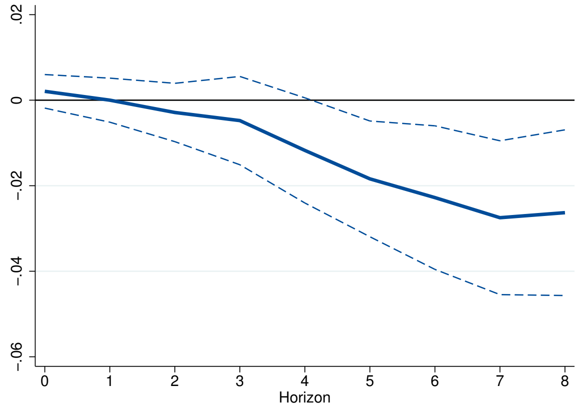
(f) Risk-free, ex. Chile



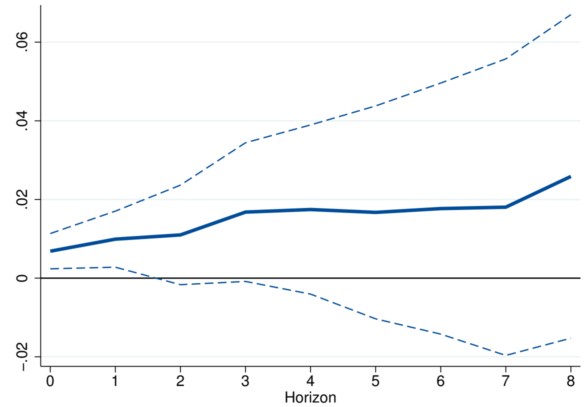
Note: The figure shows coefficient estimates from Equation (3.3.5). Panels (a) and (b) exclude Argentina; (c) and (d) exclude Brazil; (e) and (f) exclude Chile. x-axes show the horizon h (quarterly frequency). The vector of controls includes firms' sales growth, investment, fiscal quarter, size, and share of current assets. All controls are standardized. Standard errors are clustered by firm and year. Dashed lines represent 90% confidence intervals.

Figure C.12: Sensitivity by Country

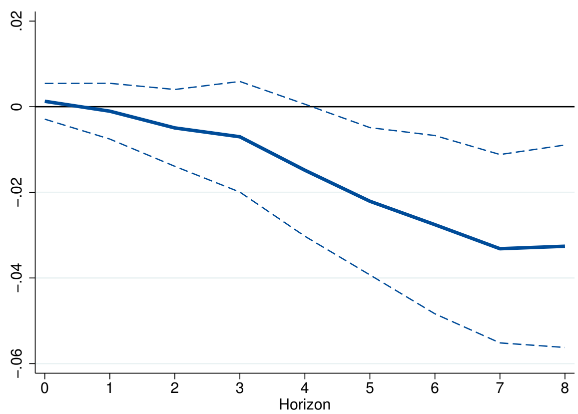
(a) Risky, ex. Colombia



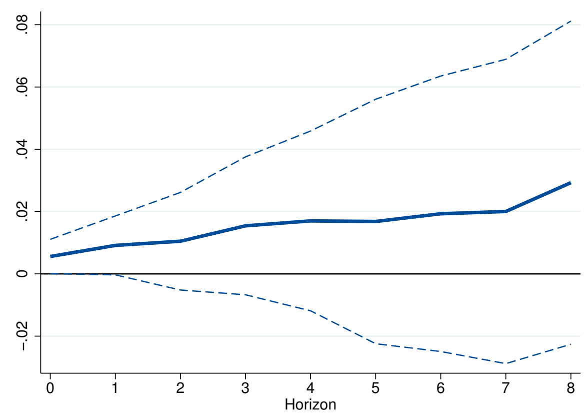
(b) Risk-free, ex. Colombia



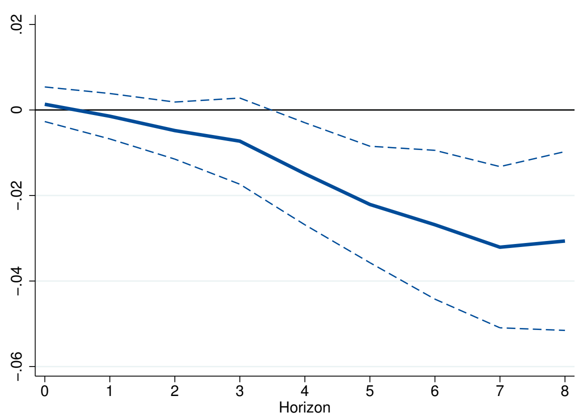
(c) Risky, ex. Mexico



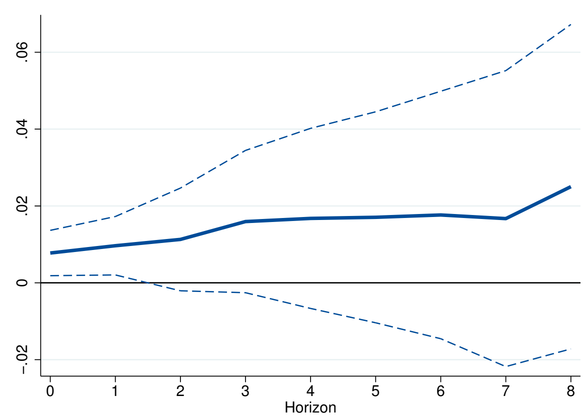
(d) Risk-free, ex. Mexico



(e) Risky, ex. Peru



(f) Risk-free, ex. Peru



Note: The figure shows coefficient estimates from Equation (3.3.5). Panels (a) and (b) exclude Colombia; (c) and (d) exclude Mexico; (e) and (f) exclude Peru. x-axes show horizon h (quarterly frequency). The vector of controls includes firms' sales growth, investment, fiscal quarter, size, and share of current assets. All controls are standardized. Standard errors are clustered by firm and year. Dashed lines represent 90% confidence intervals.

C.2. Quantitative Appendix

C.2.1 Model-implied Measure of Risk Premia

We describe here the process to construct the model-implied measure of risk premia. We first define the internal rate of return of a bond b as the rate $r(.)$ that satisfies

$$q\left(k', b', z, \boldsymbol{S}\right) = \frac{m + (1-m)\left(\upsilon + q\left(k', b', z, \boldsymbol{S}\right)\right)}{1 + r(k', b', z, \boldsymbol{S})}.$$

The spread of the bond with respect to the risk-free rate, r_f, is defined as $sp(k', b', z, \boldsymbol{S}) = \left(\frac{1+r\left(k', b', z, \boldsymbol{S}\right)}{1+r_f}\right) - 1$. To compute the model-implied measure of the risk premium, we need to solve for debt prices under a hypothetical risk-neutral lender. Taking the firms' optimal default and debt policies as given, the risk-neutral pricing kernel would be given by

$$\begin{aligned}\tilde{q}\left(k', b', z, \boldsymbol{S}\right) = \mathbb{E}_{\left(z', \boldsymbol{S'}\right)|(z, \boldsymbol{S})}\Bigg[\beta^{\star}\Bigg(& \left[1 - h\left(k', b', z', \boldsymbol{S'}\right)\right] \times \mathbb{R}^r_f(k', b', z', \boldsymbol{S'}) + \\ & + h\left(k', b', z', \boldsymbol{S'}\right) \times \mathbb{R}^d_f\left(k', z', \boldsymbol{S'}\right)\Bigg)\Bigg],\end{aligned}$$

where $\mathbb{R}^r_f(k', b', z', \boldsymbol{S'}) \equiv (1-m)\left(\upsilon + \tilde{q}\left(k'', b'', z', \boldsymbol{S'}\right)\right) + m$, and the next-period policies h', k'', and b'' are obtained under the assumption that foreign lenders are risk averse. Let $\tilde{sp}(.)$ be the spread of the bond under risk-neutral pricing. Our model-implied measure of risk premium is given by

$$RP(k', b', z, \mathbf{S}) = sp(k', b', z, \boldsymbol{S}) - \tilde{sp}(k', b', z, \boldsymbol{S}). \tag{B.1}$$

C.2.2 Computational Algorithm

Our model features several state variables including the firm distribution (an infinite dimensional object) and aggregate uncertainty, which makes it challenging to solve. The aggregate state of the problem can be written as $\boldsymbol{S} \equiv (A, \kappa, \Omega)$, where $\boldsymbol{s} = (A, \kappa)$ denotes the exogenous processes, a is the stock of households' debt, and Ω denotes the firms' distribution across the three idiosyncratic states (k, b, z).

To solve for the equilibrium of the model numerically, we follow a bounded rationality type of approach, as in Krusell and Smith (1998), and use as state variables a set of statistics that summarize the distribution of firms. Such distribution is a relevant variable to solve the firms' problem because of its implications on the economy's aggregates, prices, and real wages. First, let $\tilde{K}_t \equiv \int z_{i,t} \times (k_{it})^{\frac{\alpha\chi}{\varsigma}}$ denote the economy's production capacity. Notice that this is just a function of the economy's stock of capital, weighted by each firms' productivity. It is useful to include this variable as a state, since it allows us to pin down wages. Second, we use the economy's exports, $Z_t = \left(\frac{\xi_t}{P_{H,t}}\right)^{\eta} Y_F^{\star}$, as auxiliary variable (i.e., a co-state). Although Z_t is not observed at the beginning of each period, we include Z_t as an auxiliary aggregate variable in the firms' problem and, in the simulation stage, we then solve for the value of Z_t such that the H-good market clears. Once we know $(\tilde{K}_t, Z_t)$, we can compute all the prices of the economy. Combined with a conjectured law of motion for $(\tilde{K}_t, Z_t)$, we then have all the information needed to solve for the firms' and households' problems.

Embedded inside $(\tilde{K}_t, Z_t)$, we have all the relevant information describing the firms' distribution across capital and leverage. In other words. Other moments summarizing the firm distribution (average leverage, cross-sectional standard deviation of capital) are only relevant for forecasting $(\tilde{K}_{t+1}, Z_{t+1})$. However, to keep the solution tractable, we assume a forecasting rule independent of other moments of the firm distribution. Let $\tilde{\boldsymbol{S}} = \left(A, \kappa, \tilde{K}, Z\right)$ denote the (bounded) state space. We consider the following forecasting rule for $\tilde{K}'$:

$$\tilde{H}_K\left(\tilde{\boldsymbol{S}}\right) = e^{\Lambda_0 + \Lambda_1\left(\tilde{\boldsymbol{S}}\right)}. \tag{B.2}$$

As for $\tilde{Z}'$, we consider the following state-contingent forecasting rule:

$$\tilde{H}_Z\left(\tilde{\boldsymbol{S}}, A', \kappa', \tilde{K}'\right) = e^{\Theta_0 + \Theta_1\left(\tilde{\boldsymbol{S}}, A', \kappa', \tilde{K}'\right) + \Theta_2(Z)} \tag{B.3}$$

The algorithm consists of three main steps. First, we guess the coefficients of the conjectured law of motions. Given these conjectures, we solve for the firms' optimal choices following these sub-steps:

1. Guess the value function $V^r\left(k, b, z, \tilde{\boldsymbol{S}}\right)$ and the pricing kernel $q\left(k', b', z, \tilde{\boldsymbol{S}}\right)$ for each point of the state space and for each possible choice of (k', b').

2. Taking the pricing kernel as given, solve the firms' problem and update the value function accordingly.

3. Using the optimal policies computed in the previous step, update the pricing function.

4. Iterate until convergence of both $V^r(.)$ and $q(.)$.

Since the firms' problem presents several non-convexities, we use a global optimization algorithm to solve for k' and b'. This step of the algorithm relies on the use of graphics processing units (GPUs) to speed up the computations. We approximate all functions using linear interpolation. The firm's idiosyncratic productivity (z) and the aggregate TFP processes (A) are discretized using Tauchen's method. Grids of evenly distributed points are constructed for all states. We use 20 points for k, 20 points for b, 9 points for z, 7 points for A, 2 points for κ, 5 points for $\tilde{K}$, and 5 points for Z.

The last step of the algorithm consists on simulating the economy in order to update the aggregate conjectures. The simulation follows Young's (2010) non-stochastic approach. By not relying on the simulation of individual firms, this approach avoids the sampling error associated with individual firm simulation. This is important in the context of the model, given that due to the firm's default cutoff, small sampling errors may lead to large swings in the aggregate default rate and, thus, on Z and $\tilde{K}'$. In each step of the simulation, we use a simple bisection algorithm to solve for the value of the auxiliary variable Z. In particular, we solve for the value of Z such that the H-good market clears. We simulate the economy T periods and use the simulated objects to update the coefficients of the aggregate conjectures $\tilde{H}_{\tilde{K}}$ and $\tilde{H}_Z$. We iterate on this algorithm until convergence of these coefficients.

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