

Wealth, Job Search, and Social and Private Insurance: The Roles of Progressive Taxation and Parental Wealth

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Sungwon Moon

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Supervised by

Jake Bradley
Richard Upward

School of Economics

University of Nottingham

Abstract

In this dissertation, I study how workers' wealth and access to insurance affect labor market behavior in frictional labor markets with on-the-job search and precautionary savings. The first chapter analyzes the role of social insurance provided by progressive labor income taxation in a quantitative general-equilibrium on-the-job search model with precautionary savings, and evaluates its implications for job search behavior, wage dispersion, and social welfare. The second chapter focuses on private insurance in the form of parental wealth for young workers entering the labor market with little or no assets of their own, and studies how differences in family wealth affect job finding, job stability, and early-career wage dynamics. Together, the two chapters provide an integrated view of how social and private insurance mechanisms interact with workers' labor market behavior and thereby influence labor market dynamics and aggregate economic outcomes.

In Chapter 1, "On-the-Job Search, Precautionary Savings, and Labor Income Tax Progressivity," I examine how progressive labor income taxation affects social welfare, wage inequality, and aggregate outcomes in an environment where workers can insure labor income risk only imperfectly. I develop a random on-the-job search model with incomplete markets that jointly determines workers' job search and precautionary savings behavior, firms' wage and vacancy posting, and the equilibrium risk-free interest rate. Quantitatively, moving from a no-tax benchmark to a regime akin to the current UK system raises utilitarian social welfare by about 2.4% in a

normalized utilitarian welfare index (no-tax = 100), while replacing this regime with a less progressive, revenue-neutral US-style schedule would lower welfare by about 0.6%. In this framework, taxes not only redistribute post-tax wages but also alter the returns to searching for better jobs and to accumulating assets, reshaping the structure of the job ladder and the relative role of the labor market and asset market in providing insurance. Progressive taxation compresses wage offers along the job ladder and, through higher firm profitability induced by reduced vacancy posting, increases the risk-free return on workers' assets, which strengthens the incentive to save and to insure against earnings risk through asset income. By comparing versions of the model with and without endogenous wage formation, vacancy creation, and interest rate determination, I show that these general-equilibrium channels are central for evaluating the equity–efficiency trade-off associated with progressive labor income taxation and for assessing its implications for social welfare.

Chapter 2, "Job Mobility of Young Workers and Parental Wealth: Does a 'Gold Spoon' Premium Exist in the Labor Market?," documents how early-career labor market outcomes of young workers in South Korea vary with parental wealth. Motivated by the "spoon-class" discourse, which highlights parental wealth as a perceived determinant of socioeconomic outcomes in the Korean labor market, I adopt a search-and-savings perspective in which young workers self-insure against labor income risk through both asset buffers and labor market choices. For young workers at labor market entry, who typically have little or no wealth of their own, parental wealth can serve as an important source of private insurance. Using monthly panel data from the Korean Labor Income Panel Study, I estimate random-effects discrete-time logit models for job finding and cause-specific competing-risks discrete-time models for employment exits, distinguishing separations into non-employment from direct job-to-job transitions. I find that workers from poorer families have higher job-finding hazards and shorter non-employment spells, but enter lower-paying and less stable jobs, with the excess employment-exit risk concentrated

in separations into non-employment rather than direct job-to-job mobility. Parental wealth is also strongly associated with starting wages at labor market entry, while its association with re-employment wages becomes small and imprecisely estimated once previous wages and job characteristics are controlled for. These patterns are robust to alternative measures of parental wealth and are consistent with the interpretation that parental wealth may operate as private insurance, allowing better-off young workers to search more selectively in the early career. The theoretical framework is used to organize these conditional associations and to clarify how parental wealth may shape search selectivity, accepted wages, and early-career job stability.

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Chapter 1

On-the-Job Search, Precautionary Savings, and Labor Income Tax Progressivity

Abstract This chapter studies how progressive labor income taxation affects social welfare, wage inequality, and aggregate outcomes in a frictional labor market where workers can only imperfectly insure labor income risk. I address this question using a random on-the-job search model with incomplete markets that jointly endogenizes workers' job search and precautionary savings, firms' wage and vacancy posting, and the equilibrium risk-free interest rate, so that progressive taxation not only redistributes post-tax wages but also reshapes the job ladder and the way labor income risk is insured through the asset market by altering wage offers, vacancy creation, firm profits, and asset returns. Taking these firm-side and asset-market channels into account, I show that moving from a no-tax scenario to a regime akin to the current UK raises utilitarian social welfare by about 2.4% relative to the no-tax benchmark, whereas replacing this regime with a less progressive regime akin to the US would lower welfare by about 0.6%.

1.1 Introduction

Labor income taxation is a key tool for governments to redistribute income, with progressivity being a crucial feature of the labor income tax system. The question of how progressive labor income taxation affects social welfare has remained a central research question over the last few decades. In a seminal paper from 1971, Mirrlees frames this question as a trade-off between equity and efficiency: taxation affects workers' welfare through two opposing forces, a positive effect through the social insurance it provides and a negative effect through the distortions it creates in labor supply.

Extensions of the Mirrlees (1971) framework to include frictional labor markets have studied how taxation affects workers' job search behavior and how the resulting search responses influence the equity–efficiency trade-off (Shephard, 2017; Sleet and Yazici, 2017; Bagger et al., 2018): on the equity side, a social planner can use a more progressive tax system to redistribute labor income toward workers with higher marginal utility; on the efficiency side, by compressing the net wage gains from moving up the wage ladder, greater progressivity weakens incentives to search intensely for better jobs, leading to worse matching efficiency and higher unemployment and, through the job ladder, lower average wages. Recent work in macro-labor economics, such as Lise (2013), Chaumont and Shi (2022), and Kaas et al. (2023), develops on-the-job search models with precautionary savings in which workers face uninsured unemployment and earnings risk in an incomplete asset market and can self-insure only by accumulating a non-contingent asset and adjusting their job search, generating both a precautionary savings motive and a precautionary search motive so that low-wealth workers tend to either search harder or accept safer, lower-wage jobs, while high-wealth workers can afford to be more selective and target riskier, higher-wage positions. By linking wealth and job search through these two self-insurance channels, these models provide a framework for studying re-

distributive policies such as unemployment insurance and progressive labor income taxation, and my analysis builds directly on this mechanism.

Specifically, this paper proposes a novel approach to the classic Mirrleesian equity–efficiency trade-off by studying the general equilibrium effects of progressive labor income taxation in an environment with incomplete markets and labor market frictions. Because workers can insure labor income risk only imperfectly through a non-contingent risk-free asset, and because labor market frictions affect employment transitions and wage outcomes, the no-tax decentralized equilibrium—laissez-faire—need not be undistorted or efficient: it can already be normatively suboptimal, and potentially constrained inefficient, even before taxation is introduced. In this setting, progressive labor income taxation is not merely a tool for redistribution that pursues equity through the social welfare function, at the cost of distorting labor supply across workers with different abilities. It can also improve welfare relative to laissez-faire by providing social insurance against uninsured unemployment and earnings risk. To focus on this mechanism, I abstract from redistribution across ex ante ability types and instead study redistribution among ex ante identical workers who become ex post heterogeneous because of idiosyncratic labor market shocks. Rather than treating the equity–efficiency trade-off as a redistribution-versus-labor-supply problem, I recast it as a trade-off between the insurance and equity gains from progressive taxation, on the one hand, and distortions to workers' search and saving decisions, firms' wage and vacancy posting, and equilibrium asset returns, on the other. This framework is therefore well suited to quantify the general equilibrium welfare and distributional effects of progressive labor income taxation in a frictional labor market, and to characterize how the classic equity–efficiency trade-off is modified when taxation affects not only redistribution, but also insurance provision, precautionary behavior, wage setting, and equilibrium asset returns.

Quantitatively, the model implies that moving from a no-tax scenario to a tax regime akin to the UK system raises utilitarian social welfare by about 2.4% in a

normalized utilitarian welfare index (no-tax = 100). Relative to the no-tax scenario, higher progressivity lowers average search intensity, leading to a modest increase in unemployment and a decrease in mean wages and wage dispersion. In general equilibrium, firms respond with lower wage offers and reduced vacancy posting, and the risk-free rate rises because these adjustments raise firms' net profits and dividends, which—under mutual-fund ownership—translate into a higher return on the risk-free asset; mean wealth remains nearly unchanged despite a modest decline in average consumption. Consistent with these patterns, a regime akin to the UK dominates both the no-tax scenario and a less progressive, revenue-neutral US regime: if the UK were to adopt a regime akin to the US that raises the same revenue, aggregate welfare in the calibrated economy would fall by about 0.6%.

The model incorporates three endogenizing components. First, on the worker side, workers use precautionary savings and precautionary search to protect themselves against unemployment risk. In the incomplete asset market, high-paid workers accumulate assets to buffer the drop in labor income during unemployment, whereas workers with few assets search more aggressively to raise expected future income. The model integrates on-the-job search into a standard precautionary-savings environment in the style of Aiyagari (1994), building on the partial-equilibrium model of Lise (2013), so that endogenous job search and savings jointly determine how wealth inequality from the incomplete asset market interacts with income inequality from the labor market.

Second, I introduce explicit labor demand: heterogeneous firms post both wages and vacancies. Although firms are initially identical, they become heterogeneous ex post in a match-specific productivity upon meeting a worker and choose wages conditional on the productivity draw. Free entry ensures that the value of posting a vacancy is zero, so the vacancy measure, labor demand, and the equilibrium job-offer arrival rate are determined in equilibrium, and the wage policy trades off expected profits per worker against hiring and retention motives as a best response

to workers' optimal search and savings. In this way, my model extends Lise (2013) by endogenizing vacancy creation and the entire wage-offer distribution, which are central for evaluating progressive labor income taxation.

Lastly, I solve the model in general equilibrium and determine the risk-free interest rate endogenously. Workers own firms in the form of mutual funds that pay out all profits as dividends, so the equilibrium interest rate depends on the distribution of workers' wealth and firms' net profits after vacancy costs. A key feature of the model is thus the endogeneity of three modeling ingredients—workers' job search and savings, firms' labor demand through wage and vacancy posting, and the equilibrium interest rate—allowing for a quantitative analysis of the economy-wide effects of changes in labor income tax progressivity.

Among existing macro-labor models, this paper is the only random on-the-job search framework that simultaneously endogenizes all three blocks. Prior studies endogenize only subsets of these ingredients. For example, Lise (2013) develops a partial-equilibrium random on-the-job search model with precautionary savings that endogenizes workers' search and savings decisions but treats labor demand, the wage-offer distribution, and the interest rate as exogenous. Closely related, Michau (2021) studies insurance against search-induced wage fluctuations in a partial equilibrium random on-the-job search model with precautionary savings, examining how changes in transfer progressivity affect equilibrium search behaviour and welfare while keeping labour demand, the wage-offer distribution, and the interest rate exogenous. Moreover, some studies embed random search in frictional or monopsonistic labor markets and endogenize worker search and firm wage posting, but abstract from incomplete markets and endogenous asset returns by assuming complete insurance or representative agents (Sleet and Yazici, 2017; Bagger et al., 2018). Other incomplete-markets models incorporate labor market frictions and endogenize worker search, wealth accumulation, and often the interest rate, but treat firm behavior and wage formation as competitive (Cajner et al., 2025), or, instead of

modeling explicit job search, introduce labor market imperfections through firm wage-setting power, as in Mousavi (2022). Finally, a small number of studies combine all three building blocks, but either rely on random matching with binary search effort and ex post wage bargaining rather than wage posting (Kaas et al., 2023), or adopt directed search with endogenous wage posting and wealth accumulation while keeping the interest rate exogenous (Chaumont and Shi, 2022; Eeckhout and Sepahsalari, 2024).

For the purposes of the current study, I choose the model's parameters so that it targets key moments from prior literature and UK Household Longitudinal Survey (UKHLS) data on UK labor market mobility, earnings, and wealth, including unemployment, job-to-job transitions, and the joint distribution of earnings and savings. With all the parameters in place, I apply the algorithm developed for continuous-time heterogeneous-agent macro models (Achdou et al., 2022) to quantitatively solve the model and evaluate the impacts of changes in labor income taxation.

Using quantitative analysis, I conduct counterfactual experiments that vary the progressivity of labor income taxation, comparing a no-tax scenario to tax regimes akin to those of the US and the UK.[1]

An increase in tax progressivity generates key general-equilibrium effects in the frictional labor market and the incomplete asset market. On the worker side, higher progressivity reduces the return to climbing the wage ladder by decreasing wage differences across rungs, which weakens the precautionary search motive and lowers job search effort for both unemployed and employed workers. On the firm side, the decline in search effort reduces both the probability that a vacancy meets a worker and the probability that an incumbent worker receives an outside offer, thereby weakening firms' hiring and retention motives. Firms respond by posting

[1] Appendix 1.G extends the counterfactual analysis to an empirically relevant upper benchmark and to a simple progressivity grid in order to clarify how equilibrium outcomes and welfare vary with tax progressivity.

fewer vacancies and offering lower wages, which in turn lowers job offer arrival rates, job-finding rates, and average labor income, while raising equilibrium unemployment. In the asset market, lower wage payments and reduced vacancy posting makes hiring and retention less costly, increasing firms' profits and, through dividend payments, pushing up the risk-free interest rate. Workers then partially substitute away from precautionary search toward precautionary savings, so that asset holdings rise slightly despite the reduction in labor income risk. Overall, these forces generate a modest decline in aggregate consumption but an increase in social welfare, as the equity gains from reduced wage dispersion and improved insurance outweigh the efficiency costs from weaker search, lower vacancy posting, and higher unemployment.

To assess the role of endogenization, I compare the effects of moving from a no-tax scenario to labor income tax regimes akin to the US and the UK across three models that differ in the degree of endogenization. The baseline is a fully endogenized general equilibrium random on-the-job search model in which workers' search and savings, firms' wage and vacancy posting, and the risk-free interest rate are all determined in equilibrium. I then construct a less endogenous general equilibrium model by shutting down firm-side wage formation and entry, and a further simplified partial equilibrium model following Lise (2013) by additionally taking the interest rate as given, so that only workers' search and savings remain endogenous while wages, vacancies, and the job offer arrival rate are held fixed. When switching from no labor income taxation to less or more progressive tax regimes, akin to the US and the UK policies, respectively, the precautionary search motive is further weakened in the fully endogenized model, compared to the other two models. Workers search least and move up the wage ladder slowest, due to decreases in the mean wages and the level of vacancies. On the other hand, the precautionary savings motive does not change much in the fully endogenized model, while it is weakened significantly in the partial equilibrium model, akin to Lise (2013). With progressive labor income

taxation, the alleviated labor income risk weakens both precautionary motives (i.e., search and savings). However, in a general equilibrium model with an endogenous interest rate, the precautionary search motive is also partially replaced by the precautionary savings motive, which implies that workers choose to rely more on the asset market to self-insure. This effect is more pronounced in the fully endogenized model because lower wages and reduced vacancy costs increase the firm profits, which are paid out to shareholders, driving the interest rate to the highest level. Finally, progressive labor income taxation leads to the greatest welfare improvement in the fully endogenized model, as it results in the smallest decline in total labor and interest income.

To sum up, the contribution of this paper is to endogenize, within a unified quantitative framework, three key modeling ingredients—workers' job search and savings, firms' wage and vacancy posting, and the equilibrium interest rate—and to use this framework to study how progressive labor income taxation shapes the joint distribution of wages and wealth, as well as social welfare. By nesting models with different degrees of endogenization, the analysis isolates which margins (i.e., worker self-insurance, firm wage setting, and the asset market) are quantitatively important for the impact of labor income tax progressivity on the job ladder, macroeconomic outcomes, and welfare.

1.2 Related Literature

My model has been developed based on two key macroeconomic models: (1) the incomplete market model (Bewley, 1986; Huggett, 1993; Aiyagari, 1994) and (2) the search frictions model (Burdett and Mortensen, 1998).

In the standard incomplete market model of Aiyagari (1994), Bewley (1986), Huggett (1993), workers face uninsurable income risks and borrowing limits, but the labor

market is Walrasian, where wages are determined competitively. My model aligns to Aiyagari's (1994) model in terms of the investment cost due to the presence of the vacancy cost. The search frictions model, originally described by Burdett and Mortensen (1998), has on-the-job search in a random search environment, yet does not consider the wealth accumulation of workers. Among the extensions to this original model, my model is closely related to that of Bontemps et al. (1999), who introduce firm heterogeneity, which aligns with the heterogeneity in match productivity in my model.

Over the last few decades, models of frictional labor market with precautionary savings have been proposed, which combine the incomplete market model and the search frictions model. For example, Krusell et al. (2010) develop the standard Diamond-Mortensen-Pissarides (DMP) model to consider asset accumulation of workers. In this model, jobs are created endogenously and wages are set from Nash bargaining. Without on-the-job search, their model presents the opposing savings behavior where the employed save and the unemployed dissave. Next, Lise (2013) integrates on-the-job search into models of precautionary savings in the style of Bewley (1977), Huggett (1993), Aiyagari (1994). It investigates the relationship between workers' optimal search and savings and the distribution of income and assets. My contribution to Lise (2013) is twofold. First, my model incorporates firms' profit maximizing motives in their wage offer. This consequently provides endogenously determined wage distribution to be matched by that in the data. Second, the model allows for a quantitative analysis of taxation. Specifically, by solving the model in a general equilibrium, it can find the steady states of the economy with a wide range of labor income tax progressivity.

More recently, several extensions of the pioneering models of Krusell et al. (2010) and Lise (2013) have been put forward, primarily by Eeckhout and Sepahsalari (2024) and Chaumont and Shi (2022), who developed a general equilibrium on-the-job search model in a directed search environment. Specifically, Eeckhout and

Sepahsalari (2024) address the sorting between worker heterogeneity in assets and job productivity. Relatedly, Chaumont and Shi's model (2022) includes job ladders with worker (ex-post) heterogeneity in asset holdings; however, in this model, the interest rate is exogenous.

In addition to the models outlined above, the current paper builds upon existing literature around the equilibrium search model with taxes. Michau (2021) is closely related to the present paper. In a partial equilibrium wage ladder model with on-the-job search and precautionary savings calibrated to low-skilled US workers, he studies insurance against search-induced wage fluctuations by varying the degree of progressivity of a balanced-budget transfer schedule and shows that welfare within this restricted class is maximized at a relatively low degree of progressivity. Relative to Michau (2021), my framework endogenizes firms' wage and vacancy posting and the equilibrium risk-free interest rate, allowing the analysis to capture the firm-side and asset-market general-equilibrium effects of progressive labor income taxation.

Bagger et al. (2018) propose the equilibrium search model with two-sided heterogeneity, endogenous search effort and wage formation, and endogenous firm entry and exit. Specifically, they assess the effects of the income taxation reform using the matched employer-employee data. While Bagger's model is conducted within a complete markets equilibrium, my model is conducted in an incomplete markets equilibrium. In Bagger et al. (2018), income redistribution therefore happens between high-ability and low-ability workers. If the workers are homogeneous in their ability, there would be no redistribution. On the other hand, my model sheds light on the role of income taxation redistributing income from workers with high wealth to those with low wealth, and shows how this redistributing tool influences the welfare of the economy. Further, similar to my model, Kaas et al. (2023) propose a general equilibrium job ladder model with endogenous wage formation and interest rate. On the other hand, unlike my model, workers only decide whether to search actively or passively. In this paper, search effort is endogenously determined from

the workers' optimization. Consequently, my model provides insights on the point where workers' search effort reacts to the return of the search, determining the workers' inflows and outflows across the wage and asset holdings.

Regarding income tax progressivity, this paper builds on the extensive literature on progressive taxation and its impact on labor supply. Specifically, I use the functional form of income taxation, as discussed in works such as Heathcote et al. (2017).

Lastly, methodologically, I borrow the algorithm for solving the continuous-time heterogeneous-agent model from Achdou et al. (2022) to solve the model on a computer.

Relation to Existing Models Here, I show how the present framework is situated within the macro-labor literature by highlighting how existing models endogenize different combinations of the three building blocks and how my model extends these approaches.

As discussed in the introduction, my framework can be viewed as combining three building blocks: (i) workers' job search and savings decisions in an incomplete asset market, (ii) firms' wage and vacancy posting, and (iii) the determination of the risk-free interest rate in general equilibrium through workers' asset holdings and firm profits. The related literature has developed a variety of models that endogenize different subsets of these blocks.

Some studies focus primarily on the first component—the worker side (search and savings)—and incorporate frictional or monopsonistic labor markets into precautionary savings models, while abstracting from incomplete asset markets and an endogenous interest rate (Sleet and Yazici, 2017; Bagger et al., 2018; Mousavi, 2022). Lise (2013) develops a closely related partial-equilibrium framework with random on-the-job search and precautionary savings that endogenizes workers' search and

savings decisions in an incomplete asset market, but takes the wage offer distribution and the interest rate as exogenous and leaves the firm side in reduced form. A second group of contributions considers incomplete markets models with random job search and solves them in general equilibrium, thereby endogenizing workers' savings and, in many cases, the risk-free rate, while keeping firm behavior relatively simple (Cajner et al., 2025). A third strand of the literature introduces directed search into incomplete-markets environments. In these models, wages and tightness are determined in submarkets chosen by workers, and wealth accumulation interacts with search behavior, but the interest rate is typically taken as exogenous rather than determined in general equilibrium (Eeckhout and Sepahsalari, 2024; Chaumont and Shi, 2022).

Kaas et al. (2023) provide the closest work to the present paper, with a general-equilibrium random search model that features a job ladder and wealth dynamics and in which all three blocks are, in principle, endogenized: workers search on and off the job and save in an incomplete asset market, firms post vacancies and negotiate wages in bilateral relationships, and the interest rate is determined in an asset market in which households hold claims on firms. However, even in this class of models, search effort is typically restricted to discrete choices (such as active versus passive search), wage formation is governed by ex post bargaining tightly linked to match productivity rather than ex ante wage posting, and the firm side does not feature the same degree of flexibility in the wage offer distribution and vacancy posting as in my framework. The framework developed in the next section jointly determines random on-the-job search in a job ladder, precautionary savings in an incomplete asset market, wage and vacancy posting, and an endogenous risk-free interest rate in equilibrium.

1.3 Model

I study how income inequality arising from the labor market interacts with wealth inequality arising from an incomplete asset market, and how progressive labor income taxation affects this interaction. The analysis is conducted within an equilibrium on-the-job search model with two-sided heterogeneity, endogenous worker job search and savings in an incomplete asset market, endogenous firm wage and vacancy posting, and an endogenously determined risk-free interest rate.

On the worker side, risk-averse workers face an exogenous job separation shock and choose search effort and (positive or negative) savings in a risk-free asset.The labor market is organized as an asymmetric wage ladder: successful search leads to incremental wage improvements, while job loss entails a discrete fall to the bottom of the wage distribution.

On the firm side, establishments are heterogeneous in match-specific productivity and post wages contingent on their productivity. Firms choose wage-offer menus and vacancy posting to maximize profits, and free entry drives the value of a vacancy to zero, pinning down the equilibrium vacancy measure and job finding rates.

In the asset market, workers own firms through a mutual fund that pays out firm profits as dividends. The risk-free interest rate is determined in general equilibrium by the interaction of workers' savings decisions and firms' vacancy and wage-setting choices. The government levies a progressive labor income tax and redistributes the resulting revenue subject to a balanced-budget constraint.

1.3.1 Environment

We consider the continuous-time heterogeneous-agent model, where the future is discounted at rate ρ. There are three agents in this model: workers, firms, and the

government. Output is produced by a match between a worker and a firm, using labor as the only input. There is no aggregate uncertainty, and the model is in steady state.

Ex-post heterogeneity of workers and firms There is a continuum of identical workers and firms. On the worker side, they are subject to idiosyncratic labor income risks, with the lowest income state interpreted as the home production of unemployed workers. Because these income risks are only partially insurable through a risk-free asset, workers' assets and wages evolve with their job search and employment histories. Therefore, workers are ex-ante identical, but become endogenously heterogeneous ex post in their assets $a \in [\underline{a},\ \infty)$, wages $w \in [b,\ \infty)$, and search effort $\sigma \in [\underline{\sigma},\ \infty)$.[2] This free search level, $\underline{\sigma} > 0$, not only helps to avoid the Diamond (1971) paradox, but also makes the search technology more realistic for job finding in frictional labor markets. Empirically, many job offers are unsolicited. Using survey data on US workers, Faberman et al. (2022) show that a sizable fraction of offers to both unemployed and employed workers arrive without any active search. I therefore interpret the strictly positive lower bound $\underline{\sigma}$ as capturing these unsolicited job contacts that workers receive even when they exert no active search beyond the baseline level, so that $\lambda\underline{\sigma}$ denotes the arrival rate of such offers.

On the firm side, firms are ex-ante identical, but become heterogeneous in a match-specific productivity z, which is drawn from an exogenous distribution $\Gamma(z)$ after forming a match. Output is linear in productivity.

Worker preferences Workers derive utility from consumption of a composite good c and disutility from job search effort σ. The utility function $u(c)$ and the

[2]Formally, I assume $\sigma \geq \underline{\sigma} > 0$. A strictly positive lower bound on search effort rules out completely free search at all effort levels, which in frictional labor markets with free entry can lead to the Diamond (1971) paradox in which the equilibrium wage offer distribution collapses to a degenerate reservation-wage outcome.

search cost function $\psi(\sigma)$ are continuously differentiable with $u'(\cdot) > 0$, $u''(\cdot) < 0$, $\psi'(\cdot) > 0$, and $\psi''(\cdot) > 0$.

Wage ladder Lise (2013) develops a partial-equilibrium random on-the-job search model with precautionary savings in which the worker side of the labor market is organized as an asymmetric wage ladder. In that structure, unemployment is the bottom of the ladder, employed workers continue to search while on the job, and job-to-job transitions occur only when workers receive offers that pay more than their current wage, so wage growth reflects gradual movement to better-paying jobs whereas job loss entails a discrete fall back to unemployment. This model takes this canonical worker-side structure as its starting point and extends Lise (2013) by embedding it in an environment with explicit labor demand and general equilibrium, in which the wage-offer distribution, vacancy creation, and the job-offer arrival rate are determined endogenously through firms' wage posting and free entry.[3]

Within this worker-side structure, workers search for jobs both off and on the job. Let a denote the worker's asset holdings. When unemployed, a worker with asset level a and home production value b chooses search effort $\sigma(a, b)$. When employed at wage w, a worker with assets a chooses search effort $\sigma(a, w)$. The job finding rate follows a Poisson arrival process, with its intensities depending positively on the worker's search effort: conditional on exerting effort σ, offers arrive at rate $\lambda\sigma$, where $\lambda > 0$ is the job offer contact rate per unit of search effort. Thus, an unemployed worker receives offers at Poisson rate $\lambda\sigma(a, b)$, while an employed worker currently earning w receives offers at rate $\lambda\sigma(a, w)$.

[3]By construction, employed workers move only when they receive a strictly higher wage offer, while downward wage adjustments are absorbed into exogenous separation into unemployment. The model therefore speaks most directly to the wage-upgrade by on-the-job search rather than to all observed job-to-job mobility, which may also reflect downward moves and non-wage job attributes. This shows one clear channel of the progressive labor income tax distortion through the return to climbing the wage ladder, but it also implies that the model may overstate the response of total job mobility to tax progressivity if a sizable share of job changes in the data is less tightly linked to wage gains.

Each job contact generates a wage offer drawn from the endogenous wage-offer distribution $F(w)$, which in turn is induced by firms posting wage menus $w(z)$ as a function of their productivity z. A match forms when the worker accepts an offer, and output is then produced and shared between the worker and the firm. Matches can end in two ways. First, the worker can be laid off exogenously at rate δ, in which case the worker becomes unemployed and receives home production b. Second, a worker can quit and move to another firm offering a higher wage as a result of successful on-the-job search.

To describe this job-to-job mobility, note that an employed worker currently earning w will only accept offers that strictly exceed w. Given the wage offer distribution $F(w)$, the probability that a random offer exceeds the current wage w is

$$\overline{F}(w) \equiv 1 - F(w),$$

the survivor function of the wage offer distribution. The instantaneous rate at which a worker employed at wage w and holding assets a receives acceptable (i.e. higher-wage) offers is therefore the product of the contact rate and this acceptance probability,

$$\lambda\sigma(a, w)\,\overline{F}(w).$$

The job finding rate $\lambda\sigma(a, w)\overline{F}(w)$ varies with both current wage w and assets a. It depends on w through two mechanisms. First, there is a selectivity effect: as current wage w rises, fewer firms offer wages above w, so the survivor function $\overline{F}(w)$ falls and acceptable offers become rarer. A worker who already has a high wage is less likely to encounter an even better job in any given contact. Second, search effort $\sigma(a, w)$ may itself decrease with higher wages: workers in high-paying jobs have smaller potential gains from switching, reducing their incentive to search intensively. Assets a affect job finding through search intensity as well. Workers with high asset holdings face less liquidity risk and can smooth consumption with their savings,

so they may optimally choose a lower search effort $\sigma(a, b)$ when unemployed and $\sigma(a, w)$ when employed. In contrast, workers with low assets are more constrained and have stronger incentives to search hard, resulting in higher job finding rates both out of unemployment and along the wage ladder.

Meeting Let us denote the aggregate measure of job search by S, and a measure of total meetings by M. A meeting becomes a match only if the worker accepts the firm's offer, so the number of matches is generally smaller than the measure of meetings. S is the aggregate search intensity in the economy, defined as the weighted sum of all individual search efforts with weights given by the joint distribution of workers over assets and income:

$$S := \int^{\overline{a}} \left(\sigma(a', b) g(a', b) + \int_{b^+}^{\infty} \sigma(a', w') g(a', w') dw' \right) da'.$$

The first term captures search effort supplied by unemployed workers with home production b, and the second term captures search effort supplied by employed workers with wage w'. Because both unemployed and employed workers choose state-dependent search effort, there is a continuum of search intensities across workers. Hence, instead of using the number of unemployed workers as in a standard matching function, I take the search input in the meeting technology to be the aggregate search intensity S, i.e. the total amount of search effort supplied by all workers.

M is assumed to be a function of the aggregate search (S) and the total vacancies level (v), $M = m(S, v)$. We assume a constant-returns-to-scale Cobb–Douglas meeting function with efficiency $A > 0$ and elasticity with respect to total search given by α:

$$m(S, v) = A S^{\alpha} v^{1-\alpha},$$

so that the job offer arrival rate (the number of meetings per unit search effort) is

$$\lambda = \frac{m(S,v)}{S} = A\left(\frac{v}{S}\right)^{1-\alpha},$$

and the vacancy filling rate (the number of meetings per vacancy) is

$$\lambda_f = \frac{m(S,v)}{v} = A\left(\frac{S}{v}\right)^{\alpha}.$$

Relative to the standard matching specification that uses unemployment and vacancies, this formulation replaces unemployment with aggregate search intensity S to capture both on-the-job and off-the-job search and the heterogeneity in workers' search effort.

Asset market clearing condition In equilibrium, the riskless interest rate r clears the incomplete asset market by the following conditions: (i) firms are owned by workers through a mutual fund; and (ii) firm profits are paid back to shareholders in the form of dividends. A filled job with match-specific productivity z and wage $w(z)$ generates flow profits

$$\pi(z) \equiv z - w(z).$$

Let $\mu(z)$ denote the cross-sectional distribution of active matches over productivity. Aggregate firm profits are then

$$\pi \equiv \int \pi(z)\, d\mu(z).$$

Firms also incur vacancy posting costs κ per vacancy. With the Cobb–Douglas meeting function $m(S,v) = AS^{\alpha}v^{1-\alpha}$, the job-offer arrival rate is $\lambda = A(v/S)^{1-\alpha}$, which can be inverted to give the vacancy stock

$$v = S\left(\frac{\lambda}{A}\right)^{\frac{1}{1-\alpha}}.$$

Net dividends paid out by firms (profits net of vacancy costs) are therefore

$$D \equiv \pi - \kappa v.$$

Workers trade a single risk-free asset a, which represents a claim on the mutual fund that owns all firms. For a worker with asset holdings a and current labor or home income $y \in \{b, w\}$, the continuous-time budget constraint is

$$\dot{a} = ra + y - c,$$

so interest income ra is the channel through which firm dividends are passed on to households. Let $g(a, b)$ and $g(a, w)$ denote the stationary joint distributions of unemployed and employed workers over assets and income. Aggregate asset holdings of workers are then as follows:

$$AS(r) \equiv \int_{\underline{a}}^{\infty} \left[a\, g(a, b) + \int_{b^+}^{\infty} a\, g(a, w')\, dw' \right] da.$$

In steady state, the asset market clearing condition requires that aggregate interest payments to workers equal net dividend payments from firms,

$$r \times AS(r) = D = \pi - \kappa v.$$

Equivalently, the riskless interest rate r adjusts so that the flow of profits net of vacancy costs exactly finances the interest payments on workers' aggregate savings $AS(r)$, ensuring consistency between firm profits, dividend payments, and the asset market in general equilibrium.

Intuitively, this condition can be viewed as the intersection of an upward-sloping asset-supply schedule and a downward-sloping asset-demand schedule. A higher interest rate r raises the return on savings and thus increases workers' asset supply

$AS(r)$, while at the same time reducing firms' asset demand $\frac{(\pi-\kappa v)}{r}$. The unique equilibrium risk-free rate is the value of r at which these two schedules meet.

Labor income taxation We denote the gross labor income of an individual as w, the net labor income as w', and the labor income tax revenues as $T(w)$ at every pretax income level w. We introduce a labor income taxation system, in which high-paid workers are taxed, such that their gross labor income is higher than their net labor income and low-paid workers are subsidized by the government, such that their gross labor income is lower than their net labor income. The log-linear form of $T(w)$ is borrowed from the literature (Benabou, 2002; Heathcote et al., 2017) as follows:

$$T(w;\tau,\epsilon) = w - \epsilon w^{1-\tau}, 0 \leq \tau < 1$$

where τ reflects the degree of labor income tax progressivity, and ϵ shifts the tax function and therefore controls the average tax rates.[4] $T(w)$ is continuously differentiable with $0 \leq \tau'(w) < 1$. The net income w' is given as follows:

$$w' = \epsilon w^{1-\tau} \tag{1.1}$$

Taking logs on both sides of equation (1.1) yields:

$$log(w') = log\epsilon + (1-\tau)logw,$$

where $1-\tau$ denotes the elasticity of the net income to gross income, which means when the gross income increases by 1%, the net income increases by $(1-\tau)$%. Importantly, $1-\tau$ can be described as the ratio of marginal to average tax rates:

$$\frac{1-T'(w)}{1-\frac{T(w)}{w}} = 1-\tau$$

[4]This tax function form has been used in much of the labor and public policy literature (Heathcote et al., 2017).

Thus, the tax progressivity is characterized in the sense that the marginal rate $T'(w)$ is greater than the average tax rate $\frac{T(w)}{w}$. Therefore, the labor income tax progressivity of the taxation scheme is represented by a single parameter τ. When $\tau > 0$, it signifies the marginal tax rate is greater than the average rate, implying the progressive taxation scheme. On the other hand, $\tau < 0$ indicates a regressive taxation scheme. When $\tau = 0$, the marginal rates and average rates are always constant as $1 - \epsilon$ for each gross wage level w, representing a flat tax. Consequently, an increase in parameter τ indicates a more progressive tax scheme. In my model, τ is exogenous, and will be varied in policy, while the tax scale ϵ is endogenous given the balanced budget. Here, I note that labor income taxes can take on both positive and negative values, redistributing labor income.

1.3.2 Workers' Problem

There is a continuum of workers who are risk averse. They save using a riskless interest rate r in the incomplete asset markets, where a worker could only partially insure against the idiosyncratic unemployment risk. Given the environment, each worker chooses consumption c_t and search effort σ_t to maximize the expected present discounted utility of consumption minus search costs, discounted at rate ρ, as follows:

$$\max_{c_t \geq 0, \sigma_t \geq \underline{\sigma}} E_0 \int_0^\infty e^{-\rho t} \big[u(c_t) - \psi(\sigma_t) \big] dt,$$

subject to the budget constraint and the asset accumulation and borrowing constraints given below.

A worker is paid the gross labor income w_t from a match between a worker and a firm, and could consume or save a net of tax labor income $\epsilon w_t^{1-\tau}$. A worker's wealth evolves as follows:

$$\dot{a}_t = \epsilon {w_t}^{1-\tau} + r_t a_t - c_t.$$

The risk-free interest rate r is assumed to be less than the discount rate ρ, so as to prevent workers from being too patient to accumulate the assets infinitely due to the precautionary savings motive. A worker also faces the borrowing limit at zero:

$$a_t \geq 0,$$

meaning that borrowing is not permitted.[5] Finally, workers' gross labor income evolves stochastically over time. Here, I assume that the home production value of an unemployed worker b is also taxable. The changes in the gross labor income are as follows:

$$dw_t = \begin{cases} dq_{\lambda\sigma} 1\big(v^e(a_t, \tilde{w}_t) \geq v^u(a_t, b)\big) \left[\tilde{w}_t - b\right] & \text{when unemployed,} \\ dq_{\lambda\sigma} 1\big(v^e(a_t, \tilde{w}_t) \geq v^e(a_t, w_t)\big) \left[\tilde{w}_t - w_t\right] + dq_\delta \left[w_t - b\right] & \text{when employed,} \end{cases}$$

where $1(\cdot)$ is the indicator function, $v^e(a, w)$ is the value of being employed with labor income w and assets a, $v^u(a, b)$ is the value of being unemployed with home production value b and assets a, and the wage offer $\tilde{w} \in [b,\ \infty)$ is drawn from the endogenous wage offer distribution $F(w)$.

Suppose that there is an unemployed or employed worker with income $w(b)$ and assets a. The worker faces the job offer contact with Poisson probability $\lambda\sigma$, which is increasing with worker's search effort σ, and accepts the offer when the value of being employed with $\tilde{w}$ is greater than remaining at the current status. Subsequently, $dq_{\lambda\sigma}$ denotes whether the event of a job offer occurs or not, and therefore, $dq_{\lambda\sigma} = 1$ if a job offer arrives and 0 otherwise. dq_δ denotes whether the event of a job separation occurs or not, and therefore, $dq_\delta = 1$ if a job is exogenously destroyed and 0 otherwise. Facing the uncertainty of the time when a job offer arrives or the

[5] More generally, one could allow borrowing up to the natural borrowing limit, $a_t \geq -\frac{\epsilon w^{1-\tau}}{r}$, following Acemoglu and Pischke (1999). In this paper, I impose $a_t \geq 0$ for simplicity and consistency with the interpretation of a_t as a claim on the mutual fund. Allowing $a_t < 0$ would require introducing an additional credit or short-selling, which I abstract from.

current job is destroyed, as well as the potential wages offered, workers decide how much to consume and how much effort to expend in searching for work.

The workers' problem is represented as a Hamilton-Jacobian-Bellman (HJB) equation that solves for the optimal savings and search effort policies, given prices and the distribution of workers. The HJB equations for the unemployed and the employed are as follows, respectively[6]:

$$\rho v^u(a) = \max_{c\geq 0,\sigma\geq\underline{\sigma}} \Bigg\langle u(c) + \lambda\sigma \int \max\left(v^e(a,\tilde{w}) - v^u(a), 0\right) dF(\tilde{w}) + v^u_a(a)\left(\epsilon b^{1-\tau} + ra - c\right) - \psi(\sigma) \Bigg\rangle \qquad \text{when unemployed,} \tag{1.2}$$

$$\rho v^e(a,w) = \max_{c\geq 0,\sigma\geq\underline{\sigma}} \Bigg\langle u(c) + \lambda\sigma \int \max\left(v^e(a,\tilde{w}) - v^e(a,w), 0\right) dF(\tilde{w}) + \delta\left(v^u(a) - v^e(a,w)\right) + v^e_a(a,w)\left(\epsilon w^{1-\tau} + ra - c\right) - \psi(\sigma) \Bigg\rangle \qquad \text{when employed,} \tag{1.3}$$

where $v^u(a)$ denotes the value of unemployment of a worker with asset holdings a, and $v^e(a,w)$ denotes the value of employment of a worker working at the offered wage w with asset holdings a. When being unemployed, the value of unemployment is discounted at rate ρ on the left hand side. The right hand side of equation (1.2) maximizes the flow utility (disutility) from consumption and search effort. The value of unemployment changes in expectation in one of two ways. Firstly, there is an expected increase of future labor income when a worker succeeds in finding a job, which is represented by the second term on the right hand side. Secondly, workers also consider how the value changes along their law of motion of assets in the third term. For the employed, workers have the additional route of expected

[6]Appendix 1.A provides intuition and a formal derivation of (1.2) and (1.3) by starting from the familiar discrete-time Bellman equation with period length Δ_t and taking the continuous-time limit as $\Delta_t \to 0$. The argument shows how flow payoffs, Poisson transition terms, and the asset accumulation effect term (with progressive labor-income taxation) combine to deliver the HJB.

decrease in labor income, which is associated with job destruction rate δ.

Workers' decisions are threefold: how much to consume, how much search effort to expend to look for a job, and which job offers to accept. The first two decisions are determined by the first order conditions given as follows:

when unemployed,

$$u'(c) = v_a^u(a, b) \tag{1.4}$$

$$\psi'(\sigma) = \lambda \int \max\left(v^e(a, \tilde{w}) - v^u(a, b), 0\right) dF(\tilde{w}) \tag{1.5}$$

when employed,

$$u'(c) = v_a^e(a, w) \tag{1.6}$$

$$\psi'(\sigma) = \lambda \int \max\left(v^e(a, \tilde{w}) - v^e(a, w), 0\right) dF(\tilde{w}). \tag{1.7}$$

Looking at unemployed workers, equation (1.4) is the Euler equation that solves for the standard consumption-savings problem. It chooses the optimal consumption such that the marginal utility of consumption is equal to the marginal value of assets. Equation (1.5) requires the marginal cost of search effort to be equal to the marginal expected return from search. Similarly, employed workers optimally choose the consumption using equation (1.6), and the search effort using equation (1.7). This condition determines how fast the employed workers move up the wage ladder, affecting their asset accumulation.

Lastly, workers choose which job offers to accept conditional on their current wage. Because the search technology, characterized by λ and $\psi(\sigma)$, is the same in unemployment and employment, the reservation wage of an unemployed worker is equal to the home production value b and does not depend on assets. Intuitively, remaining unemployed yields the same continuation value as working at wage b. Consequently, unemployed workers optimally accept any wage offer strictly above

b.[7]

Consequently, unemployment with the home production value b is interpreted as the lowest rung of the wage ladder, and job loss means a precipitous drop to the bottom of the wage ladder with the lowest labor income. This means that the superscripts can be omitted for simplicity, and therefore, the two HJB equations (1.2) and (1.3) can be combined as a single equation as follows:

$$\rho\upsilon(a,w) = \max_{c\geq 0,\sigma\geq\underline{\sigma}} \Bigg\langle u(c) + \lambda\sigma \int \max\left(\upsilon(a,\tilde{w}) - \upsilon(a,w), 0\right) dF(\tilde{w}) + \delta\left(\upsilon(a,b) - \upsilon(a,w)\right) + \upsilon_a(a,w)\left(\epsilon w^{1-\tau} + ra - c\right) - \psi(\sigma) \Bigg\rangle \tag{1.8}$$

where $\upsilon(a,b)$ and $\upsilon(a,w)$ denote the value of unemployment and employment, respectively. I then employ Lemma 1.

Lemma 1. *The value function in the HJB equation* (1.8) *is strictly increasing in wages and assets.*

Proof. See Appendix 1.C □

Lemma 1 implies that the value of status in equation (1.8) is strictly increasing in wages. Subsequently, the optimal acceptance decision is to accept any wage offer higher than the wages currently being paid, or the home production value if currently in the unemployment. This also implies that the higher the current wage, the lower the job finding rates, as the share of job offers that a worker can accept decreases. Additionally, the Euler equation can be extended to the differential

[7] This result parallels Proposition 1 in Lise (2013). Appendix 1.B adapts his proof to the present environment with progressive labor income taxation.

equation that solves the optimal consumption growth as follows:

$$\frac{\dot{c}}{c} = \frac{1}{\gamma}\left(r - \rho - \lambda\sigma\left((1 - F(w)) - \int_w^\infty \frac{u'(c(a,\tilde{w}))}{u'(c(a,w))}dF(\tilde{w})\right) + \delta\left(\frac{u'(c(a,b))}{u'(c(a,w))}\right)\right), \tag{1.9}$$

along with the law of motion of assets

$$\dot{a} = \epsilon w^{1-\tau} + ra - c,$$

and the borrowing limit

$$a_t \geq 0.$$

In equation (1.9), the search technology represented by λ, and the job separation represented by δ have opposing influences on the optimal consumption growth. Given the savings determined by the interest rate r relative to the time preference ρ, a higher λ implies higher wage growth, making workers less likely to save assets, while a higher δ requires more asset buffer to confront negative labor income shocks. Given any wage level w, the target asset level $a^*(w)$ is determined at the point where the consumption growth is equal to zero, meaning consumption equals the net-of-tax wage plus interest income. Consequently, given any wage w, the savings motive of workers decreases as they accumulate assets.

1.3.2.1 Steady-state Distribution

Given the workers' optimal choices on search and savings, and firms' wage policy, the Kolmogorov-Forward (KF) equations characterize the joint distribution of workers

on assets and income, denoted by $g(a, w)$, as follows[8]:

for the unemployed

$$\frac{\partial}{\partial a}\left(s(a,b)g(a,b)\right) = \delta \int_{b^+}^{\infty} g(a,w')dw' - \lambda\sigma(a,b)\left(1-F(b)\right)g(a,b) \tag{1.10}$$

for the employed

$$\begin{aligned}\frac{\partial}{\partial a}\left(s(a,w)g(a,w)\right) = &-\left(\delta+\lambda\sigma(a,w)\left(1-F(w)\right)\right)g(a,w) \\ &+\lambda f(w)\int_{b^+}^{w}\sigma(a,w')g(a,w')dw' + \lambda f(w)\sigma(a,b)g(a,b),\end{aligned} \tag{1.11}$$

where $s(a, w)$ and $\sigma(a, w)$ are the optimal policy functions of workers for savings and search effort, respectively, and the wage w is the firm's best response to the workers' decisions. We assume that the model is in the stationary environment, setting the changes of the joint distribution over time as zero. For both the unemployed and employed, the left-hand side of the KF equation captures the effects of the asset accumulation on the distribution of workers. The right-hand side of the unemployed consists of the flows in and out of the unemployment due to exogenous job destruction at rate δ, and job finding of the unemployed workers, respectively. For the employed, the right-hand side entails the flows in and out of the employment status of assets a and wage w: the first term represents the possibility of the outflow to unemployment (denoted by δ) or higher-paying firms (denoted by $\lambda\sigma(a, w)(1 - F(w))$). The inflows from other low-paying firms and unemployment are captured by the second and third terms, respectively.

1.3.2.2 Incomplete Asset Market

Asset market is incomplete. Workers own firms in the form of mutual fund. Therefore, the equilibrium risk-free interest rate is determined such that all the firm

[8]See Appendix 1.D for the derivation.

profits are paid out to shareholders in the form of dividends. The aggregate supply of assets is defined as the sum of assets weighed by the steady-state joint distribution $g(a, w)$, which is derived by the set of KF equations in the section 1.3.2.1. The asset supply conditions the interest rate r, as the interest rate determines the savings motive of workers.

$$AS(r) \equiv \int_{\underline{a}}^{\infty} \int_{b^+}^{\infty} ag(a, w)dwda + \int_{\underline{a}}^{\infty} ag(a, b)da$$

Firm period profits are the sum of the firm surplus from the match, weighed by the steady-state joint distribution of the employed workers.

$$\pi \equiv \int_{\underline{a}}^{\infty} \int_{b^+}^{\infty} (z(w) - w)g(a, w)dwda$$

Since the total measure of workers and firms is normalized to one, this quantity π can be interpreted as both aggregate profit and profit per worker in the one-worker–one-firm environment. Therefore, in equilibrium, the asset market clearing condition holds as follows, in per-worker terms:

$$r \times AS(r) \quad = \quad \pi - \kappa v \tag{1.12}$$

1.3.3 Firms' Problem

Conditional on entry, a firm solves profit maximization given workers' decisions on search and savings, workers' distribution over assets a and wages w, other firms' wage posting strategies, and the labor income tax system. The wage menu is posted ex ante meeting a worker, implying that the realization of worker assets does not affect the wage offer. In this framework, firms consider only wages in $[b, \infty)$. A firm could offer $w < b$, but no worker would accept it, since b represents the value of the outside option or home production. Assuming a negligible cost of posting a

wage offer, I can restrict attention to $w \in [b, \infty)$ without loss of generality. A firm therefore posts wages only in the match-specific productivity $z \in [b, \infty)$

$$w(z) \ : \ [b, \infty) \mapsto [b, \infty).$$

There is free entry of firms with entry decisions based on the present expected discounted value of the profit flows. The entry game pins down the measure of the vacancies v, as well as the equilibrium job offer arrival rate λ.

1.3.3.1 Profit maximization

Firms offer wages optimally, and thus the wage offer distribution $F(w(z))$ is endogenously determined. I assume the contractual environment as follows. First, contracts are anonymous. A firm must offer the same contract to the whole stock of searching workers, regardless of their employment status or asset holdings. Second, a firm pre-commits to a wage menu $w(z)$, for any match quality z. When a firm matches with a worker, the actual level of z is realized. This means that, prior to drawing a match quality from the exogenous distribution $\Gamma(z)$, the firm posts how the output will be shared between the firm and the worker, conditional on the productivity z. Lastly, a firm fully commits to the wage policy. It cannot deviate from the wage policy during the employment spell. This restricts the form of the contract to a flat wage scheme. Specifically, firms cannot design an upward sloping scheme to increase the incentive for the worker to stay with the firm in the future. Firms also cannot employ a downward sloping scheme to reduce the future job switching probability by supporting the asset accumulation of the hired worker at the beginning of the employment spell.

Let $J(a, w, z)$ denote the expected present discounted value of a filled job for a firm with match-specific productivity z, employing a worker with asset holdings a and

wage w. Conditional on entry, the firm has already chosen its wage menu $w(z)$ and takes workers' optimal savings and search policies, $s(a, w)$ and $\sigma(a, w)$, as given. Once the match is formed, there is no further control variable at the firm level, so the problem reduces to characterizing the value function $J(a, w, z)$.

The evolution of $J(a, w, z)$ can be described in continuous time. Firms discount the value function $J(a, w, z)$ by the equilibrium interest rate r, as their source of capital is mutual funds, which pay the riskless rate of return r. At any instant, as long as the match survives, the firm receives flow profits equal to output minus the wage, $z - w$. The worker's asset position evolves according to the optimal savings policy,

$$\dot{a}_t = s(a_t, w_t),$$

so that the deterministic contribution of asset accumulation to the evolution of the match value is captured by the term $J_a(a, w, z)s(a, w)$. $J_a(a, w, z)$ measures how sensitive the match value is to marginal changes in assets, while $s(a, w)$ captures the speed at which assets evolve over time. Higher asset holdings weaken the worker's search motive, leading search effort to decline with asset holdings a. Asset accumulation therefore increases the expected duration of the current match, thereby generating the additional impact to the value of the match.

In addition, there are two Poisson events that destroy the match. First, the job is exogenously destroyed at rate δ. When this happens, the worker separates from the firm and the value of the filled job changes discretely from $J(a, w, z)$ to zero. Second, the worker may receive and accept an outside offer with a higher wage. Offers arrive with intensity $\lambda\sigma(a, w)$, and the worker accepts only offers with $\tilde{w} > w$, which occurs with probability $1 - F(w)$. Hence, the endogenous separation rate is $\lambda\sigma(a, w)(1 - F(w))$, and when such an event occurs the firm again loses the match and its value falls from $J(a, w, z)$ to zero.

Using the continuous-time Bellman equation, the firm's value function therefore satisfies

$$rJ(a,w,z) = \underbrace{(z-w)}_{\text{flow profit}} + \underbrace{J_a(a,w,z)s(a,w)}_{\text{asset accumulation effect}} + \underbrace{\delta\big(0-J(a,w,z)\big)}_{\text{exogenous separation}} + \underbrace{\lambda\sigma(a,w)\big(1-F(w)\big)\big(0-J(a,w,z)\big)}_{\text{endogenous separation}}.$$

The first term on the right-hand side is the flow profit of the match. The second term captures how the value of a filled job changes along the law of motion of assets, through the product of the savings policy function and the marginal value of assets. The last two terms represent the expected change in the value of a filled job due to exogenous job destruction and due to the worker moving to a better-paying job, respectively.

Collecting terms in $J(a,w,z)$ yields

$$\big(r+\delta+\lambda\sigma(a,w)(1-F(w))\big)J(a,w,z) = z-w+J_a(a,w,z)s(a,w). \tag{1.13}$$

When a firm considers hiring a worker, it samples the potential workers across assets and wages. The sampling distribution is given by the joint Cumulative Distribution Function (CDF) of job search in the worker population:

$$\Phi(a,w) := \frac{1}{S}\int^{a}\left(\sigma(a',b)g(a',b) + \int_{b^+}^{w}\sigma(a',w')g(a',w')dw'\right)da',$$

where S is the aggregate measure of job search,

$$S := \int^{\overline{a}}\left(\sigma(a',b)g(a',b) + \int_{b^+}^{\infty}\sigma(a',w')g(a',w')dw'\right)da'.$$

Then, I denote $\Phi_a(a,w)$ by the marginal CDF of assets a from the sampling distribution, $\Phi(a,w)$. The marginal CDF of assets a is the measure of searching workers

located at each asset level a, earning less than w:

$$\begin{aligned}\Phi_a(a,w) &= \frac{1}{S}\left(\sigma(a,b)g(a,b) + \int_{b^+}^{w} \sigma(a,w')g(a,w')dw'\right) \\ &= Pr(\text{Worker with } a \text{ accepts } w)\end{aligned}$$

This can be interpreted as the probability that the firm offering the wage level w and the worker with asset holdings a accepts the offer. The matching probability therefore positively depends on the wage offer w.

Finally, conditional on the match productivity z, a firm optimally posts the wage $w(z)$ that solves

$$w(z) \in \arg\max_{w} \int J(a,w,z)\Phi_a(a,w)\,da.$$

Let $\Pi(z)$ denote the maximized expected steady state firm profits:

$$\Pi(z) = \max_{w} \int J(a,w,z)\Phi_a(a,w)\,da.$$

The profits from a worker with asset holdings a are calculated as the product of the firm value with match quality z, paying the wage w, and the probability that the worker accepts the offer. Then, it is weighted by the asset distribution of workers. The first order condition from this profit maximization gives an Ordinary Differential Equation (ODE) for the wage policy:

$$\int J(a,w,z)\Phi_{aw}(a,w)da = -\int J_w(a,w,z)\Phi_a(a,w)da, \tag{1.14}$$

with initial condition

$$w(b) = b,$$

and where

$$\Phi_a(a,w) = \frac{1}{S}\left(\sigma(a,b)g(a,b) + \int_{b^+}^{w} \sigma(a,w')g(a,w')\,dw'\right),$$

and

$$\Phi_{aw}(a,w) = \frac{1}{S}\sigma(a,w)g(a,w)$$

represent the marginal CDF of assets a and the marginal Probability Density Function (PDF), respectively.

In equation (1.14), firms trade off the hiring and retention of workers against the reduced firm profits due to a higher wage cost. Firms consider three margins when increasing their wage offer value: (i) how much the wage will decrease the flow profits; (ii) how many more workers will accept the wage offer (hiring motive); and (iii) how the wage increase will affect the expected duration of the match. On the left-hand side of equation (1.14), $J(a,w,z)$ represents the reduced expected profits, and $\Phi_{aw}(a,w)$ represents the expected increase in the hiring motive, when offering a higher wage. On the right-hand side, the term $J_w(a,w,z)$ consists of the marginal cost of paying the additional wage and the expected increase in the retention motive. The retention motive arises from the expected increase in the firm value due to the extended match duration as a worker accumulates assets. Consequently, the ODE requires the marginal cost of the wage increase to be equal to the marginal benefits from the hiring and retention motives.

1.3.3.2 Vacancy posting

Let us denote the value of a vacancy by V, the vacancy cost by κ, and the total measure of the vacancies by v. Assuming a firm can post only one vacancy, the present discounted value of a vacancy (and hence of the firm) is given by the

expected steady state firm profits minus the vacancy cost, as follows:

$$rV = -\kappa + \lambda_f \int \Pi(z) d\Gamma(z),$$

where

$$\lambda_f = A\left(\frac{S}{v}\right)^{\alpha} = \frac{S}{v}\lambda,$$

and

$$\Pi(z) = \max_{w} \int J(a, w, z)\Phi_a(a, w)\, da.$$

Note that the probability of filling a vacancy, λ_f, depends on the efficiency A, the total search of workers S, and the total vacancies v. The expected firm value, $\Pi(z)$, is optimally obtained from the firms' profit maximization, and then measured upon the probability of meeting a worker across assets a, given the optimum wages. There is free entry of firms with vacancy posting decisions prior to forming a match and drawing a match-specific productivity z. Free entry ensures that, in equilibrium, the number of vacancies v is pinned down such that the expected steady state profits are offset by the vacancy cost flow κ:

$$\kappa = \lambda_f \int \Pi(z) d\Gamma(z). \tag{1.15}$$

This condition requires the expected value of a vacancy to be zero ($V = 0$). With a positive value of V, more firms will post vacancies, lowering λ_f until V becomes zero. In this sense, v is endogenously determined to pin down the vacancy filling rate λ_f, and therefore the job offer rate λ, endogenizing the labor demand.

1.3.3.3 Government

Government imposes progressive labor income taxation through a non-linear tax and transfer function

$$T(w;\tau,\epsilon) = w - \epsilon w^{1-\tau}, \quad 0 \leq \tau < 1, \tag{1.16}$$

where the parameter τ determines the degree of tax progressivity, while ϵ controls the overall scale of the tax and transfer system.[9] The net-of-tax labor income used in the workers' problem is therefore given by $\epsilon w^{1-\tau}$.

By specifying the two parameters τ and ϵ, the non-linear taxation function $T(w;\tau,\epsilon)$ captures both taxes and transfers. For low levels of labor income w, the schedule may imply $T(w;\tau,\epsilon) < 0$, in which case the government makes net transfers, whereas for higher w it implies $T(w;\tau,\epsilon) > 0$ and workers are net taxpayers. Hence, by choosing a suitable combination of τ and ϵ, the government can achieve a balanced budget.

Given any tax progressivity value $0 \leq \tau < 1$, the government sets ϵ such that there is a balanced budget in equilibrium:

$$0 \equiv \int_{\underline{a}}^{\infty} \int_{b^+}^{\infty} T(w;\tau,\epsilon)\, g(a,w)\, dw\, da \; + \; \int_{\underline{a}}^{\infty} T(b;\tau,\epsilon)\, g(a,b)\, da. \tag{1.17}$$

The first term is total net tax revenue from employed workers, and the second term is total net taxes (possibly negative, i.e., net transfers) associated with the home production value b of unemployed workers. Because $T(\cdot)$ captures both taxes and transfers, the government can adjust the scale parameter ϵ so that the budget

[9] Given the focus of this chapter on progressive labor income taxation, I represent the policy environment using a tax schedule on labor income only. The objective of the chapter is to isolate the channel through which taxation directly changes the return to climbing the wage ladder and hence workers' search effort, congestion in the matching process, firms' wage and vacancy posting, and equilibrium asset returns. In the present environment, introducing wealth taxation would require a separate specification of the tax base and its equilibrium incidence, since asset holdings serve both as a self-insurance device and as claims on firm profits through mutual-fund ownership. I therefore abstract from wealth taxation here and leave a joint analysis of labor income and wealth taxation for future work.

constraint (1.17) holds. For each given degree of tax progressivity τ, this equilibrium condition determines a unique value of ϵ such that the government budget is balanced.

The imposed labor income taxation thus affects workers' net labor income, which in turn determines the value of employment and, consequently, social welfare:

$$W \equiv \int_{\underline{a}}^{\infty} \int_{b^+}^{\infty} v(a,w)\, g(a,w)\, dw\, da + \int_{\underline{a}}^{\infty} v(a,b)\, g(a,b)\, da.$$

1.3.3.4 Stationary Equilibrium

A stationary equilibrium consists of the policy functions of workers ($c(a,w)$,$\sigma(a,w)$), firms ($w(z)$), and the government (ϵ) equilibrium distribution of workers $g(a,w)$, equilibrium wage offer distribution $F(w)$, the job offer contact rate λ and the interest rate r, that satisfy requirements (i) - (vi) below:

(i) The equilibrium consumption level $c(a,w)$ and search intensity $\sigma(a,w)$ satisfy the HJB equation (1.8), given income and wealth.

(ii) The equilibrium distribution of workers $g(a,w)$ satisfies the KF equations (1.10) and (1.11), given the optimal choices of workers, firms, and the government.

(iii) Wage offer policy of firms given the productivity, $w(z)$ gives an endogenous wage offer distribution $F(w)$, see (1.14).

(iv) The job offer contact rate λ is endogenously determined by the free entry (1.15), given the optimal search of workers.

(v) The interest rate r satisfies the asset market clearing condition (1.12).

(vi) The tax scale parameter ϵ is chosen such that the government has a balanced budget (1.17).

1.4 Quantitative Framework

1.4.1 Empirical Evidence

Before conducting a model-simulated quantitative analysis, I explain the data and provide the empirical specification guided by the model. The regression coefficients from the empirical analysis are used for the model calibration. I show that, when I estimate model-guided empirical relationships in the data, wages and precautionary savings enter workers' job-finding, job-to-job, and separation hazards in the way implied by on-the-job search models with precautionary savings, providing evidence that the model's mobility mechanism is present in the data.

1.4.1.1 Data

I use the data from the UK Household Longitudinal Survey (UKHLS), an annual longitudinal study tracking approximately 40,000 UK households. The data have been collected since 2009, succeeding the British Household Panel Survey (BHPS) which ran from 1991 until 2008. Using the monthly calendars of activities and job history modules collected from UKHLS data from 2009 to 2019 (waves 1–10), I construct a monthly panel data set of labor market variables (employment histories, worker flows, and log real labor income) and asset-market variables (log real savings). In defining and constructing these variables, I follow Postel-Vinay and Sepahsalari (2023).

In each wave, individuals are interviewed once a year and asked to recall all jobs and non-employment spells since their previous interview, and I exploit this information to assign to every person-month a labor market state (employment, unemployment, or inactivity), transitions between states (including job-to-job transitions), weekly hours, and monthly earnings from employment and from savings

and investment income. For each wave I keep core demographics (sex, year of birth, education, race/ethnicity), interview dates, job-status variables, job start and end dates, unemployment-benefit receipt, job search indicators, hours worked, and income measures. I assign to each person a single highest education category observed over the sample period, treating education as the highest qualification ever reported rather than a time-varying characteristic.

I apply a series of restrictions to obtain a balanced sample of workers with well-measured monthly employment histories and earnings. The target sample is full-time workers aged between 16 and 60 for the years 2009–2018. The focus on full-time workers is due to the recognized systematic difference in earnings and job search activities between full-time and part-time workers (Peters et al., 1981; Farber, 1999).[10] Because the target sample is full-time employees, I then impose restrictions on hours and wage quality. Full-time work is defined as working at least 30 hours per week. After these steps, individuals who are never observed in a full-time paid employee job drop out of the sample, because they have no remaining in-work months. For these reasons, the sample should not be interpreted as all British workers. It is a cleaned UKHLS panel of relatively stable, working-age individuals with at least some full-time employee experience, designed specifically to study monthly worker stocks, flows, and wage dynamics.

I construct consistent monthly employment histories by combining information on the interview date, job start and end dates (including retrospective job histories since the previous interview), and reported labor market status at the interview date. Following the "closest interview" approach described by Postel-Vinay and Sepahsalari (2023), inconsistencies between reported start and end dates, or between information from different waves, are corrected using simple deterministic rules:

[10]Peters et al. (1981) showed that full-time workers' actual turnover is well predicted by the five variables that are related to job search motives, while none of the five variables are significantly correlated with part-time workers' turnover. Farber (1999) found that workers significantly choose to be in both temporary and involuntarily part-time jobs as a response to job loss.

for all non-left-censored spells I systematically set the start date of a new spell equal to the end date of the previous spell so as to remove gaps and overlaps, and when different waves provide conflicting information about the same spell I give precedence to the information reported in the interview closest in time to that spell. This procedure yields a balanced monthly panel and mitigates the impact of recall noise and irregular interview spacing on the transition rates used in the calibration. I do not use pre-panel job histories collected at the first interview; respondents enter the data on the date of their first interview.

Labor market participation and the definition of states are based on the raw job-status variable, which distinguishes self-employment, paid employment, unemployment, retirement, maternity leave, family care, full-time study, long-term sickness, government training schemes, work in a family business, apprenticeships, and a residual "other" category. I map these into three labor market states: employment, unemployment, and inactivity, but for the transition analysis I focus on the distinction between being in work and being unemployed. Employment includes paid employees, women on maternity leave, apprentices, participants in government training programs, and unpaid family workers. Unemployment combines self-reported unemployment with individuals who are out of work but either searched for a job in the past four weeks or receive unemployment benefits while not reporting employment. Inactivity collects all remaining non-employment states—long-term sick, full-time students, family carers, retirees, and "other" states—when they are not accompanied by search or benefit receipt. I exclude individuals who never participate in the labor market, and drop all persons who are never observed either in paid employment as an employee or unemployed. This removes people who are always inactive, as well as those who are always self-employed and never appear in paid employee jobs or unemployment.

Workers' savings and labor income are observed biennially and annually respectively. For workers' labor income, I use the self-reported monthly earnings for em-

ployed workers. Regarding the savings variable, each respondent is asked whether they save any of their income and how much they save on average per month; the first question gives me a binary indicator of saving status, and the second provides a continuous measure of the monthly amount saved in pounds. I recode the saving-status variable into a dummy equal to 1 if the worker reports saving and 0 otherwise, and keep the reported monthly saving amount for those with valid answers. I treat savings as fixed between interviews: for a given person and interview wave, the saving status and monthly amount are carried forward to all months until the next interview, so changes in saving behavior can occur only at interview dates.[11] I convert the nominal monthly saving amounts and gross monthly labor income to real terms using the Consumer Prices Index (CPI, 2015=100) and work with the logarithm of real monthly labor income and real monthly savings for individuals who report strictly positive labor income/saving.

Table 1.1 reports summary statistics for the analysis sample of workers drawn from the UKHLS. The sample includes 34,774 workers, 47.8% of whom are female. The average age observed in the panel is 38.4 years, reflecting the focus on prime-age individuals who are observed in full-time employment at least once during the sample period. Educational attainment is as follows: 6.2% have other or no formal qualification, 20.4% hold GCSE or an equivalent qualification, 24.4% have A-level or an equivalent qualification, and 49.0% hold a bachelor's degree or higher (MSc, PhD), so that roughly one half of the sample has tertiary education. Birth cohorts are spread across the working-age population, with 16.0% born in 1951–1960, 24.7% in 1961–1970, 24.0% in 1971–1980, 23.6% in 1981–1990, and 11.6% in 1991–2000.

All monetary variables are expressed in real 2015 pounds. Average monthly labor income is £2,379, with a cross-sectional standard deviation of £1,493, indicating substantial heterogeneity in earnings across workers.

[11] More than three quarters of workers (76.9%) have reported that their savings are regular.

The average savings participation rate is 50.6%.[12] Conditional on positive saving, average monthly savings is £287, with a standard deviation of £667, which reflects considerable dispersion in saving behavior even among those who save. On a person-month basis, 79.5% of observations are in employment, 4.8% in unemployment, and 15.8% in inactivity; the high employment share and relatively low inactivity share are mechanical consequences of restricting the sample to individuals who are ever observed in full-time paid employment. To illustrate the dispersion of monetary outcomes, the table also reports quartile means. Average labor income in the first to fourth quartiles is £1,107, £1,651, £2,381, and £4,377, respectively. Average savings in the first to fourth quartiles is £44, £118, £243, and £758, respectively, indicating both strong inequality in earnings and a highly skewed distribution of savings, with a small group of workers holding very high saving amounts.

1.4.1.2 OLS regressions for labor market transitions

The descriptive models on the UKHLS data are estimated using the pooled ordinary least squares (OLS) method. The regressions show how labor market flows change depending on current wages and savings:

$$J2U_{i,t} = \alpha_1 + \alpha_{1,X} X_i + \epsilon_{1,i,t}, \tag{1.18}$$

$$J2J_{i,t} = \alpha_2 + \alpha_{2,X} X_i + \beta_{2,\text{Wage}}\, Wage_{i,t-1} + \beta_{2,\text{Save}}\, Save_{i,t-1} + \epsilon_{2,i,t}, \tag{1.19}$$

$$U2J_{i,t} = \alpha_3 + \alpha_{3,X} X_i + \beta_{3,\text{Save}}\, Save_{i,t-1} + \epsilon_{3,i,t}, \tag{1.20}$$

[12] The savings participation rate is based strictly on explicit "no saving" responses to the UKHLS question 'Do you save any amount of your income?'. The question therefore captures active saving out of income rather than asset holdings. A participation rate around one half is not unusually low: existing work using the same UKHLS/BHPS savings module typically finds saving rates in the range of roughly 0.37–0.46 in broader working-age samples, or around 40% when asking about saving over the previous year (Brown et al., 2021). My estimate is slightly higher, which is consistent with the fact that my analysis sample is restricted to individuals who are ever observed in full-time paid employment and thus tend to have stronger labor market attachment and greater capacity to save.

Table 1.1: Summary statistics[1)]

Demographics	Mean	Distribution	Mean
Female (%)	47.8	Average labor income (2015, £)[2)]	
Observation age	38.4	- 1st quartile	1,107
Educational attainment (%)		- 2nd quartile	1,651
- Other or no qualification	6.2	- 3rd quartile	2,381
- GCSE or equivalent	20.4	- 4th quartile	4,377
- A-level or equivalent	24.4	Average savings (2015, £)[4)]	
- Degree or higher	49.0	- 1st quartile	44
Birth cohort		- 2nd quartile	118
- 1951–1960	16.0	- 3rd quartile	243
- 1961–1970	24.7	- 4th quartile	758
- 1971–1980	24.0		
- 1981–1990	23.6		
- 1991–2000	11.6		
Average labor income (2015, £)[2)]	2,379		
	(1,493)		
Average savings participation rate (%)[3)]	50.6		
Average savings (2015, £)[4)]	287		
	(667)		
Share of employment (%)	79.5		
Share of unemployment (%)	4.8		
Share of inactivity (%)	15.8		
Number of workers	34,774		

Notes: 1) Numbers in parentheses are standard deviations.
2) Labor income is defined as real gross monthly labor income from the main current job. Nominal labor income is reported in 2015 prices. I use only months in which the individual is in full-time paid employment; months in unemployment or inactivity are excluded from the wage statistics.
3) Save1 is a dummy equal to 1 if the respondent answers 'yes' to the UKHLS question 'Do you save any amount of your income?' and 0 if they explicitly answer 'no'.
4) Save2 denotes monthly savings based on the self-reported average amount saved per month, recorded only for respondents who report saving. Nominal amounts are variables are reported in 2015 prices.

where

- $J2U_{i,t}$, $J2J_{i,t}$, and $U2J_{i,t}$ are binary indicators for the transitions out of employment, job-to-job transitions, and the transitions into employment of worker i in month t, respectively.

- X_i is the set of control variables. Controls include gender and education level. Both variables are binary. Male is one, female is zero. For education, if a

worker's highest qualification is equal to or less than A-level diploma, it is assigned a value of one. Otherwise, when the highest qualification is a college degree or higher, it is assigned a value of zero.

- $Wage_{i,t-1}$ is the log monthly labor income of worker i in the previous month $(t-1)$. When a worker experiences a job-to-job transition, the newly offered $Wage_{i,t}$ is not the motive for job searching. Therefore, the lagged variable $Wage_{i,t-1}$ determines job-to-job mobility.

- $Save_{i,t-1}$ is the savings variable of worker i in the previous month $(t-1)$. Two variables of savings ($Save1$ and $Save2$) are estimated separately. $Save1$ is a binary indicator for whether a worker saves, and $Save2$ is the logged value of monthly savings if one saves. Due to collinearity, the coefficients of $Save1$ and $Save2$ cannot be estimated in the same model.

- $\epsilon_{k,i,t}$, $k \in \{1,2,3\}$, is the error term for transition type k of worker i in month t, where $k=1$ corresponds to $J2U$, $k=2$ to $J2J$, and $k=3$ to $U2J$.

In table 1.2, I regress the labor market transition probabilities on the variables guided by the model: wages and savings. First, in column (1), I regress the estimate of the job-to-unemployment transition probability, which is defined as the share of (salaried) employed workers who lose a job in the following month. As the model assumes exogenous job destruction shock, no dependent variables are included in the regression.

Second, in column (2) and (3), the job-to-job transition probability is defined as the share of (salaried) employed workers who change jobs without experiencing any interim period of non-employment in the following month, and is regressed on savings and wages-related variables. The regressions aim to show that high asset holdings or current wages significantly reduce the job-to-job transition probability, which is implied by the model. One limitation of the UKHLS is the lack of the

individual and household asset holdings information, where only the financial assets are partially observable. Here, two variables on savings, (i) whether they save or not, and (ii) the amount of savings, are used as the proxy variables for asset holdings. Column (2) includes the savings dummy and log real labor income, and column (3) includes the amount of log real savings in a month and log real labor income, respectively. The savings-related variable $Save1$ and $Save2$ should be interpreted as measures of the flow of savings. In particular, $Save2$ is constructed from the reported monthly amount that worker i puts aside out of current income at $t-1$, so it is closer to a saving rate or change in wealth than to the stock of wealth itself. In this framework, where individual assets evolve according to the asset accumulation equation $\dot{a}_t = \epsilon w_t^{(1-\tau)} + ra_t - c_t$, this empirical savings variable corresponds to the $\dot{a}_t$ term. As a result, the coefficients on the savings-related variables in columns (2) and (3) capture how marginal changes in asset accumulation are related to job-to-unemployment and job-to-job transition probabilities, rather than how differences in the underlying asset stock a affect those transitions. The fact that the savings-related variables have positive coefficients is consistent with the relationships among variables in the model, in that, holding labor income constant, workers' savings decrease as their asset holdings increase, and search effort also decreases with asset holdings. Therefore, columns (2) and (3) show that the low-paid workers are more likely to move to higher-paying jobs as they search harder, as well as, wealthier workers have a lower possibility of leaving a current job, because they exert less search effort.

Lastly, columns (4) - (6) show the results of the regression of the unemployment-to-job probability. In column (4), no other dependent variables are included as they have no labor income and do not save in the model. In columns (5) and (6), two savings-related variables in columns (2) and (3) are included, because, in real world, the unemployed can save using, for example, the transfer from the parents.

Table 1.2: OLS Regressions for Labor Market Transitions[1)2)3)4)]

Independent Variables	Dependent Variables					
	J2U	J2J			U2J	
	(1)	(2)	(3)	(4)	(5)	(6)
Wage[5)] (log real labor income)		-0.0028^{***} (0.0002)	-0.0034^{***} (0.0003)			
Save1[6)] (savings dummy)		0.0010^{***} (0.0002)			0.0391^{***} (0.0029)	
Save2[7)] (log real savings)			0.0006^{***} (0.0001)			0.0154^{***} (0.0024)
Constant	0.0041^{***} (0.0001)	0.0007^{*} (0.0004)	0.0035^{***} (0.0007)	0.0754^{***} (0.0015)	0.0616^{***} (0.0023)	0.1762^{***} (0.0123)
Observations	1,254,331	615,670	310,410	70,542	34,181	9,525
Controls	YES	YES	YES	YES	YES	YES

Notes: 1) Robust standard errors are in parentheses.
2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
3) Controls include gender and education level (equal or less than A-level/college degree or higher).
4) Three types of labor market transitions are tracked: (1) transitions out of employment (J2U), (2) job-to-job transitions (J2J), and (3) the transitions into employment (U2J).
5) Labor income is defined as real gross monthly labor income from the main current job.
6) Save1 is a dummy equal to 1 if the respondent answers 'yes' to the UKHLS question 'Do you save any amount of your income?' and 0 if they explicitly answer 'no'.
7) Save2 denotes monthly savings based on the self-reported average amount saved per month, recorded only for respondents who report saving.

1.4.2 Calibration

We set the borrowing constraint at $\underline{a} = 0$. For computation, we use grids with 500 asset grid points and 101 wage grid points.[13] This section demonstrates how the model is calibrated at an annual frequency to match the microdata of the UK economy between 2009 and 2019. There are fourteen model parameters, where the first six parameters are externally set, and the remaining eight are jointly estimated to replicate eleven target moments. The model is solved at an annual frequency, and monetary quantities are measured in units of £10,000 per year.

[13]101 wage grid points include 100 rungs of the wage ladder and unemployment.

1.4.2.1 Functional forms and distributional assumptions

The worker preferences are represented by the Constant Relative Risk Aversion (CRRA) utility function, and the power function for disutility:

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma} \quad \text{and} \quad \psi(\sigma) = \frac{\mu}{\eta}(\sigma - \underline{\sigma})^{\eta},$$

where $\gamma > 0$ is the coefficient of relative risk aversion, $\eta > 1$ is the elasticity of search costs, $\mu > 0$ is a scaling parameter, and $\underline{\sigma} > 0$ is free search.

The meeting technology, as seen in Section 1.3.1, has constant returns to scale Cobb-Douglas function with the efficiency A and elasticity α, yielding the job offer arrival rate

$$\lambda = \frac{m(S,v)}{S} = A\left(\frac{v}{S}\right)^{1-\alpha},$$

and the vacancy filling rate

$$\lambda_f = \frac{m(S,v)}{v} = A\left(\frac{S}{v}\right)^{\alpha}.$$

The output function equals the match-specific productivity level z, which is distributed with the log-normal distribution $\Gamma(z; \mu_z,\ \sigma_z)$ with mean μ_z and variance σ_z^2.

1.4.2.2 External parameters

Prior to estimation, six parameters are externally set. The rate of time preference ρ is assumed to be at 5% annually, and the coefficient of relative risk aversion γ to 2, following Lise (2013). The labor income tax system in this paper follows Heathcote et al. (2017) and is given by the tax function in equation (1.16),

$$T(w; \tau, \epsilon) = w - \epsilon w^{1-\tau}, \quad 0 \leq \tau < 1,$$

where w denotes gross labor income, τ governs the progressivity of the labor income tax, and ϵ is a scale parameter.

For the baseline calibration, I use the UK estimate of tax progressivity from Holter et al. (2019), who compute $\tau = 0.2$ using UK labor income tax data. Under the balanced budget assumption, this UK value of τ implies a tax scale parameter of $\epsilon = 1.2188$ in equation (1.16). Substituting these values into the tax function yields the UK tax schedule used in the model,

$$T(w; 0.2, 1.2188) = w - 1.2188\, w^{0.8}.$$

Next, the parameters for search technology, the search scale μ and the search convexity η, are not separately identified, as they both target the coefficients of the job-to-job transitions. I normalize the search scale parameter μ as one, and leave the search convexity η free to match the empirical moments. Lastly, there are two parameters of the meeting function, the meeting efficiency A and meeting elasticity α. Without loss of generality, I normalize $A = 1$, and externally set $\alpha = 0.5$, as for every combination of A and α there always exists a unique value of vacancy posting cost that ensures free entry condition. The value of the meeting function elasticity $\alpha = 0.5$ is in line with previous empirical work (e.g., Petrongolo and Pissarides, 2001; Moscarini and Postel-Vinay, 2018; Bagger et al., 2021).[14] The parameters are presented in Table 1.3.

[14] The meeting function selected for the current research differs from that observed in the classic matching function in prior literature. Specifically, while the classic matching function depends on the number of unemployed workers, in the current model, the total number of meetings $m(S, v) = AS^{\alpha}v^{1-\alpha}$ depends on the aggregate search effort S of all searching workers, both employed and unemployed. The rationale is based on previous models utilizing different structures of matching. For example, the job ladder model of Moscarini and Postel-Vinay (2018) chose $\alpha = 0.5$ with the meeting function of the number of searching workers. Similarly, Bagger et al. (2021) included on-the-job search and endogenous search effort of workers, and chose $\alpha = 0.5$.

Table 1.3: Externally Calibrated Parameters

	Parameter	Value	Source
ρ	Time preference	0.05	5% annual
γ	Relative risk aversion	2	Lise (2013)
τ	Tax progressivity	0.2	Holter et al. (2019)
μ	Search cost scale	1	Normalization
A	Meeting efficiency	1	Normalization
α	Meeting elasticity	0.5	Petrongolo and Pissarides (2001)

1.4.2.3 Internally calibrated parameters

The remaining model parameters $\theta = \{\mu_z,\ \sigma_z,\ \bar{z},\ b,\ \delta,\ \eta,\ \sigma_0,\ \kappa\}$ are chosen internally to match the equilibrium risk-free interest rate of 4%[15] and the following ten key data moments: (i) mean log savings, (ii) mean log wages, (iii) the job finding rate of the unemployed, (iv) the mean-min wage ratio, (v) the job separation rate, (vi) the regression coefficients of the job-to-job transition rate on log savings (dummy variable for positive savings) and log real wages, and (vii) mean job offer of the employed not looking for a job.[16] The ten data moments are calculated using a monthly frequency.

I apply the simulated method of moments (SMM), which minimizes the following objective function $\theta = (\mu_z,\ \sigma_z,\ \bar{z},\ b,\ \delta,\ \eta,\ \sigma_0,\ \kappa)$ over the parameter space

[15] I follow Chaumont and Shi (2022) and Kaas et al. (2023) and set the risk-free rate of return of an investment to be 4%.

[16] The job-to-job transition rate is defined as the share of (salaried) employed workers who change jobs without experiencing any interim period of non-employment in the following month. The job separation rate is the share of (salaried) employed workers who lose a job in the following month. The job finding rate is the share of unemployed workers who find a job in the following month. The mean-min ratio of wages is calculated as the ratio of the average wage to the wage at the first percentile, which is proposed by Carrillo-Tudela (2012). The estimated coefficients of the job-to-job transition rate on savings-related variables and wage-related variables are based on the regressions in Section 1.4.1.2. The mean job offer of the employed not looking for a job is defined by Faberman et al. (2022) as the fraction of the employed who are not looking for a job and receive at least one formal offer, including unsolicited job offers.

Θ ($\theta \in \Theta$):

$$\hat{\theta} \;=\; \arg\min_{\theta} \left(\frac{1}{N} \sum_{n} m_n(\theta) - m \right)' \Omega \left(\frac{1}{N} \sum_{n} m_n(\theta) - m \right) \quad ,$$

where the model is simulated N times, $m_n(\theta)$ is a (11×1) vector of the model-simulated moments from the nth simulation, m is a vector of their counterpart moments in the data, and Ω is a (11×11) weight matrix.[17] Specifically, for any candidate parameter vector θ, I solve the stationary equilibrium and simulate N monthly worker histories from the stationary distribution. From each simulated panel, I reproduce the empirical moments in the UKHLS: I define the same transition indicators and wage and saving variables, restrict the samples as in the UKHLS, and then compute the model counterparts of the 11 targeted moments.Thus, the objective function is the sum of squared percentage distances between the average of N simulated moments and their target data moments.

Although the parameters are jointly calibrated, thereby affecting each targeted moment, I will discuss which specific moments are most relevant to each parameter. First, the mean and standard deviation of the productivity distribution μ_z and σ_z are set to 0.8 and 0.17, respectively. The productivity is drawn from the log-normal distribution, which has the valid range of $[0, \infty)$. The $\overline{z}$ should just be high enough not to matter. One needs a bounded support on the computer. To compute the model with finite productivity grids, the log-normal distribution is truncated at its upper threshold. The threshold of the truncated log-normal distribution is set to 8.5 to fit its heavy tail, yielding $P(\overline{z} > z) \approx 0$. The wage offer of a firm is the function of the drawn match productivity, which means that the wage offer distribution is specified by the productivity distribution. The wage distribution is then endogenously determined by the wage offer distribution and the free entry condition.

[17] The weight matrix Ω is defined as the diagonal matrix of the inverse of squared data moments.

The calibration targets mean log wages and mean log savings.[18] The wage and saving moments are constructed using the same conditioning in the data and in the model. In the data, wages are observed only for employed workers, and saving amounts are observed only for workers who report positive savings. The model counterparts are therefore constructed using the same sample definitions and conditioning rules, so that wage moments are based on employed workers and saving moments are based on observations with positive savings. For ease of interpretation, in Table 1.4, the level mean x is also reported separately in parentheses. Note that the simulated model moments are smaller than their data targets in both mean wages and savings. While the simulated mean wages are only slightly smaller (£5) than their data target, the difference in the simulated mean savings and their data target is larger (£42), which implies that there is another source of savings other than the precautionary savings motives in the data (e.g. life cycle savings, investment). These estimated parameters also target the job finding rate of the unemployed workers, as the wage distribution decides the expected future wage increases of the unemployed, and consequently, their search effort. The job finding rate in the model is higher than that of the data, which implies that workers choose to exert more effort to find a job, rather than to save more buffers. Further, differences in the savings and search motives of the model stem from the model's endogeneity.

Next, the home production parameter b pins down the outside option of unemployment and the lower bound of the wage ladder.[19] Following Hornstein et al. (2011), I use the ratio of the mean to the minimum wage (the mean-min wage ratio) as a summary statistic for frictional wage dispersion. Following Carrillo-Tudela (2012), the home production value b is set to match the mean wage to the wage at the first percentile of the employed wage distribution, not to the literal minimum wage, and calculated from the sample of homogeneous full-time middle-skill workers in the UK

[18] For calibration, mean log wages and mean log savings are measured as $ln(x/10,000)$, where x denotes the level in pounds(£).

[19] $b = 1$ corresponds to £10,000 per year, or about £833 per month in gross terms; it should therefore not be interpreted as £1 per month.

in the BHPS dataset.[20]

Regarding the mean-min ratio, a well-known result is that standard equilibrium search models calibrated to match observed worker flows can generate only very small frictional wage dispersion, and hence a mean-min ratio that is far below the empirical values.[21] In particular, the mean-min ratio is tightly linked to the option value of continued search: if accepting a low-paying job implies giving up many future opportunities, workers will not accept such jobs, and equilibrium wage dispersion must be limited.

Bradley and Gottfries (2021) revisit this issue in a job ladder model with stochastic employment opportunities. Building on the insight of Hornstein et al. (2011), they interpret the mean-min ratio as a measure of the foregone search option associated with employment. In a setting where access to suitable vacancies does not deteriorate sharply upon being employed, workers do not give up much of the search option when they take a job. As a result, their model can match a mean-min ratio close to the empirical value without requiring an implausibly low flow value of unemployment, in contrast to the benchmark Burdett-Mortensen model estimated under the same flow data.[22]

In my calibration, I target the empirical mean-min wage ratio directly when choosing the home production parameter b (see Table 1.4). The model delivers a mean-min ratio of about 1.8, close to the data target of 1.7. Relative to the baseline

[20] In the benchmark UK calibration, workers' flow income is $1-\epsilon w^{(1-\tau)}$. Hence the home production flow associated with $b = 1$ is $\epsilon b^{(1-\tau)} = 1.2188$, which corresponds to about £1,016 per month. In the simulation, the mean/first-percentile wage ratio is computed from the stationary employed wage distribution by excluding the unemployment state, cumulating the mass of employed workers from the lowest wage rung upward, and taking the wage at which cumulative employment reaches 1%.

[21] Hornstein et al. (2011) show that when standard equilibrium search models of the Burdett-Mortensen type are calibrated with plausible parameter values, they typically generate a mean–min ratio of about 1.05, far below the empirical range of 1.5–2.

[22] See Bradley and Gottfries (2021), who show that the Burdett-Mortensen model needs a large negative flow value of unemployment to generate a mean-min ratio around two, whereas their stochastic-opportunities model matches the same frictional wage distribution with replacement rates in the range of 25-50%.

search models studied by Hornstein et al. (2011), two features help to relax the mean-min constraint. In my framework, the mean-min wage ratio is extended from both the bottom and the top of the wage distribution. On the lower side, equal-search-technology assumption is precisely what helps generate lower-tail frictional wage dispersion: accepting a low wage does not mean giving up the option to keep searching (since on-the-job search is equally available), so workers will accept even very low-wage jobs above b. As a result, the equilibrium wage distribution can have mass arbitrarily close to b, ensuring downward wage dispersion. On the upper side, the endogenous wage posting policy $w(z)$ embeds a strong retention motive: when a firm draws a high match-specific productivity z, losing the worker implies a large loss in future surplus, so the firm has an incentive to offer a relatively high wage in order to discourage on-the-job search and reduce the separation hazard. Moreover, in the model there is an additional asset-accumulation channel: when a worker earns a high wage and accumulates assets more rapidly, their on-the-job search effort is further weakened. This makes the wage-productivity schedule steeper than in benchmark Burdett-Mortensen–type models with constant search intensity. Taken together, these mechanisms lower the minimum accepted wage while pushing up wages in high z matches, thereby generating greater frictional wage dispersion and a higher mean-min wage ratio than standard equilibrium search models.

The exogenous job separation rate δ is set to 0.049 to match the mean monthly separation rate into unemployment.

In terms of search costs, the search cost convexity η is set to match four regression-based moments that summarize how job-to-job mobility covaries with wages and saving measures in the data, while normalizing the search cost scale to one. The moments are borrowed from the two pooled OLS specifications in Section 1.4.1.2 for the monthly job-to-job transition probability: (i) the regression on log real savings and log real wages, and (ii) the regression on a positive saving dummy and log real

wages.[23] In the SMM procedure, the four resulting model-implied coefficients—one wage coefficient and one saving coefficient from each regression—are matched to their empirical counterparts. The search cost convexity η is set to 2.8, which is substantially higher than quadratic. Higher convexity of search cost means a weakened search motive, relative to the classic assumption of the quadratic search costs. In the data, the estimated coefficients of the savings-related variables are positive, while those of the wages-related variables are negative. The signs of the coefficients estimated using the model-simulated data are consistent with the target moments. To interpret the sign of the savings coefficient, it is important to distinguish the worker's asset holdings a from the empirical savings variable. In the model, the instantaneous job-to-job hazard for an employed worker at state (a, w) is given by

$$\lambda\sigma(a, w)[1 - F(w)].$$

The empirical variable $Save2$ is not a measure of the asset stock a. Rather, as discussed in Section 1.4.1.2, it is interpreted as a proxy for monthly saving flow, which in the model corresponds to the asset accumulation term

$$\dot{a} = \epsilon w^{1-\tau} + ra - c(a, w).$$

Holding current wages fixed, the model implies that higher asset holdings reduce on-the-job search and hence lower the job-to-job hazard. At the same time, saving flows also decline with asset holdings. Therefore, on the positive saving sample for which $Save2$ is observed, a positive reduced form coefficient on log monthly savings is consistent with a negative structural effect of asset holdings on job-to-job mobility. In magnitude, while the regression coefficients of the savings-related variables using

[23]The regressions in Section 1.4.1.2 are not structural equations estimated for the model parameters. They are reduced form equations used to examine the empirical relationship between labor market transition probabilities and wages and savings measures, guided by the model. Among the regressions in Section 1.4.1.2, only the coefficients for the job-to-job probability from the equation (1.19) are included in the SMM objective; the job-to-unemployment and unemployment-to-job regressions are reported as model-guided descriptive evidence and are not targeted directly.

the model-simulated data are similar to the target moments, the simulated search motive turns out to be substantially stronger than that found in the data.

The free search $\underline{\sigma}$ is set to match the mean job offer of the employed not looking for a job at 0.053, which is taken from Faberman et al. (2022). Here, the mean offer of the employed not looking for a job is the fraction of workers who do not actively look for a job, but receive at least one formal offer.[24] The free search targets the equilibrium monthly probability that an employed worker at the free search receives at least one offer, given that the highest paid workers exert only the amount of search effort that does not impose any cost. Under the UK calibration, $\underline{\sigma} = 0.35$ implies a model counterpart of 0.054.[25]

Finally, the equilibrium riskless interest rate r is endogenously targeted. In the model, the free entry condition finds the vacancy measures v, which rationalize the given interest rate, and the asset market clearing condition finds the equilibrium interest rate r. Here I set the vacancy cost κ to 0.4897 so that the equilibrium interest rate $r = 4\%$ is endogenously achieved by the asset market clearing condition and the following vacancy measures v by the free entry condition.

The fit of the calibration is not consistently strong. As shown in Table 1.4, the model comes reasonably close to mean wages, the mean-min ratio, the separation rate, the mean offer received by employed workers who are not actively searching, and the target interest rate. At the same time, it understates mean savings, overpredicts the job-finding rate of unemployed workers, and implies stronger wage effects in the job-to-job transition regressions than in the data. I therefore interpret the calibration

[24] Faberman et al. (2022) uses the Job Search Supplement to the Survey of Consumer Expectations (SCE), which includes data from 1,300 household heads in the US during the period of 2013 – 2017.

[25] The size of the free-search should be interpreted through the implied baseline mean job offer $\lambda\bar{\sigma}$ rather than through $\bar{\sigma}$ in isolation. Under the UK calibration, it implies a monthly offer probability of about 0.054 for workers at the search floor, matching the empirical target, and accounts for about 67% of gross mean offers in the model economy. The closest counterpart in Faberman et al. (2022) is around 61%.The quantitative role of this free search for total offer arrivals and job mobility is discussed after reporting equilibrium results.

as a useful but imperfect quantitative discipline, rather than as a close overall fit. These discrepancies likely reflect both measurement and structure. On the empirical side, the UKHLS does not provide a direct measure of worker-level asset holdings, so I rely on self-reported monthly saving amounts as the empirical counterpart. Those data are flow measures—closer to changes in wealth than to the stock of assets itself—whereas the model is organized around asset holdings as the key state variable, so the mapping between model and data is necessarily imperfect, especially for mean savings and savings-related transition moments.

On the structural side, the model captures precautionary saving only, so it abstracts from other motives that likely affect observed saving behavior in the data, such as life-cycle saving, planned expenditures, and investment motives; this makes it harder for the model to match both the level of savings and the relationship between savings and mobility. The model also imposes exogenous job separations that are identical across jobs, so it cannot capture the empirical tendency for higher-wage or better matches to be more stable; as a result, it has limited ability to jointly match the observed relationships among wages, job finding, job-to-job mobility, and separation outcomes. In addition, because the estimation minimizes a weighted SMM criterion, the selected parameter vector is best understood as a compromise across moments. I also cannot completely rule out that a more exhaustive search over the parameter space would improve the objective function.

1.4.3 Algorithm

The algorithm nests three iterative blocks: (i) an inner loop that solves the worker HJB and KF equations for given $(r, \lambda, w(z))$; (ii) a firm block that solves for the optimal wage schedule and updates the offer arrival rate via the free-entry condition; and (iii) an outer loop that adjusts the interest rate so that the asset market clearing condition holds. All steps are implemented in continuous time using upwind finite

Table 1.4: Internally Calibrated Parameters

Parameter		Value	Moment (monthly)	Model	Target
Productivity					
μ_z	Mean log productivity	0.8	Mean log savings	–4.390	–4.098
			(mean savings, £)[1)]	(124)	(166)
σ_z	Log productivity var.	0.17	Mean log wages	–1.554	–1.552
			(mean wages, £)[1)]	(2,113)	(2,118)
$\bar{z}$	Threshold of the truncated dist.	8.5	Job finding prob. of the unemp.	0.117	0.075
Labor income risk					
b	Home production	1	Mean-min ratio[2)]	1.798	1.7
δ	Job destruction rate	0.049	Job separation prob.	0.0041	0.0041
Search of workers and firms					
η	Search cost convexity	2.8	J2J prob. on savings & wages[3)]	0.0005 – 0.0081	0.0006 – 0.0034
			J2J prob. on savings dummy wages[3)]	0.0007 – 0.0382	0.0010 – 0.0028
$\underline{\sigma}$	Free search	0.35	Mean offer of the emp. not looking[4)]	0.054	0.053
κ	Vacancy cost	0.4897	Annual risk-free interest rate[5)]	0.04	0.04

Notes: Targeted moments are based on prior literature and the UKHLS data calculations. The model-simulated data are calculated in the monthly frequency to match the target moments. The target moments, excluding those discussed in the notes, are calculated using the UKHLS data, specifically from the sample of the employed full-time workers.
1) The calibration targets mean log wages and mean log savings are measured as $ln(x/10,000)$, where x denotes the level in pounds(£). For ease of interpretation, the level mean x is also reported separately in parentheses.
2) The model is solved at an annual frequency and monetary quantities are measured in units of £10,000 per year. Thus, $b = 1$ corresponds to about £833 per month in gross terms. The mean-min ratio denotes the ratio of the mean wage to the wage at the first percentile of the employed wage distribution, and is taken from Carrillo-Tudela (2012).
3) The coefficients of the regressions of the J2J transition probability on log savings (savings dummy variable) and log wages are targeted. The savings-related variables are included as control variables in place of data on workers' asset holdings. This is based on the model in which workers with low asset holdings accumulate more assets, resulting in higher savings. The regressions are estimated using pooled OLS, and all regression coefficients are statistically significant at the 1% significance level. Details are provided in Section 1.4.1.2
4) The mean offer of the employed not looking for a job is measured as the monthly probability of receiving at least one job offer over the last four weeks, calculated from Faberman et al. (2022).
5) The risk-free rate is annual (4%).

differences and sparse linear algebra, which allows me to efficiently compute the stationary equilibrium under different tax regimes.[26]

1.5 Results

In this section, I answer the following question: How large are the effects of the progressivity of labor income taxation on labor market outcomes, and consequently, on the social welfare of workers? This question is addressed by conducting counterfactual analyses with different levels of tax progressivity τ across models with different levels of endogenization.

I first compare three labor income taxation scenarios in the baseline model (no tax, a tax regime akin to the US, and a more progressive regime akin to the UK) and highlight the main effects on welfare and key labor market and asset market variables. I then study how these effects change across three models with different degrees of endogenization. Finally, I discuss the economic mechanisms that link progressive labor income taxation to workers' search behavior, firms' wage and vacancy posting, and the equilibrium interest rate.

1.5.1 Three labor income taxation scenarios

Poorer workers search more intensively than rich workers, and a higher tax progressivity reduces the search effort of workers overall. At the same time, progressive taxation changes the return to saving via the equilibrium interest rate, so the net effect on the joint distribution of wealth and wages is, ex ante, theoretically ambiguous.

Table 1.5 shows the labor market outcomes across three different labor income tax-

[26]For detailed explanation on computation, see Subsection 1.E.

ation scenarios. Across specifications, only two parameters vary: tax progressivity, τ, and the scale parameter, ϵ, which is adjusted to balance the government budget. All other parameters are held at their UK-calibrated values. The experiment therefore consists of moving the UK from its current tax schedule to either a US-style schedule or a flat tax schedule, while keeping all other parameters at their UK values.

The first column represents a no taxation scenario with $\tau = 0$. In the second column, τ rises to 0.137, which represents a tax policy akin to the US. In the third column, τ rises to 0.2, a tax policy akin to the UK in the counterfactual economy. All scenarios set the tax scale parameter ϵ's that achieve a balanced budget. The τ values for the US (0.137) and the UK (0.2) are taken from Holter et al. (2019), who estimate these progressivity parameters using micro data for the US and the UK. Finally, the fourth column represents how changes in τ affect the labor market outcomes at the steady state, when τ changes from 0 to 0.2.

Overall, progressive labor income taxation is beneficial to the workers on average, achieving higher social welfare. Among the three regimes, a tax regime akin to the UK, which is the most progressive, yields the highest social welfare. The impacts on labor market equilibrium outcomes are also significant. Progressive labor income taxation affects both the incomplete asset market and the frictional labor market. In terms of the asset market, the risk-free interest rate increases, encouraging workers' asset accumulation. With regards to the labor market, workers search less, leading to higher unemployment, and firms post fewer vacancies with lower wage rates, leading to a lower job offer arrival rate and lower average labor income.

Quantitatively, the tax system akin to the UK regime ($\tau = 0.2$) raises utilitarian social welfare by 2.37% in a normalized utilitarian welfare index relative to the no-tax benchmark. As higher progressivity compresses the net wage gains from climbing the wage ladder, it weakens incentives to search aggressively for better jobs

and induces workers to rely more on precautionary saving and less on precautionary search to smooth labor income risk. The disincentivized search effort dampens job finding and job-to-job mobility, which reduces mean wages (-3.29%), compresses labor income dispersion—as measured by the cross-sectional variance of pre-tax labor income(-17.63%), and increases unemployment ($+0.22$ % points), while the resulting higher demand for the risk-free asset pushes up the equilibrium interest rate ($+0.76$ % points) and leaves average wealth nearly unchanged ($+0.70\%$) despite a modest fall in average consumption (-0.39%). In the welfare dimension, a tax regime akin to the current UK policy dominates both a no-tax benchmark and a less progressive regime akin to the US tax policy: if the UK were to adopt a tax regime akin to the US that raises the same revenue, aggregate welfare in the calibrated economy would fall by 0.64 points in the normalized welfare index, from 102.37 to 101.73.

Specifically, Table 1.5 shows that progressive labor income taxation reduces workers' search effort, firms' vacancy posting, and the number and value of job offers. These changes in the labor market outcomes arise from the distortion of the future expected income increase on the worker side, and of firms' wage offers on the firm side. Progressive labor income taxation reduces the search effort of workers, as higher tax progressivity reduces the wage differences between each rung of the wage ladder. This reduced search effort disincentivizes the hiring and retention motive of firms, because the probability of a vacancy meeting a worker and the probability of a hired worker receiving a higher wage offer both fall. Firms have less incentive to attract a new worker, or to pay higher wages to keep a hired worker, which leads to decreases in the offered wage value and the number of vacancies. While both workers' search effort and firms' vacancy posting are weakened, vacancies fall by more than search. The job offer rate λ therefore decreases only slightly in equilibrium, because the meeting technology and free-entry condition dampen the number of job offers that arrive per unit of search. Accordingly, mean job offers fall by 4.85%

because, even though the equilibrium contact rate λ decreases only slightly, weaker search by unemployed workers and weaker on-the-job search by employed workers—reflected in slower upward job-to-job mobility—reduce the number of offers received by the average worker.[27] The weakened search effort of unemployed workers results in a lower job finding rate and a higher equilibrium unemployment rate.

In the asset market, the tax system akin to the UK regime raises the risk-free interest rate and leads to only a slight increase in average asset holdings. The increase in the equilibrium interest rate is caused by the weakened hiring and retention of firms: hiring and retention activities become less costly, as firms pay workers less and post fewer vacancies, which increases profits that are paid out to shareholders as higher returns on their asset holdings. Average asset holdings increase only modestly because two opposing forces offset each other: (i) due to the reduced labor income risk, there is a lower precautionary savings motive; (ii) due to the higher interest rate, workers choose to save more rather than search for a higher-paying job. The reduced labor income leads to a small decline in consumption, while the welfare gains reported above arise from improved insurance and equity that more than offset these modest efficiency costs.

Additional appendix counterfactuals show that the welfare gains from higher progressivity remain positive over a broader range of τ, although they become progressively smaller as tax progressivity rises.

[27] Mean Job Offer $= \lambda \int_{\underline{a}}^{\infty} \Big[\sigma(a,b)g(a,b) + \int_{b^+}^{\infty} \sigma(a,w)g(a,w)\,dw\Big]da = \lambda\bar{\sigma} + \lambda \int_{\underline{a}}^{\infty} \Big[(\sigma(a,b) - \bar{\sigma})g(a,b) + \int_{b^+}^{\infty} (\sigma(a,w) - \bar{\sigma})g(a,w)\,dw\Big]da$

In Table 1.5, mean job offers fall from 1.041 to 0.990, or by about 4.9%. This decline is almost entirely driven by lower endogenous search, since the free-search part changes only from 0.665 to 0.662, whereas the endogenous part falls from 0.376 to 0.328. For accepted upward job-to-job transitions, free search explains about one half of the level in both regimes, but the decline is driven by the endogenous part: the free-search contribution rises slightly from 0.0550 to 0.0573, while the endogenous contribution falls from 0.0526 to 0.0478.

Table 1.5: Three Tax Regime Outcomes

	No Tax ($\tau = 0$)	US ($\tau = 0.137$)	UK ($\tau = 0.2$)	% Changes (UK – No Tax)
Aggregate Welfare[1)]	100	101.73	102.37	+ 2.37%
		Labor Market		
Mean Wages (£)[2)]	2,184	2,132	2,113	– 3.29%
Labor Income Variance[3)]	1.29	1.11	1.06	– 17.63%
Unemployment Rate (%)	2.86	3.01	3.08	+ 0.22%p
Job Offer Rate (λ)[4)]	1.899	1.892	1.892	– 0.41%
Mean Job Offer[4)]	1.041	1.005	0.990	– 4.85%
Mean Search Effort[1)]	100	96.91	95.54	– 4.46%
Total Vacancies Measure	1.9772	1.9015	1.8735	– 5.25%
		Incomplete Asset Market		
Mean Assets (£)	94,772	95,446	95,437	+ 0.70%
Interest Rate (%)	3.24	3.80	4.00	+ 0.76%p
Mean Consumption (£)[2)]	2,440	2,433	2,431	– 0.39%
ϵ	1	1.1472	1.2188	

Notes: The simulation results are presented in an easily interpretable unit.
1) The outcomes for aggregate welfare and mean search effort in the no-tax scenario are normalized to 100 to illustrate the changes under US and UK taxation policies, as the numeric values in the model do not have intrinsic meaning.
2) Mean wages and mean consumption are calculated on a monthly frequency.
3) Reported labor income variance refers to the cross-sectional variance of pre-tax labor income in the stationary equilibrium.
4) The job offer rate λ represents the mean of job offers received per unit of search effort over a year. The mean job offer refers to the mean of job offers an individual worker receives annually.

1.5.2 The effects of labor income taxation across three models

The purpose of this exercise is to show why extending the partial-equilibrium framework of Lise (2013) to a full general equilibrium environment with endogenous labor demand, wage posting, and an endogenous risk-free interest rate is crucial for understanding the effects of progressive labor income taxation. By systematically comparing tax experiments across three models with different degrees of endogenization, the subsection highlights how the quantitative and welfare implications of higher

progressivity change once firms' vacancy posting and wage offers, as well as the equilibrium interest rate, are allowed to respond, and it shows that the most economically relevant mechanisms through which tax progressivity operates—particularly the profit and asset-price channels—emerge only in the fully specified general equilibrium case.

Specifically, I compare the effects of two different tax regime scenarios—tax akin to the US and tax akin to the UK— across three models with different levels of endogenization. The first model is a general equilibrium model with three endogenous components, which is the baseline model discussed above. The equilibirum objects are as follows: the workers' problem choosing search effort $\sigma(a, w)$ and consumption policies $c(a, w)$, the firms' problem determining the endogenous wage offer distribution $F(w)$, the vacancy measure v and job offer arrival rate λ, and last, asset market clearing which determines the equilibrium interest rate r.

Next, the second model modifies the baseline model by shutting down the endogenous wage formation and firm entry. This leads to a general equilibrium model without the firm endogeneity. This model is similar to much of the existing literature in random on-the-job search models (Mousavi, 2022; Cajner et al., 2025).

Lastly, the third model is a partial equilibrium model with endogenous worker job search and savings, taking the risk-free interest rate r given. This model is similar to the partial equilibrium model of Lise (2013) in that it only focuses on how workers' decisions on savings and search affect each other, given the prices and job offer arrival rate are fixed.

Figure 1.1 displays the effects of moving from the no-tax benchmark to US- and UK-style tax regimes across three models with different degrees of endogenization. Panels (e) and (f) summarize the main differences in welfare and unemployment. In the partial equilibrium model, welfare decreases when progressive labor income taxation is introduced, from -1.51% under the US regime to -2.15% under the UK

regime, while the unemployment rate decreases only modestly, by 0.03 percentage point under both regimes. In the general equilibrium model with an exogenous wage offer distribution, welfare improves under more progressive taxation, from 0.95% to 1.33%, and the unemployment rate rises from 0.09 to 0.14 percentage point, as the higher interest rate strengthens the precautionary savings motive and partially replaces precautionary search. In the fully endogenized baseline model, welfare increases the most, from 1.73% under the US regime to 2.37% under the UK regime, but the unemployment rate also rises the most, from 0.15 to 0.22 percentage point, reflecting the strongest weakening of the search motive. The patterns in panels (a)–(d) are consistent with these welfare and unemployment results: mean wages and wage dispersion fall most in the baseline model, mean wealth rises slightly only in the baseline model, and the risk-free interest rate rises most in the baseline model, where firm profits and asset returns adjust in general equilibrium.

The economic mechanisms behind these differences operate through the interaction of precautionary search, precautionary saving, and firm profits. Panels (a) and (b) relate to the precautionary search margin. Progressive labor income taxation reduces the wage differences between each rung of the wage ladder, which weakens the expected gains from future wage improvements and lowers workers' incentives to search aggressively for better jobs. In the fully endogenized model, workers' disincentivized search reduces firms' wage policies, the level of vacancies, and the mean job offers that workers receive. Lower search induces firms to cut wages and vacancies, which further reduces the return to search, so workers search least in the baseline model. This is why mean wages fall by 2.43% under the US regime and 3.29% under the UK regime in the baseline model, compared with 0.59% and 0.87% in the model with exogenous wages and only 0.12% and 0.21% in partial equilibrium. Similarly, wage variance declines by 13.09% and 17.63% in the baseline model, compared with 1.09% and 1.62% in the model with exogenous wages and 0.46% and 0.72% in partial equilibrium. In the general equilibrium model with an exogenous

Figure 1.1: Changes under US/UK tax policies across Three models



(a) Mean Wages[1)] (b) Wage Variance[1)]

(c) Mean Wealth[1)] (d) Interest Rate[2)]

(e) Welfare[1)] (f) Unemployment Rate[2)]

Notes: 1) Changes from no-tax scenario to US/UK tax policies are in percent (%).
2) Changes from no-tax scenario to US/UK tax policies are presented in percentage point (%p).

wage distribution, and in the partial equilibrium model, firms' wage policies and the level of vacancies do not react to disincentivized search, so the feedback from lower search into wages and vacancies is muted. In all three models, however, lower search makes workers move up the wage ladder more slowly and leads to a greater concentration of wages at the lower end, so wage variance declines as shown in panel (b).

Panels (c) and (d) highlight the precautionary savings and asset market channel. As

tax progressivity τ increases, firm profits increase as the wage–productivity share decreases and vacancy costs fall, especially in the baseline model where vacancy posting is endogenous. Therefore, the market interest rate r rises the most in the baseline model, by 0.56 percentage point under the US regime and 0.76 percentage point under the UK regime. Compared to a partial equilibrium model with a fixed interest rate, the reduction in the precautionary savings motive is offset to a large extent by the higher return on assets, so workers choose to save more rather than search for a higher-paying job. Accordingly, mean wealth in the baseline model rises slightly to 0.71% under the US regime and remains positive at 0.70% under the UK regime. The slight decline in mean wealth when moving from the US to the UK regime reflects the fact that the stronger wage compression in the UK case—mean wages fall by 3.29% rather than 2.43%—reduces labor income and partially offsets the additional saving incentive coming from the higher interest rate. In the general equilibrium model with an exogenous wage offer distribution, the increase in r is smaller, at 0.25 percentage point under the US regime and 0.37 percentage point under the UK regime, because asset demand does not change significantly when wages fall by less and vacancy costs remain fixed. As a result, mean wealth falls by 9.64% under the US regime and 13.67% under the UK regime. In the partial equilibrium model, where the interest rate is fixed, mean wealth falls much more sharply, by 28.61% under the US regime and 40.13% under the UK regime. Finally, firm profits tie these mechanisms together across models. Progressive labor income taxation compresses wages and reduces vacancy posting, so that labor costs fall by more than revenues. In the fully endogenized model, this raises profits and, through the mutual-fund ownership structure, translates into a higher risk-free return on workers' assets. When wages and vacancies are held exogenous, as in the general equilibrium model without firm-side endogeneity and in the partial equilibrium model, this profit channel is muted or shut down. As a result, the interest rate responds less and the additional insurance that workers can obtain through the asset market is weaker. Firm profits therefore play a central role in amplifying both

the welfare gains and the unemployment costs of progressive labor income taxation in the fully endogenized environment.

1.5.3 Comparison with Michau (2021)

Relative to Michau (2021), the relevant comparison is his fixed-progressivity exercise rather than his fully optimal nonlinear policy. In that exercise, Michau (2021) studies a partial-equilibrium worker-side environment with random on-the-job search, precautionary savings, an exogenous wage-offer distribution, and an exogenous interest rate. He shows that higher progressivity raises unemployed workers' search intensity and lowers unemployment, while reducing on-the-job search and output; with private savings, welfare gains within this restricted class are maximised at a low degree of progressivity and turn negative as progressivity rises further. The partial-equilibrium version of my model is closest to this environment, since it likewise isolates workers' search and saving responses while shutting down firm-side feedback. In that sense, the partial equilibrium results in my model should be read through the same worker-side insurance–incentives logic as in Michau (2021): greater progressivity compresses the gains from climbing the wage ladder, weakens the precautionary search motive, slows job-to-job mobility, and can therefore generate weak welfare effects, or even welfare losses.

Once the equilibrium interest rate is endogenized, workers substitute away from precautionary search towards precautionary savings, moving the economy away from Michau (2021)'s partial equilibrium model. Once firm wage posting and vacancy creation are also endogenized, lower search feeds back into fewer vacancies, lower wage offers, and lower mean wages, so unemployed workers face not only safer earnings if employed but also fewer and worse job opportunities. The comparison across the three models can therefore be read as tracing the economy from a Michau-style worker-side benchmark to a fully endogenous environment in which labor

demand and asset returns also respond; this is why the fully endogenous model produces the largest changes in wages, vacancies, unemployment, and welfare.

1.6 Conclusion

This paper has asked how progressive labor income taxation affects social welfare, wage inequality, and macroeconomic outcomes in a frictional labor market where workers can only imperfectly self-insure. I study this equity–efficiency trade-off in a random on-the-job search model with incomplete markets that endogenizes three key blocks: workers' job search and precautionary savings, firms' wage and vacancy posting, and the equilibrium risk-free interest rate. In this environment, taxes change not only the distribution of post-tax wages but also the returns to search and savings, the structure of the job ladder, and the way risk is insured through the labor market and the asset market.

Quantitatively, the analysis shows that a tax regime akin to the current UK system raises utilitarian social welfare relative to a no-tax benchmark, and that this welfare gain is large enough for the UK-style regime to dominate a less progressive, revenue-neutral US-style schedule. In the model, higher progressivity mainly operates by affecting the search and saving motives: compressed wage gains along the job ladder weaken search incentives and slow job finding and job-to-job upgrading, while lower labor costs raise firm profits and, through mutual-fund ownership, the risk-free interest rate. As a result, in addition to the equity gains from redistribution, progressive labor income taxation lowers wages and increases unemployment but compresses mean and dispersion of wages and improves insurance, with asset income cushioning the loss in labor income so that the net effect on social welfare is positive. This welfare improving pattern extends to a broader range of tax progressivity, while the marginal welfare gain becomes smaller at higher values of

τ.

Relative to Lise (2013), who study workers' search and savings in partial equilibrium with exogenous wages and interest rates, my framework adds explicit labor demand and full general equilibrium. Firms post wages and vacancies, free entry pins down the vacancy measure and job-offer arrival rate, and workers own firms so that the risk-free interest rate is determined endogenously. By nesting two simpler environments—a general equilibrium model without firm-side wage formation and entry, and a partial equilibrium model with an exogenous interest rate—I show that endogenizing both labor demand and the asset market is crucial for evaluating progressive labor income taxation: in the partial equilibrium model, progressive taxation lowers welfare, whereas in the fully endogenized model the profit and interest rate channels are strong enough to generate welfare gains.

The analysis has limitations in its model set-up. First, the separation rate is exogenous and identical across jobs, so the model cannot capture the empirically observed pattern that high-wage jobs tend to be more stable. This likely understates the stability premium from moving up the job ladder and may overstate the attractiveness and acceptance of low-wage jobs, with implications for the model's job mobility patterns. In addition, the framework does not model heterogeneity in assets at labor market entry, such as student debt and tight liquidity constraints faced by young workers; in practice, negative wealth can push debt-laden entrants into low-wage, low-stability jobs and generate path dependence and early-career scarring in lifetime earnings that the current model cannot fully capture. Allowing for endogenous separations and a life-cycle structure with realistic entry assets and debt would provide a richer assessment of how progressive labor income taxation interacts with job ladder dynamics.

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Appendix

1.A Derivation of the HJB equation

This appendix derives the workers' Hamilton–Jacobi–Bellman (HJB) equation from a discrete time equation with time periods of length Δ_t and then taking the limit as $\Delta_t \to 0$, and shows that the HJB equations of the unemployed and the employed can be written as the single equation. The derivation uses a standard continuous time Bellman equation approach and follows Lise (2013, Appendix A.1), but is adapted here to the present environment with progressive labor income taxation and the notation of this study.

$$
\begin{aligned}
\upsilon(a,w,t) = \max_{c\in[0,a-\underline{a}],\sigma\geq 0} \Bigg\langle & \left[u\left(c(a,w,t)\right) - \psi(\sigma(a,w,t)\right]\Delta_t \\
& + \frac{1}{1+\rho\Delta_t}[\lambda\sigma\Delta_t \int \max\{\upsilon(a+\Delta_a,\tilde{w},t+\Delta_t),\ \upsilon(a+\Delta_a,w,t+\Delta_t)\}dF(\tilde{w}) \\
& + \Delta_t U(a+\Delta_a,t+\Delta_t) + (1-\lambda\sigma\Delta_t-\delta\Delta_t)\upsilon(a+\Delta_a,\ w,\ t+\Delta_t) + o(\Delta_t)] \Bigg\rangle
\end{aligned}
$$

where $o(\Delta_t)$ is the term that goes to zero faster than Δ_t. Multiplying $1+\rho\Delta_t$ yields

$$
\begin{aligned}
\rho\Delta_t\upsilon(a,w,t) = \max_{c\in[0,a-\underline{a}],\sigma\geq 0} \Bigg\langle & (1+\rho\Delta_t)\left[u\left(c(a,w,t)\right) - \psi(\sigma(a,w,t)\right]\Delta_t \\
& + [\lambda\sigma\Delta_t \int \max\{\upsilon(a+\Delta_a,\tilde{w},t+\Delta_t) - \upsilon(a+\Delta_a,w,t+\Delta_t),\ 0\}dF(\tilde{w}) \\
& + \delta\Delta_t[U(a+\Delta_a,t+\Delta_t) - \upsilon(a+\Delta_a,w,t+\Delta_t)] + [\upsilon(a+\Delta_a,w,t+\Delta_t) \\
& - \upsilon(a,w,t)] + o(\Delta_t)] \Bigg\rangle
\end{aligned}
$$

Dividing by Δ_t and taking the limit as $\Delta_t \to 0$, I obtain

$$\begin{aligned}\rho\upsilon(a,w,t) = \max_{c\in[0,a-\underline{a}],\sigma\geq 0} \Bigg\langle & (1+\rho\Delta_t)\left[u\left(c(a,w,t)\right) - \psi(\sigma(a,w,t)\right] \\ & + \left[\lambda\sigma \int \max\{\upsilon(a+\Delta_a,\tilde{w},t+\Delta_t) \; - \; \upsilon(a+\Delta_a,w,t+\Delta_t),\; 0\} dF(\tilde{w})\right. \\ & + \delta[U(a+\Delta_a,t+\Delta_t) \; - \; \upsilon(a+\Delta_a,w,t+\Delta_t)] \\ & \left. + \frac{\upsilon(a+\Delta_a,w,t+\Delta_t) \; - \; \upsilon(a,w,t)}{\Delta_t} \; + \; \frac{o(\Delta_t)}{\Delta_t}\right] \Bigg\rangle\end{aligned}$$

Since $lim_{\Delta_t\to 0}\frac{\upsilon(a+\Delta_a,\,w,\,t+\Delta_t)\,-\,\upsilon(a,\,w,\,t)}{\Delta_t} = \upsilon_a\frac{da}{dt}$ and $lim_{\Delta_t\to 0}\frac{o(\Delta_t)}{\Delta_t} = 0$,

$$\begin{aligned}\rho\upsilon(a,w,t) = \max_{c\in[0,a-\underline{a}],\sigma\geq 0} \Bigg\langle & \left[u\left(c(a,w,t)\right) - \psi(\sigma(a,w,t)\right] \\ & + \left[\lambda\sigma \int \max\{\upsilon(a,\tilde{w},t) \; - \; \upsilon(a,w,t),\; 0\} dF(\tilde{w})\right. \\ & \left. + \delta[U(a,t) \; - \; \upsilon(a,w,t)] \; + \; \upsilon_a(a,w,t)\left(\epsilon w^{1-\tau} + ra - c\right)\right] \Bigg\rangle\end{aligned}$$

1.B Reservation wage

This appendix adapts the proof of Proposition 1 in Lise (2013, Appendix A.1) to the present model and notation, which include progressive labor income taxation. Let the reservation wage at each asset level a be denoted by $\tilde{w}(a)$, defined implicitly by

$$\upsilon^e(a,\tilde{w}(a)) = \upsilon^u(a).$$

The value of unemployment, $\upsilon^u(a)$, depends only on the asset level a, reflecting the fact that the reservation wage of the unemployed does not depend on the current wage level.

Using the relationship between employment with the reservation wage and unem-

ployment, the HJB equation of the unemployed gives

$$\begin{aligned}\rho v^u(a) &= u\left(c(a,b)\right) + \lambda\sigma(a,b)\int_{\tilde{w}(a)}\left[v^e(a,x) - v^u(a)\right]dF(x)\\ &\quad + v^u_a(a)\left(\epsilon b^{1-\tau} + ra - c(a,b)\right) - \psi(\sigma(a,b))\\ &= u\left(c(a,\tilde{w}(a))\right) + \lambda\sigma(a,\tilde{w}(a))\int_{\tilde{w}(a)}\left[v^e(a,x) - v^e(a,\tilde{w}(a))\right]dF(x)\\ &\quad + v^e_a(a,\tilde{w}(a))\left(\epsilon\tilde{w}(a)^{1-\tau} + ra - c(a,\tilde{w}(a))\right) - \psi(\sigma(a,\tilde{w}(a)))\\ &= \rho v^e(a,\tilde{w}(a)).\end{aligned}$$

Using the first order conditions for consumption in the HJB equation, I substitute $u'(c) = v^u_a(a) = v^e_a(a,\tilde{w}(a))$, yielding

$$\begin{aligned}&u\left(c(a,b)\right) - u\left(c(a,\tilde{w}(a))\right) + \left[\lambda\sigma(a,b) - \lambda\sigma(a,\tilde{w}(a))\right]\int_{\tilde{w}(a)}\left[v^e(a,x) - v^e(a,\tilde{w}(a))\right]dF(x)\\ &+ v^u_a(a)\left(\epsilon b^{1-\tau} + ra - c(a,b)\right) - v^e_a(a,\tilde{w}(a))\left(\epsilon\tilde{w}(a)^{1-\tau} + ra - c(a,\tilde{w}(a))\right)\\ &- \psi(\sigma(a,b)) + \psi(\sigma(a,\tilde{w}(a))) = 0,\end{aligned}$$

which shows the solution as follows:

$$\sigma(a,\tilde{w}(a)) = \sigma(a,b),\ \ c(a,\tilde{w}(a)) = c(a,b),\ \ \tilde{w}(a) = b.$$

Thus, as in Lise (2013), the reservation wage is constant and equal to b, and hence independent of the asset position a.

1.C HJB increasing in w and a

The monotonicity of the value function is standard; see (Lise, 2013, Appendix A, Lemma A4). While my proof works directly with a single continuous-time Bellman equation and first-order conditions, and thus differs from Lise (2013), it establishes

the same result as in Lise (2013), adapting to a tax environment in which net-of-tax income $\epsilon w^{1-\tau}$ is increasing in w.

Define the superscript * to denote an agent's optimal decision. Given assets a and income w, c^* defines optimal consumption level, σ^* the optimal search effort and W^* the set of all wage offers one will accept. Substitute these optimal decisions and the first order condition for consumption gives the expression

$$\upsilon(a,w) = \frac{1}{\rho+\delta+\lambda\sigma^*}\Big(u(c^*) + \lambda\sigma^* \int_{\tilde{w}\in W^*} \upsilon(a,\tilde{w})dF(\tilde{w}) + \delta\upsilon(a,b) + u'(c^*))\left(ra + \epsilon w^{1-\tau} - c^*\right) - \psi(\sigma^*)\Big).$$

where for example, c^* is the optimal level of consumption, given a and w, by the envelope condition for arbitrary $\hat{a}$ and $\hat{w}$ we know that

$$\upsilon(\hat{a},\hat{w}) \geq \frac{1}{\rho+\delta+\lambda\sigma^*}\Big(u(c^*) + \lambda\sigma^* \int_{\tilde{w}\in W^*} \upsilon(\hat{a},\tilde{w})dF(\tilde{w}) + \delta\upsilon(\hat{a},b) + u'(c^*))\left(r\hat{a} + \epsilon \hat{w}^{1-\tau} - c^*\right) - \psi(\sigma^*)\Big).$$

Substituting in the expression for $\upsilon(a,w)$ gives

$$\upsilon(\hat{a},\hat{w}) \geq \upsilon(a,w) + \frac{u'(c^*))\left(r(\hat{a}-a) + \epsilon(\hat{w}^{1-\tau} - w^{1-\tau})\right)}{\rho+\delta+\lambda\sigma^*}.$$

Thus for $\hat{a} > a$, $\upsilon(\hat{a},w) > \upsilon(a,w)$ and for $\hat{w} > w$ and $\tau \neq 1$, $\upsilon(a,\hat{w}) > \upsilon(a,w)$.

1.D Joint distribution of assets and income

In this appendix, I derive the Kolmogorov–Forward equations that characterize the stationary joint distribution of workers over assets and income, $g(a,w)$.

Forgetting temporarily about income changes, assuming $s(a,w) \leq 0$, the case of

$s(a,w) > 0$ is symmetric.

$$\Pr(\tilde{a}_{t+\Delta_t} \leq a) = \underbrace{\Pr(\tilde{a}_t \leq a)}_{\text{already below threshold } a} + \underbrace{\Pr(a \leq \tilde{a}_t \leq a - \Delta_t s(a,w))}_{\text{cross threshold } a} = \Pr(\tilde{a}_t \leq a - \Delta_t s(a,w))$$

So, the probability a worker of wage w has assets $a' \in (a - \Delta_a, a + \Delta_a]$ is given by

$$\begin{aligned}\Pr(a - \Delta_a < \tilde{a}_{t+\Delta_t} \leq a + \Delta_a) = \Pr(\tilde{a}_t &\leq a + \Delta_a - \Delta_t s(a + \Delta_a, w)) \\ &- \Pr(\tilde{a}_t \leq a - \Delta_a - \Delta_t s(a - \Delta_a, w))\end{aligned}$$

Define the cdf $G(a,w,t)$ as the measure of workers earning less than a wage w and endowed with assets less than a at time t.[28] The cdf $G(a,w,t)$ is defined the integral of the joint pdf $g(a,w,t)$, such that

$$G(a,w,t) = \int^{w} \int^{a} g(a',w',t) da' dw'.$$

Thus the derivative of $G(a,w,t)$ with respect to w is labelled $G_w(a,w,t)$ and is the measure of workers earning a wage w with assets less than or equal to a. Consider an unemployed worker with income b. The change in the measure of workers with assets $a' \in (a - \Delta_a, a + \Delta_a]$ in a period of time Δ_t is given by the expression below.

$$\begin{aligned}&G_w(a + \Delta_a, b, t + \Delta_t) - G_w(a - \Delta_a, b, t + \Delta_t) = \\ &\quad \Big(1 - \Delta_t \lambda \sigma(a,b)\Big(1 - F(b)\Big)\Big)\Big(G_w(a + \Delta_a - \Delta_t s(a + \Delta_a, b), b, t) \\ &\qquad\qquad - G_w(a - \Delta_a - \Delta_t s(a - \Delta_a, b), b, t)\Big) \\ &\quad + \Delta_t \delta \int_{b^+}^{\overline{w}} \left(G_{w'}(a + \Delta_a - \Delta_t s(a + \Delta_a, w'), w', t) - G_{w'}(a - \Delta_a - \Delta_t s(a - \Delta_a, w'), w', t)\right) dw'\end{aligned}$$

The first term on the right hand side are those workers who do not find a better paying job and remain in the asset bound. The second term captures workers who were previously employed and are laid off and fall within the asset boundary. Sub-

[28] In steady-state the distribution will be time invariant but it helps with the exposition to include t at this stage.

tract both sides by $G_w(a+\Delta_a, b, t) - G_w(a-\Delta_a, b, t)$, divide by Δ_t, and take limit as $\Delta_t \to 0$. The left hand side of the expression becomes:

$$\begin{aligned}
\text{LHS} &= \lim_{\Delta_t \to 0} \left\langle \frac{G_w(a+\Delta_a, b, t+\Delta_t) - G_w(a+\Delta_a, b, t)}{\Delta_t} - \frac{G_w(a-\Delta_a, b, t+\Delta_t) - G_w(a-\Delta_a, b, t)}{\Delta_t} \right\rangle \\
&= \partial_t G_w(a+\Delta_a, b, t) - \partial_t G_w(a-\Delta_a, b, t) \qquad \text{which in steady-state} \\
&= 0
\end{aligned}$$

The first term on the right hand side becomes:

$$\begin{aligned}
\text{RHS}_1 &= \lim_{\Delta_t \to 0} \left\langle \frac{G_w(a+\Delta_a - \Delta_t s(a+\Delta_a, b), b, t) - G_w(a+\Delta_a, b, t)}{\Delta_t} \right\rangle \\
&= \lim_{x \to 0} \left\langle \frac{G_w(a+\Delta_a - x, b, t) - G_w(a+\Delta_a, b, t)}{x} \right\rangle s(a+\Delta_a, b) \\
&= -s(a+\Delta_a, b) g(a+\Delta_a, b, t) \qquad \text{given, steady-state} \\
&= -s(a+\Delta_a, b) g(a+\Delta_a, b)
\end{aligned}$$

Dropping the t subscripts, the whole expression can be written as

$$\begin{aligned}
0 = &-s(a+\Delta_a, b) g(a+\Delta_a, b) + s(a-\Delta_a, b) g(a-\Delta_a, b) \\
&- \lambda \sigma(a, b) \left(1 - F(b)\right) \Big(G_w(a+\Delta_a, b) - G_w(a-\Delta_a, b) \Big) \\
&+ \delta \int_{b^+}^{\overline{w}} \left(G_{w'}(a+\Delta_a, w') - G_{w'}(a-\Delta_a, w') \right) dw'
\end{aligned}$$

Dividing by $2\Delta_a$ and take limit as $\Delta_a \to 0$.

$$\frac{\partial}{\partial a} \left(s(a, b) g(a, b) \right) = -\lambda \sigma(a, b) \left(1 - F(b)\right) g(a, b) + \delta \int_{b^+}^{\overline{w}} g(a, w') dw'$$

(KF: unemployed)

For $w > b$, the same approach is followed, so

$$
\begin{aligned}
&G_w(a+\Delta_a, w, t+\Delta_t) - G_w(a-\Delta_a, w, t+\Delta_t) \\
&\quad = \big(1-\Delta_t\delta - \Delta_t\lambda\sigma(a,w)\big(1-F(w)\big)\big)\Big(G_w(a+\Delta_a - \Delta_t s(a+\Delta_a, w),\, w,\, t) \\
&\qquad\qquad - G_w(a-\Delta_a - \Delta_t s(a-\Delta_a, w),\, w,\, t)\Big) \\
&\qquad + \Delta_t\lambda f(w)\int_{b^+}^{w}\sigma(a,w')\Big(G_{w'}(a+\Delta_a - \Delta_t s(a+\Delta_a, w'),\, w',\, t) \\
&\qquad\qquad - G_{w'}(a-\Delta_a - \Delta_t s(a-\Delta_a, w'),\, w',\, t)\Big)\, dw' \\
&\qquad + \Delta_t\lambda f(w)\sigma(a,b)\Big(G_w(a+\Delta_a - \Delta_t s(a+\Delta_a, b),\, b,\, t) \\
&\qquad\qquad - G_w(a-\Delta_a - \Delta_t s(a-\Delta_a quad \qquad\qquad b),\, b,\, t)\Big).
\end{aligned}
$$

Successively, both sides of the above expression are subtracted by $G_w(a+\Delta_a, w, t) - G_w(a-\Delta_a, w, t)$, divided by Δ_t, and the limit taken as $\Delta_t \to 0$.

$$
\begin{aligned}
0 = &-s(a+\Delta_a, w)g(a+\Delta_a, w) + s(a-\Delta_a, w)g(a-\Delta_a, w) \\
&- \left(\delta + \lambda\sigma(a,w)\left(1-F(w)\right)\right)\Big(G_w(a+\Delta_a, w) - G_w(a-\Delta_a, w)\Big) \\
&+ \lambda f(w)\int_{b^+}^{w}\sigma(a,w')\left(G_{w'}(a+\Delta_a, w') - G_{w'}(a-\Delta_a, w')\right)dw' \\
&+ \lambda f(w)\sigma(a,b)\left(G_w(a+\Delta_a, b) - G_w(a-\Delta_a, b)\right)
\end{aligned}
$$

Dividing by $2\Delta_a$ and take limit as $\Delta_a \to 0$.

$$
\begin{aligned}
\frac{\partial}{\partial a}\left(s(a,w)g(a,w)\right) = &-\left(\delta + \lambda\sigma(a,w)\left(1-F(w)\right)\right)g(a,w) + \lambda f(w)\int_{b^+}^{w}\sigma(a,w')g(a,w')dw' \\
&+\ \lambda f(w)\sigma(a,b)g(a,b) \qquad\qquad \text{(KF: employed)}
\end{aligned}
$$

1.E Computation

I solve the model numerically as a coupled system of Hamilton-Jacobi-Bellman (HJB) and Kolmogorov-Forward (KF) equations in continuous time. Given an in-

terest rate r, a job offer arrival rate λ, and a wage schedule $w(z)$, I first solve the worker block and the stationary distribution; taking these as given, I then solve firms' value and wage posting problem and impose a free-entry condition to pin down λ. Finally, I update the interest rate using the asset market clearing condition. The overall algorithm is thus a fixed point in $(r, \lambda, w(\cdot), g(\cdot))$.[29]

State space and grids The continuous state space consists of assets $a \in [\underline{a}, \bar{a}]$ and match-specific productivity z. I discretize the asset space on an equidistant grid of size A between a borrowing limit $\underline{a} = 0$ and an upper bound $\bar{a}$, and discretize z on a $(Z+1)$-point grid constructed from a truncated lognormal distribution. Wages are represented by a wage schedule $w(z)$ defined on the z-grid. The interest rate r is an endogenous object; numerically, I search over an interval $[r_{\min}, r_{\max}]$ and update r via bisection using the asset market clearing condition.

Workers' HJB and stationary distribution Given $(r, \lambda, w(z))$, workers solve a continuous-time HJB problem with two controls: consumption $c(a, w)$ and search effort $\sigma(a, w)$. On the (a, z) grid, I approximate the derivative with respect to assets using an upwind finite-difference scheme. For each grid point, I compute the asset drift

$$s(a, w) = ra + \epsilon w^{1-\tau} - c(a, w),$$

and choose forward (backward) differences whenever $s > 0$ ($s < 0$), with a boundary condition at the borrowing limit. This yields a sparse tridiagonal operator in the asset dimension, and I add a block structure representing exogenous job separations at rate δ.

[29]For the worker block, the numerical method is based on the continuous-time HJB-KF algorithm used in recent heterogeneous-agent models with incomplete markets. For a detailed exposition in a simpler Aiyagari-Bewley-Huggett environment, see Achdou et al. (2022, Section 5).

The HJB equation is written in matrix form as an implicit time-iteration scheme,

$$(\rho + 1/\Delta)V = u(c) - \psi(\sigma) + \mathcal{A}V + V/\Delta,$$

where $\mathcal{A}$ is the sparse matrix that summarizes the discretized law of motion in the HJB, determined by $s(a, w)$ and the separation hazard. Given a current guess V, I compute forward and backward finite differences for V_a, back out optimal consumption and savings from the Euler equation, and compute search effort $\sigma(a, w)$ from the first-order condition for search using the option value of moving up the wage ladder. I then construct the sparse matrix $B = (\rho + 1/\Delta)I - \mathcal{A}$ and solve the linear system $BV = b$ for the updated value function, where b collects flow utility and search costs. This iteration continues until the change in V is below a tolerance. The resulting value function yields policy functions $c(a, w)$, $s(a, w)$, and $\sigma(a, w)$ on the grid.

Given these policy functions, I compute the stationary joint distribution $g(a, w)$ from the Kolmogorov-Forward equation based on the same finite-difference discretization. In addition to the drift in assets and exogenous job destruction, the law of motion for g incorporates flows across wage states induced by on-the-job search. In the code, I construct a large sparse transition matrix $\mathcal{A}^g$ by combining (i) the finite-difference discretization of the asset drift and separation risk and (ii) additional blocks that move mass from current wages to higher wages according to search intensity $\sigma(a, w)$, the job offer rate λ, and the wage offer distribution, and subtract the corresponding outflow. Stacking the distribution on the (a, z) grid into a vector g, the stationary distribution solves

$$(\mathcal{A}^g)'g = 0,$$

together with the normalization condition that the integral of g equals one.

Firms' value and wage posting Holding (r, λ), workers' policy functions, and the stationary distribution g fixed, I next solve the firms' problem. A vacancy meets workers in proportion to their search intensity, so the relevant cross-sectional density from the firm's perspective is

$$\Phi_{aw}(a, w) = \frac{\sigma(a, w)\, g(a, w)}{S}, \qquad S = \int \sigma(a, w)\, g(a, w)\, da\, dw,$$

and the cumulative distribution in the wage dimension is obtained by summing Φ_{aw} along the wage grid.

For each productivity grid point z_k, and for a given wage schedule $w(z)$, I solve the value of a filled job $J(a, w(z_k), z_k)$ from a linear Bellman equation,

$$(r + \delta + \lambda\sigma(a, w)\, \overline{F}(w))\, J(a, w, z) = z - w + J_a(a, w, z)\, s(a, w),$$

discretized in the asset dimension by the same upwind finite-difference scheme as in the worker problem. This yields a tridiagonal operator with an effective discount rate that collects the interest rate, separation risk, and poaching hazard. I then recover J_a by finite differences. The resulting firm value function $J(a, w, z)$ summarizes how job values vary with workers' assets and wages and with match productivity.

The optimal wage policy is computed recursively along the productivity grid. Starting from the boundary condition $w(b) = b$, I parameterize the wage schedule as

$$w(z_{k+1}) = w(z_k) + w'(z_k)\, (z_{k+1} - z_k),$$

and for each interior grid point z_k I choose the slope $w'(z_k)$ so that a discrete version of the firm's first-order condition for wage posting is satisfied. This condition balances the marginal cost of a higher wage (through lower flow profits and a lower value of a job) against the marginal benefits in terms of higher hiring and retention, and is computed using J, J_a, Φ_{aw}, and its cumulative version. Numerically, I solve for

$w'(z_k)$ by a simple bisection procedure on a compact interval, construct the implied $w(z_{k+1})$, and iterate over the grid. After constructing a candidate wage schedule $w_{\text{new}}(z)$, I update it by taking the simple average of the old and new schedules and repeat the HJB-KF-firm block until the wage policy converges.

Free entry, matching, and interest rate Once the wage schedule has converged for given (r, λ), I impose a free-entry condition to update λ. Given the firm value functions $J(a, w(z_k), z_k)$, I compute the expected value of a filled job for each productivity level,

$$\Pi(z_k) = \int J(a, w(z_k), z_k)\, \Phi_a(a, w(z_k))\, da,$$

and aggregate across productivity states using the exogenous productivity distribution Γ to obtain $\int \Pi(z)\, d\Gamma(z)$. Letting S denote aggregate search effort and $AS(r)$ denote aggregate asset holdings, the code exploits the equilibrium relationship between vacancy values, aggregate profits, interest payments, and vacancy costs to implement a scalar free-entry condition of the form

$$S\lambda \int \Pi(z)\, d\Gamma(z) = \Pi - r\, AS(r),$$

where Π is aggregate firm surplus computed from $(y(z(w)) - w)$ and $g(a, w)$. This condition is algebraically equivalent, in equilibrium, to combining the free-entry condition for vacancies with the asset market clearing condition, and allows me to update λ directly as

$$\lambda_{\text{new}} = \frac{\Pi - r\, AS(r)}{S \int \Pi(z)\, d\Gamma(z)}.$$

Given the updated λ, I compute the implied measure of vacancies from the matching function. With a Cobb-Douglas meeting function $m(S, v) = \text{match} \cdot S^{\text{elast}} v^{1-\text{elast}}$,

the job offer arrival rate satisfies $\lambda = m(S, v)/S$, which can be inverted to obtain

$$v = S \left(\frac{\lambda}{\text{match}} \right)^{1/(1-\text{elast})}.$$

The asset market clearing condition in the model reads

$$r \cdot AS(r) = \Pi - \kappa v,$$

where the right-hand side is aggregate firm profits net of vacancy costs and the left-hand side is the return on workers' asset holdings. In the code, I compute $AS(r)$ and Π from the stationary distribution and the wage schedule, construct the vacancy measure v from the matching function as above, and update the interest rate r via bisection on $[r_{\min}, r_{\max}]$ until the residual $r\,AS(r) - \Pi + \kappa v$ is sufficiently small.

1.F UKHLS analysis sample and external benchmarks for the UK working age population

The UKHLS analysis sample used in Chapter 1 is a cleaned monthly panel constructed from UKHLS waves 1–10, covering 2009–2019, and restricted to individuals aged 16–60. After imposing the hours and wage-quality restrictions, respondents who are never observed in a full-time paid employee job are excluded, so the final sample consists of individuals with at least one observed full-time paid employee spell rather than all British workers. To benchmark this selected sample, I use external official statistics aligned to 2019, the end of the UKHLS sample window. Relative to these external benchmarks, the UKHLS analysis sample has a broadly similar gender composition, but it is more strongly attached to the labor market, with a higher employment share (79.5% versus 76.1%) and a lower inactivity share (15.8% versus 20.8%); this is exactly the pattern one would expect for a sample selected on having at least some full-time paid employee experience. The education

comparison points in the same direction, in that the UKHLS sample appears somewhat more highly educated than the broader working-age benchmark. Overall, both the direction and the magnitude of the gaps therefore look plausible and support reading the external benchmark as a descriptive check on sample selection rather than as a strict definition-identical comparator; similarly, the unemployment row should be interpreted with caution because the official unemployment benchmark uses the economically active population in the denominator.

Table 1.6: UKHLS analysis sample and external benchmarks for the UK working age population[1)]

Variable	UKHLS analysis sample	UK working age benchmark
Female (%)	47.8	50.9
Educational attainment[2)]		
Other or no qualification (%)	6.2	24.4
GCSE or equivalent (%)	20.4	17.1
A-level or equivalent (%)	24.4	18.2
Degree or higher (%	49.0	40.3
Labor market states[3)]		
Share of employment (%)	79.5	76.1
Share of unemployment (%)	4.8	3.8
Share of inactivity (%)	15.8	20.8
Employment composition		
Full-time share among employed (%)	—	73.9

Sources: UKHLS analysis sample statistics are from Table 1.1 in Chapter 1. External benchmark statistics are from official ONS labour market series and APS profile data for 2019.

Notes: 1) External benchmark statistics are reported using 2019 figures. Female share, labor market state shares, and the full-time benchmark use 2019 ONS data for the United Kingdom.
2) Educational attainment benchmarks use Jan–Dec 2019 APS profile data from an archived official source, available at Great Britain level.
3) The unemployment benchmark is the official unemployment rate and therefore uses the economically active population as denominator, whereas employment and inactivity are rates for those aged 16–64.

1.G Additional Counterfactuals on Tax Progressivity

Table 1.7 extends the benchmark comparison in the main text by adding an upper-end empirical benchmark, while Table 1.8 reports outcomes on a simple progressivity grid, $\tau \in \{0, 0.1, 0.2, 0.3\}$. The benchmark table is useful for comparing empirically relevant tax systems, whereas the evenly spaced grid helps to interpret more transparently how equilibrium objects move as tax progressivity rises. I restrict attention to $\tau \in [0, 0.3]$ because this range already covers the empirically relevant upper end of progressivity: Holter et al. (2019) report Denmark, with $\tau = 0.258$, as the most progressive case in their OECD sample, so $\tau = 0.3$ is included only as a high-progressivity comparison beyond that benchmark. Values arbitrarily close to $\tau = 1$ are not reported because they are not quantitatively reliable in this environment. Since net labor income is given by $\epsilon w^{1-\tau}$, very high progressivity makes net income nearly independent of pre-tax wages, effectively flattening the wage ladder and making the equilibrium fixed point numerically fragile.

Taken together, the two tables show that higher progressivity continues to raise welfare over the range considered here, but at a diminishing rate. In Table 1.8, the normalized welfare index (no-tax scenario = 100) rises to 101.37 at $\tau = 0.1$, 102.37 at $\tau = 0.2$, and 103.09 at $\tau = 0.3$. Thus, the welfare gain is 1.37 points when moving from $\tau = 0$ to $\tau = 0.1$, 1.00 point when moving from $\tau = 0.1$ to $\tau = 0.2$, and 0.72 point when moving from $\tau = 0.2$ to $\tau = 0.3$. A similar pattern appears in Table 1.7: welfare continues to improve as progressivity rises from the US-style benchmark to the UK-style benchmark and then to the upper benchmark, but the incremental gain becomes smaller. At the same time, higher progressivity lowers mean wages, mean job offers, search effort, and vacancy posting, while raising unemployment. The equilibrium interest rate increases because lower wages and reduced vacancy costs raise firms' net profits, which strengthens the precautionary savings motive and partly offsets the decline in labor income.

Table 1.8 shows that as tax progressivity increases, mean assets rise at first but then begin to fall, while mean consumption gradually declines overall. This pattern suggests that, although the interest rate rises from 3.24% to 4.23%, the reduction in labor income due to falling mean wages—from £2,184 to £2,090—eventually outweighs the incentive effect of higher returns. Even so, aggregate welfare continues to increase, indicating that the gains from greater equity in the distribution of outcomes are valued enough to dominate these losses in average income and consumption.

These additional counterfactuals therefore make the chapter's equity–efficiency trade-off more transparent. On the equity side, greater progressivity improves insurance by compressing labor income risk and redistributing resources toward workers with higher marginal utility in an economy where the laissez-faire allocation leaves workers imperfectly insured. On the efficiency side, the same compression of net wage gains along the job ladder weakens the precautionary search motive, lowers matching efficiency, and discourages firms' hiring and retention motives, thereby reducing mean wages and vacancy creation and increasing unemployment. Over the range considered here, the economy remains on the welfare-improving side of this trade-off, in the sense that the insurance gains still outweigh the efficiency losses. However, the flatter welfare profile at higher values of τ indicates that the marginal insurance gain from additional progressivity becomes smaller, while the associated efficiency costs continue to accumulate.

Table 1.7: Benchmark Tax Regime Outcomes

	No Tax ($\tau = 0$)	US ($\tau = 0.137$)	UK ($\tau = 0.2$)	Upper Benchmark ($\tau = 0.258$)
Aggregate Welfare[1)]	100	101.73	102.37	102.86
Labor Market				
Mean Wages (£)[2)]	2,184	2,132	2,113	2,097
Labor Income Variance[3)]	1.29	1.11	1.06	1.02
Unemployment Rate (%)	2.86	3.01	3.08	3.14
Job Offer Rate (λ)[4)]	1.899	1.892	1.892	1.893
Mean Job Offer[4)]	1.041	1.005	0.990	0.978
Mean Search Effort[1)]	100	96.91	95.54	94.26
Total Vacancies Measure	1.9772	1.9015	1.8735	1.8506
Incomplete Asset Market				
Mean Assets (£)	94,772	95,446	95,437	95,052
Interest Rate (%)	3.24	3.80	4.00	4.15
Mean Consumption (£)[2)]	2,440	2,433	2,431	2,426
ϵ	1	1.1472	1.2188	1.2863

Notes: The simulation results are presented in an easily interpretable unit.
1) The outcomes for aggregate welfare and mean search effort in the no-tax scenario are normalized to 100 to illustrate the changes across tax regimes, as the numeric values in the model do not have intrinsic meaning.
2) Mean wages and mean consumption are calculated on a monthly frequency.
3) Reported labor income variance refers to the cross-sectional variance of pre-tax labor income in the stationary equilibrium.
4) The job offer rate λ represents the mean of job offers received per unit of search effort over a year. The mean job offer refers to the mean of job offers an individual worker receives annually.

Table 1.8: Outcomes across Alternative Tax Progressivity Levels

	No Tax ($\tau = 0$)	Low Progressivity ($\tau = 0.1$)	UK ($\tau = 0.2$)	High Progressivity ($\tau = 0.3$)
Aggregate Welfare[1)]	100	101.37	102.37	103.09
Labor Market				
Mean Wages (£)[2)]	2,184	2,144	2,113	2,090
Labor Income Variance[3)]	1.29	1.15	1.06	1.00
Unemployment Rate (%)	2.86	2.97	3.08	3.17
Job Offer Rate (λ)[4)]	1.899	1.894	1.892	1.895
Mean Job Offer[4)]	1.041	1.014	0.990	0.972
Mean Search Effort[1)]	100	97.71	95.54	93.57
Total Vacancies Measure	1.9772	1.9201	1.8735	1.8416
Incomplete Asset Market				
Mean Assets (£)	94,772	95,611	95,437	94,684
Interest Rate (%)	3.24	3.67	4.00	4.23
Mean Consumption (£)[2)]	2,440	2,437	2,431	2,423
ϵ	1	1.1072	1.2188	1.3248

Notes: The simulation results are presented in an easily interpretable unit.
1) The outcomes for aggregate welfare and mean search effort in the no-tax scenario are normalized to 100 to illustrate the changes across tax regimes, as the numeric values in the model do not have intrinsic meaning.
2) Mean wages and mean consumption are calculated on a monthly frequency.
3) Reported labor income variance refers to the cross-sectional variance of pre-tax labor income in the stationary equilibrium.
4) The job offer rate λ represents the mean of job offers received per unit of search effort over a year. The mean job offer refers to the mean of job offers an individual worker receives annually.

Chapter 2

Job Mobility of Young Workers and Parental Wealth: Does a "Gold Spoon" Premium Exist in the Labor Market?

Abstract This chapter studies how parental wealth, as a form of private insurance, affects job search and labor market outcomes of young workers in South Korea. Motivated by the "spoon-class" discourse, I adopt a search-and-savings perspective in which young workers self-insure against labor income risk through precautionary savings and search, and at labor market entry, parental wealth works as private insurance. Using monthly panel data from the Korean Labor Income Panel Study, I estimate a random-effects discrete-time logit model for job finding and, for exits from employment, route-specific random-effects cause-specific discrete-time logit hazards that treat separations into non-employment and direct job-to-job transitions as competing exit routes from the same employment spell. I show that youth from poorer families leave non-employment more quickly but into lower-paying,

less stable jobs and experience persistent wage gaps relative to those from wealthier families, consistent with parental wealth relaxing liquidity constraints and allowing better-off young workers to search more selectively.

2.1 Introduction

Since the early 2010s, South Koreans have increasingly used the terms "dirt spoon" (*heuksujeo*) and "gold spoon" (*geumsujeo*), adapted from the English idiom "born with a silver spoon in one's mouth". The accompanying "spoon-class" discourse reflects a prevalent view that parental wealth and family background are the primary determinants of an individual's socioeconomic outcomes. In a 2018 survey of 1,336 adults conducted by a job search platform, 90.3% agreed that this "spoon-class" discourse accurately describes contemporary Korean society; when asked to identify the most important factor for economic success, respondents ranked "parents' financial resources" well ahead of individual ability, networks, diligence, and school prestige. However, despite the prominence of these beliefs among the general population, the empirical evidence on the mechanisms that transmit intergenerational advantage in South Korea remains limited.

Globally, parental wealth is widely regarded as a central determinant of intergenerational mobility and, in particular, the labor market outcomes of the next generation. A large empirical literature consistently documents strong associations between parental wealth, schooling and educational investment (Carneiro and Heckman, 2002; Pfeffer, 2018) and, more recently, neighborhood environments (Chetty et al., 2014; Chetty and Hendren, 2018) and network connections (Staiger, 2025). These channels primarily affect human capital accumulation before labor market entry. However, much less attention has been paid to a post-entry channel: whether parental wealth operates as private insurance against labor income risks and con-

sequently changes the job search behavior of young workers.[1] This chapter does not attempt to causally isolate all of these channels. Instead, it studies a narrower question: whether the observed patterns in job finding, job stability, and accepted wages are consistent with parental wealth operating as private insurance at labor market entry, when young workers have little wealth of their own.

Therefore, I introduce the search-and-savings self-insurance perspective from frictional labor markets (Lise, 2013; Chaumont and Shi, 2022; Kaas et al., 2023; Eeckhout and Sepahsalari, 2024) to illuminate the post-entry channel of parental wealth. In incomplete markets with borrowing constraints, workers cannot fully insure against idiosyncratic labor income risk and instead smooth shocks along two margins: assets and job search. More precisely, workers accumulate assets in high-wage spells and consume them in low-wage or unemployment spells. On the other hand, those with limited assets self-insure through the labor market, by adopting less selective or more intensified search strategies. In a job-ladder environment, these choices govern flows in and out of non-employment and employment, as well as job-to-job transitions.

However, young workers face a distinct constraint set. They enter with little or no wealth of their own, and many new graduates are not yet eligible for unemployment insurance benefits. In this setting, the relevant buffer stock is often parental liquidity: financial support backed by parental wealth that relaxes borrowing constraints. With higher parental wealth, a young worker can maintain a higher reservation wage, keep search selective, and wait for offers with higher wages and/or greater employment stability. With low parental wealth, however, the worker insures primarily through the labor market, lowering reservation wages and accepting offers quickly or exerting more search effort. This implies systematically different optimal

[1] Aside from the private insurance channel, other post-entry channels through which family background affects young workers' career include networks—for example, recruitment through referrals and social contacts (Beaman and Magruder, 2012; Burks et al., 2015) — and liquidity constraints, whereby young people from wealthier families are better able to accept low-wage training positions or internships (Rothstein and Rouse, 2011; Holford, 2017).

paths of reservation wages and search effort over time across parental wealth groups. These differences should be evident in non-employment duration (job finding hazards) and, conditional on exit, in the wage level and employment stability of the accepted jobs.

To address this issue empirically, I use KLIPS (Korean Labor & Income Panel Study) waves 2–26, covering 1999–2023, and construct a linked parent–child monthly panel that combines young workers' labor market histories with parental net worth. South Korea offers an especially informative setting for examining the self-insurance role of parental wealth against children's labor income risk.

For decades, education has been regarded as the principal engine of intergenerational mobility (Yeo et al., 2007; Chung and Park, 2019). Yet the rapid expansion of tertiary education has fundamentally altered its role. As of 2021, nearly 70% of Korean youth hold a tertiary degree, the highest share in the OECD (OECD, 2022). At the same time, the labor market has exhibited a sharp rise in overqualification: approximately 31% of workers are employed in jobs below their educational level, compared with the OECD average of about 23% (OECD, 2024b). As higher education has become a less reliable ladder of upward mobility, attention has increasingly turned to the role of parental wealth. This shift is captured in the widespread public discourse on the "gold-spoon premium", which encapsulates perceived advantages conferred by rich parents. In an environment where the role of education in the labor market is weakening, parental financial support has become especially salient for understanding how young workers move up the job ladder and insure themselves against early-career income risk.

I estimate discrete-time duration models on spell-period data to document how early-career labor market outcomes vary with parental wealth. The first model is a random-effects logit hazard for the transition from non-employment to employment. Because search dynamics differ markedly between first-job entry and re-

employment after a separation, I estimate separate job finding hazards for these two transition-specific risk sets. Because job finding hazards vary sharply with elapsed non-employment duration, I include a full set of month dummy variables to flexibly control for duration dependence, so that the parental-wealth coefficients are estimated conditional on elapsed non-employment duration. For employment spells, I organize the data at the quarterly frequency and model exits from the current job as competing exit routes. Rather than estimating a single multinomial likelihood, I estimate route-specific random-effects cause-specific discrete-time logit hazards for separations into non-employment and direct job-to-job transitions. In both models, the top parental wealth quartile (Q4) is the reference group, and I assess how labor market transitions differ for the lower three quartiles (Q1–Q3). All specifications include duration indicators and control for individual and job covariates, with year and region fixed effects.

Three empirical results are central. First, job finding hazards differ systematically by parental wealth: workers from poorer families leave non-employment more quickly. This gradient is pronounced for both labor market entry and re-employment, but I interpret the estimates within each transition-specific risk set rather than as directly comparable effect sizes, because the first-job and subsequent-job samples differ in composition. Second, adding previous-job controls does not eliminate the pattern; accounting for occupation, industry, and prior wages leaves the parental-wealth gradient in re-employment hazards visible, indicating that previous-job composition alone does not explain wealth differences in job finding. Third, workers from poorer families are more likely to exit employment into non-employment and therefore experience shorter employment spells. By contrast, parental wealth has no statistically clear relationship with direct job-to-job mobility: the coefficients for poorer groups are negative but statistically indistinguishable from zero. Finally, parental wealth is strongly associated with first-job starting wages: workers from poorer families enter their first jobs at lower wages. However, once previous wages are controlled

for, parental-wealth differences in re-employment wages are small and imprecisely estimated, suggesting that later wage offers are shaped mainly by accumulated wage history rather than ongoing parental liquidity.

I compare the empirical results with the predictions of an on-the-job search-and-savings model. I build a continuous-time incomplete-markets model with on-the-job search and derive predictions for how young workers' job search and early-career transitions vary with parental wealth. This framework builds on the random on-the-job search structure in Lise (2013) and the search-savings literature (Chaumont and Shi, 2022; Kaas et al., 2023) and extends the worker's problem developed in Chapter 1. The mechanism of equilibrium on-the-job search model with precautionary savings is here applied directly to the portion of parental assets accessible to their children when children's own assets are limited. The model yields the following predictions: the job finding hazard declines with parental wealth through a higher reservation wage and lower search effort, which implies that non-employed workers with wealthier parents can afford to wait and therefore set higher reservation wages. This is consistent with the empirical results above. Entering employment at lower wages, they have stronger incentives to seek better opportunities and thus may exhibit higher job-to-job transition probabilities. However, in the data, the job-to-job transition coefficients are statistically insignificant and do not provide clear evidence that low-wealth workers engage in more job-to-job mobility. The empirical job-to-job transition pattern is therefore not consistent with the model's prediction of stronger upgrading mobility among low-wealth workers. Regarding separation into non-employment, although less selective search among low-wealth youth would be expected to raise subsequent separation risks, the model treats the separation rate as exogenously fixed and therefore neglects job separations.

The contribution of this study is therefore to connect the parental wealth literature to the search-savings framework by testing this post-entry, self-insurance channel in early careers. I study how parental wealth shifts the job finding hazards and,

conditional on exit from non-employment, the wage level and employment stability of the subsequent jobs. The focus of this thesis is on the job search behavior: when parental wealth is scarce, workers optimally lower reservation wages and reduce selectivity, which should translate into lower match quality (lower wages, shorter job durations). The findings in this thesis indicate that parental wealth is associated with differences in search strategy, job finding, and the match quality of subsequent jobs, potentially through direct and indirect support during job search. Although these effects attenuate over time, they persist even as tenure grows.

My preferred interpretation of these patterns is that they reflect a "private insurance" channel: parental wealth relaxes liquidity constraints and allows young workers to smooth consumption and adjust their search behavior. A natural alternative mechanism is a family connections channel, under which parental networks and social capital improve job finding prospects for children from wealthier families. Importantly, such connections would typically increase, rather than reduce, job finding rates for high-wealth children. To the extent that parental networks improve access to jobs, they would tend to increase job finding hazards for children from wealthier families and therefore attenuate the negative parental wealth effect in job finding hazards documented here. Under this assumption, the job finding estimates can be interpreted as a lower bound on the contribution of the private insurance channel to the observed relationship. However, the empirical analysis in this chapter is observational and does not identify a causal effect of parental wealth. Because unobserved family traits and preferences—such as patience, risk tolerance, family norms, or assortative mating—may be correlated with both parental wealth and children's search behavior, the estimated coefficients should be interpreted as conditional associations between parental wealth and early-career labor market transitions. The private insurance channel is therefore best viewed as an interpretation of the observed patterns.

2.2 Literature Review

This study draws on two core literatures—labor market mobility and intergenerational mobility—and highlights parental wealth as a key mechanism that links the two. Accordingly, I review three strands of research: (i) labor market mobility, (ii) intergenerational mobility, and (iii) the role of parental wealth in shaping intergenerational mobility, especially as it bears on children's labor market outcomes and search behavior.

2.2.1 Labor market mobility

Human capital theory provides a mechanism for job turnover. As Becker's (1962)'s original distinction of specific and general types of human capital emphasizes, firm-specific training reduces job separation through increased job attachment, while general training raises outside options by increasing productivity that is valuable across jobs, thereby increasing mobility. When workers invest more in firm-specific human capital, job change becomes more costly as it renders some of their human capital obsolete(Mincer, 1989). Consequently, firm-specific capital becomes an important ingredient for the employment relationship, so workers who accumulate more of it move less. On the other hand, general training increases mobility because it raises productivity at any firm and makes outside poaching profitable (Becker, 1964; Acemoglu and Pischke, 1999).

Jovanovic (1979) characterizes job mobility as a dynamic process of learning about match quality. In the model, workers and firms begin with imperfect information about match quality. The match quality is revealed only after experiencing jobs through tenure and performance, and turnover occurs when the updated match quality falls below a reservation threshold. Accordingly, wage-tenure profiles evolve with this learning process without requiring any human-capital accumulation.

Building on this framework, Flinn (1986) and Lane and Parkin (1998) show how unobserved heterogeneity and revelation of match quality impact separation hazards and the wage distribution. Moscarini (2005) incorporates the match-quality learning process in an equilibrium search framework, endogenizing learning about match quality, job search and wage distribution. In these frameworks, separations occur disproportionately from low-quality matches once updated beliefs about match productivity fall below a reservation threshold. This implies that workers who move are negatively selected from their current job. They therefore tend to leave low productivity and low wage matches. If wages are increasing in expected match quality, rematching to a new job with higher expected productivity generates an average wage gain around job changes even without human-capital accumulation.

Taken together, the human capital and imperfect information frameworks yield two common implications for mobility and wages: job mobility declines as workers accumulate tenure and experience; and job-to-job mobility raises wages.

Evidence supports the first implication (Topel and Ward, 1992; Farber, 1994; Mincer and Jovanovic, 1981). When graduates enter the labor market for their first job, their human capital is still limited and expected and realized job rewards often do not match. Early-career mobility is therefore high and declines rapidly with work experience.(Topel, 1991) shows that human capital accounts for much of this decline, consistent with human-capital theory.

For the second implication, while both frameworks predict that job-to-job transitions tend to raise wages as workers leave low-quality matches, some studies highlight the downside of transitions that involve interim non-employment spells. In the "job shopping" view, young workers quit to accept better matches, and job switches are frequently followed by wage gains as workers sort into higher-productivity firms (Mincer, 1986; Topel and Ward, 1992). By contrast, involuntary separations trigger unemployment spells, weaken bargaining power, and can push workers into lower-

pay matches. Moreover, repeated separations and switches erode tenure-linked wage returns. Using early-career German data, Schmelzer (2012) shows that mobility via non-employment spells carries earnings penalties and depresses long-run wages. These contrasting forces imply that whether mobility helps or harms career outcomes is an empirical matter rather than a theoretical one.

2.2.2 Intergenerational mobility and parental wealth

Social mobility arises from multiple factors, including class, status, schooling, income, and, more recently, wealth as a route for transferring advantage and disadvantage across generations (Hällsten and Pfeffer, 2017). Regarding parental wealth, a prominent channel is direct financial support from parents to young adults, observed across many countries (Schoeni and Ross, 2005; Zissimopoulos and Smith, 2011; McGarry, 2016). Many studies link parental wealth to children's educational achievement and attainment (Conley, 2001; Morgan and Kim, 2006; Haveman and Wilson, 2007; Hällsten and Pfeffer, 2017). In contrast, fewer studies examine labor market outcomes in early adulthood, though existing evidence points to associations with earnings and entry into self-employment (Fairlie and Krashinsky, 2012; Lindquist et al., 2015). In the following section I consider the literature on parental wealth and labor market outcomes in more detail.

Several mechanisms explain how parental wealth affects children's early economic outcomes. First, wealth makes educational investment affordable, consistent with work that links parental wealth and children's educational outcomes. Educational investment improves access to selective institutions and reduces dropout risk, and these schooling advantages translate into stronger employment and wage trajectories (Karagiannaki, 2017; Pfeffer, 2018). Second, especially through housing wealth, parents can purchase access to neighborhoods and schools with better environments, a channel amplified by rising residential and school segregation (Orfield and Eaton,

1996; Haurin et al., 2002; Reardon and Bischoff, 2011). Relatedly, local opportunity has recently been highlighted as a key determinant of intergenerational mobility: mobility varies sharply across places because of differences in inequality, family structure, and social capital, and higher-wealth families are better able to relocate to such high-opportunity areas (Chetty et al., 2014). Third, social capital and connections, such as internships, referrals, and other network-mediated opportunities, constitute another route through which parental advantage operates (Kramarz and Nordström Skans, 2014; Staiger, 2025).

2.2.3 Parental wealth, intergenerational mobility and labor market outcomes

As the preceding studies show, much of the intergenerational mobility literature has emphasized pre-market channels (i.e., investment in human capital, neighborhood sorting, and access to selective institutions) prior to labor-market entry. By contrast, relatively little is known about post-entry mechanisms through which parental wealth affects children's early labor market outcomes, including its effects on search strategy and job mobility, and the subsequent evolution of earnings and the worker's own wealth over early career trajectories.

More recently, a few papers have sought to identify the role of parental wealth via early labor market outcomes. With regards to the mechanisms explored, the study closest to mine is de Mel (2020), where parental wealth acts as self-insurance that lengthens job search and improves matching, thereby increasing early earnings. The evidence for this paper comes from Ghanaian survey data estimated within a structural search/choice model. However, de Mel (2020) measures stocks, not transitions: its "probability of unemployment" is a point-in-time indicator of being unemployed in the survey reference week, not a hazard of remaining unemployed for an additional period. Among Ghanaian males aged 15–29, a 1% increase in parental assets is

associated with roughly a 0.08 percentage-point higher unemployment probability, consistent with wealth-enabled "waiting". This pattern is not consistent with the relationships found in U.S. data in a study by Chetty et al. (2024), where employment generally rises with parental assets and attenuates only at the very top. Moreover, the findings from de Mel (2020) obscure the possibility that frequent movers in low-skill jobs experience short spells but more episodes of non-employment. In de Mel's (2020) estimated structural model, parental wealth has a strong positive effect on children's lifetime earnings, and it operates through two main channels: roughly 63% via the education channel and 37% via the waiting (unemployment) channel.

My study differs in two main aspects. First, I study transitions rather than stocks: for currently non-employed individuals, the dependent variable is an indicator for a job finding transition, estimated with a logit hazard; individuals are grouped by elapsed non-employment duration, so hazards are identified within duration cells. Second, anticipating non-linear effects, I proxy long-run parental wealth using the average annual parental-wealth rank over the observation window and estimate quartile dummies, rather than a linear index. In a related setting with Korean data, Oh and Lee (2022) similarly link parental wealth to early outcomes, but focus on employment status (a stock) and first-job quality. They find no clear pattern in employment rates but stronger first-job quality for families with higher financial wealth (e.g., higher starting wages, regular rather than temporary contracts, larger or higher-wage-premium firms, and more selective occupations/industries).

With regards to the model, my approach is closest to Holmberg et al. (2024), who develop a partial-equilibrium search-and-savings framework and use Swedish employer-employee data. A key difference is that Holmberg et al. (2024) model on-the-job search and job destruction, but do not model search effort as an explicit choice variable; instead, job offer arrivals and separations are governed by exogenous processes. They document a non-monotonic association between parental wealth and early career earnings and argue that between-firm allocation explains

much of this pattern. By contrast, I study South Korea using linked parent-child panel data (1991–2023) and adopt a search-and-savings, self-insurance view in which parental liquidity relaxes borrowing constraints and endogenously shifts reservation wages and search effort. Empirically, I estimate discrete-time hazard models for job entry and re-employment, as well as subsequent job spells, tracing duration dependence and match quality. My study centers on the question of how parental wealth changes the timing of job finding, the selectivity of acceptance, and the stability of accepted jobs, providing a complementary emphasis on post-entry channel. Staiger (2025) points to a complementary mechanism: access to high-paying jobs via parental networks. Using U.S. linked employer-employee data and an IV design based on idiosyncratic hiring variation at the parent's firm, Staiger shows that working for a parent's employer is common by age 30 and raises initial earnings, implying that family networks amplify the persistence of early intergenerational earnings. Whereas Holmberg et al. (2024) emphasize wealth-enabled allocation rather than direct family connections, Staiger (2025) provides causal evidence that parental networks themselves provide access to high-wage firms.

In sum, these studies, across different settings and designs, highlight how children's early-career outcomes vary with parental wealth. Building on this literature, I estimate early-career transition hazards to test whether parental wealth operates as a form of self-insurance, shifting job finding, separation, and job-to-job transitions and, through these channels, the dynamics of early-career earnings.

2.3 Data

To analyze the relationship between parental wealth and children's labor market outcomes, information on the parents' assets and the children's labor market outcomes is required, and these generations should be linked in the data. I use the

KLIPS (Korean Labor & Income Panel Study) that contains annual interviews starting from 1998 and reports on individual- and household-level adult (aged 15 years and over) information from 7 metropolitan and urban areas across 8 provinces. The KLIPS sample is an equal probability sample and was designated to yield 5,000 households each year, totaling 13,000 individuals.[2]

The KLIPS consists of three data sets: the Household data set, the Individual data set, and the Work History data set. The Household data set contains information about parental wealth, providing a basis for intergenerational analysis. The Individual data set provides information about individuals' job status at the time of each survey, job/employment status transitions over the past 12 months, and individual characteristics. The Work History data set offers a comprehensive employment record by individuals, detailing job characteristics, employment status, and wages for each job held—not only at the time of the survey but also at the start and end of each employment spell. All three data sets are combined to construct the panel data for the estimation.

I construct a monthly panel data from annual survey data covering the period from 1999 to 2023 (Wave2 - Wave26).[3] The panel dataset provides a monthly approximation of individuals' labor market status. To achieve this, I extract information on job status changes and the dates that these changes occurred between two consecutive annual interviews. Although the data are collected annually, this approach using the questionnaire on the start/end dates of employment spells allows for a dataset of labor market transitions at monthly frequency. Information related to job such as earnings, job type (part-time/full-time, regular/non-regular), occupation, industry, and worker characteristics is updated once per year based on the survey responses.

[2] For more information on the KLIPS, refer to the website (http://https://www.kli.re.kr/menu.es?mid=a50101000000).

[3] Wave 1 is excluded from the analysis due to simplified questionnaire, which lacks sufficient detail on parental wealth and workers' employment characteristics.

A key feature of my panel dataset is that it links workers across generations, forming a parent–children panel structure. Using the Work History data set, I extracted the job characteristics of children workers (i.e., the monthly dates of unemployment and re-employment, wages, working hours, occupation, industry, whether they were self-employed jobs, full-time jobs, and regular jobs). Subsequently, from the Individual data set, I extracted information of the (potential) labor market entry dates and the non-employment spells of the children workers without employment spells, who are excluded from the Work History data. Additionally, the individual characteristics of children (i.e., education, gender, region of residence, and health status) were taken from the Individual data set. Lastly, from the Household data, information on parental wealth (i.e., net worth, housing and financial assets, and financial debts), during the period from children's adolescence to after labor market entry was extracted.[4]

Parents' and children's data are linked using the household identifier (HHID) and the personal identifier (PID).[5] I first identify child workers whose HHID matches that of their parents and whose relationship to the household head was recorded as son or daughter when they were aged 15–18. Using the common HHID, I link these children to their parents and obtain parental characteristics from the Household data. Parental variables are then followed over time in the Household data using the parents' identifiers (HHID), so that time-varying parental characteristics are updated in each wave and merged to the child's record by survey year. Once a child's PID has been linked to his or her parents in at least one wave, I follow the child over time using only the PID, even after the child leaves the parental household and forms a separate household with a different HHID. Individuals who are never observed living with their parents during the survey period cannot be matched to parents and are therefore excluded from the analysis.

[4] Even after the children's labor market entry, parents' assets were tracked and linked in the dataset, rather than children's own wealth.

[5] A household may contain multiple individuals, so several personal identifiers (PID) can share the same household identifier (HHID).

2.3.1 Data Construction

The raw sample of the Parents-Children linked panel data were constructed from KLIPS comprising 12,000 workers from children's generation and 6,653 parental households. I restricted the sample applying the following sample restriction criteria:

First, following Lo Bello and Morchio (2020), I retain only children initially matched to their parents at age 15–18[6] [7] for two purposes: (i). to track young workers who do not live with their parents at some point during the survey; and (ii). to measure parental wealth over sufficiently long windows—important given the volatility of asset values. Relative to the raw sample, this restriction reduces the number of workers by about 40% and the number of observations by about 20% (Table 2.1).

Second, I exclude spells of employment and non-employment which start before the respondent is aged 18, corresponding to the typical high school graduation age in Korea. Although high school is not legally compulsory, enrollment and completion are near universal in practice with social norm of a standard and basic education.[8] Moreover, the Labor Standards Act (2021) and the Youth Protection Act (2022) impose strict limits on the employment of individuals under age 18. These include constraints on working hours, and accessible occupations and industries. Under these legal distinctions, workers younger than 18 are likely to differ systematically from adult employment. Accordingly, I drop spells which start before individuals turn 18, consequently removing 1,373 workers who are observed only between ages 15 and 18 and not subsequently tracked, and about 16% of the observations.

[6] As reported by Ermisch and Francesconi (2002), about 95% of offspring still live with their parents at that age, and therefore my restricted sample is virtually identical to a random sample. Nevertheless, due to the limited time span of the KLIPS, the results arguably hold for young offspring. See Appendix 2.B for details of the sample construction.

[7] In KLIPS, the minimal age of response is 15. Before the age of 15, children are in the survey, but are not respondents.

[8] As of 2024, the high school enrollment rate was 93.9%, and the transition rate to higher education was 73.6% (Statistics Korea, https://kosis.kr, Accessed June 2025. For more details, see Section 2.3.

Third, I restrict the sample to post-schooling labor market histories by excluding all employment spells that begin more than 12 months before completion of the worker's final educational degree, even if they continue after graduation.[9] The raw sample includes part-time jobs held prior to the completion of final education, as well as spells of non-employment for full-time students who were not actively seeking work. However, labor market activity before the completion of a final educational degree may differ significantly from the job search of individuals who enter the labor market following the completion of their final educational degrees. Under this restriction, workers who are still pursuing their final degree (currently enrolled or on leave) are excluded. Workers who obtained their final degree but whose completion month is interval-censored are retained in the post-schooling panel once degree completion is observed, but they are excluded from the first non-employment spell analysis because the exact start of the first post-schooling search spell cannot be identified.[10] This restriction excludes 1,475 individuals and reduces the total number of observations by 27.6%.

Finally, I include only employment and non-employment spells for which data are matched between the Personal Data Set and the Work History Data Set.[11] The Personal Data set is compiled annually, while the Work History Data set records individual job spells over time. Both datasets contain key job characteristics such as wages, industry, occupation, employment type (full-time or part-time), as well

[9]The purpose of this restriction is to focus on labor market behavior after the transition from school to work. Jobs that begin more than 12 months before degree completion typically reflect student employment or transitional arrangements tied to enrollment status. By excluding such spells, even when they extend beyond graduation, I avoid classifying these transitional jobs as post-schooling labor market entry and obtain a cleaner measure of early-career dynamics.

[10] Of the 4,396 workers in the final sample, 3,943 reported the exact month and year of completing their highest degree. For the remaining 453 workers, the completion month is missing and degree completion is only observed to have occurred between two survey interviews. For these cases, I treat degree completion as occurring before the first interview at which the new credential is observed and include all subsequent periods after completion in the panel. For the analysis of the first non-employment spell following degree completion, I restrict the sample to respondents with exact completion dates and exclude those with interval-censored dates. For workers excluded from that first-spell analysis, I still use their first observed job spells and any later non-employment spells in the subsequent analyses.

[11] Yet, I include the workers with non-employment spells only, because they don't have any employment spells and therefore, can be observed only in the Personal data set.

as job start and end dates. Compiling accurate transitions in employment status and job changes is critical to the study of labor market mobility. To reduce potential measurement error, the two datasets are cross-validated. Any job spells for which the start or end date is missing in either dataset, or for which the dates do not align, are excluded from the sample. Only job spells with fully matched start and end dates in both datasets are retained for analysis. The two datasets are highly consistent. Among individuals who have entered the labor market, the numbers of households and workers are unchanged, and 4,165 monthly observations are dropped due to mismatches. This corresponds to about 1.0% of the post-schooling sample after the third restriction, or 0.4 percentage points relative to the raw monthly observations. Because the resulting sample is selected from young post-schooling workers linked to parental households, Appendix 2.C compares the KLIPS Parents–Children linked sample with external benchmarks for the Korean working-age population. Appendix 2.D compares the observable composition of the first-job and subsequent-job risk sets used in the transition analyses.

Table 2.1: Sample Restriction

Sample restriction criteria	Households		Workers		Observations (monthly)	
	Number	% to raw sample	Number	% to raw sample	Number	% to raw sample
Raw sample (Parents-Children linked data)	6,653	100	12,000	100	1,053,306	100
1. Workers observed during the ages of 15 to 18	4,361	65.6	7,244	60.4	868,382	82.5
2. Data of the ages of 18 or older	3,625	54.5	5,871	48.9	697,389	66.2
3. Data after the highest level of education (Labor market entry)	2,886	43.4	4,396	36.6	406,576	38.6
4. Data matched between the Personal Data Set and the Work History Data Set	2,886	43.4	4,396	36.6	402,411	38.2
−Male			2,285		210,568	
−Female			2,111		191,843	

2.3.2 Main Variables

The core variables are: (i) labor market states (employment, non-employment); (ii) three transition types between those states—employment-to-non-employment ($E \to N$), non-employment-to-employment ($N \to E$), and job-to-job ($E \to E$); and (iii) parental wealth (net worth). I adopt this design because switches between unemployment and inactivity, and their timing, cannot be precisely separated in the KLIPS dataset.

Labor market states and transitions are constructed from the job-by-job questionnaire in the individual survey in KLIPS. For each job reported at the previous wave, the interviewer asks (i) whether the respondent is still working in that job and (ii) if not, the month and year in which the job ended. For each respondent, the survey then enumerates all new jobs that started since the last interview and, for every such job lasting more than one week, records the month and year in which it began.[12] Because KLIPS is fielded annually and start and end dates are observed for each reported job spell, I construct an approximate monthly panel of employment and non-employment by assigning each calendar month between two interviews either to one of the reported jobs or to non-employment, assuming that job spells are continuous between their reported start and end dates and that all within-year job changes lasting at least one week are captured by the job-by-job questions.

Using the self-reported start and end dates of jobs, the panel dataset assigns a monthly approximation of individuals' labor market status, based on their inferred state on the first day of each month.[13] For example, if a respondent reports a job separation in month t that occurred after the first day, the individual is coded as employed in month t.

[12] See the KLIPS integrated questionnaire, Individual Survey module, for the job-by-job employment history questionnaire, referring to the website (https://www.kli.re.kr/board.es?mid=a40301000000bid=0026).

[13] I follow the methodology in Postel-Vinay and Sepahsalari (2023) who infer the monthly labor market status based on the state of the end date of each month.

2.3.2.1 Labor market states

I distinguish between two labor market states: employment and non-employment. The definition of employment adopts a broad approach, encompassing all types of work—self-employment, paid and unpaid jobs, part-time and full-time roles, as well as regular and non-regular employment.[14] Regarding non-employment, there are two types of definitions: (i) a narrow definition—unemployment, and (ii) a broad definition—without work. The narrow definition refers to individuals actively seeking work, thereby excluding periods of economic inactivity. In contrast, the broader definition includes any month not employed, regardless of reported job search. I adopt the broad definition of non-employment, specifically defining it as the interim period between two subsequent jobs.[15]

I work with a two-state monthly classification, employment versus non-employment, because the job-based history questions provide clean information on job attachment at this frequency, whereas finer state definitions (employment, unemployment, and inactivity) would require stronger assumptions about timing and about how point-in-time survey questions map into a complete monthly history.

Moreover, standard search models allow for a continuum of search effort, while survey questions typically record only whether an individual reports active job search over a recent reference period and whether they are willing to work. These indicators are designed to capture relatively high-intensity search and are measured

[14] Rather than excluding certain types of employment based on the assumption that worker behavior varies across job types, I retain them and control for job type in the model to examine the overall relationship between parental wealth and labor market mobility.

[15] The International Labour Organization (ILO) definition of unemployment states three conditions:

(1). Without Work: Not engaged in any form of paid employment or self-employment during the reference week or period.

(2). Actively Seeking Work: Has taken specific steps to look for work, such as applying for jobs or contacting employers, within a recent defined period (e.g., the past four weeks).

(3). Available for Work: Is ready and able to start working in the next two weeks, or has already found a job and is waiting to begin it in the near future.

While the narrow definition is consistent with the ILO definition of unemployment, the broad definition in this study only satisfies the first condition.

only at the interview date, so they are likely to miss low-intensity search and do not yield a reliable month-by-month history of unemployment and inactivity spells. To avoid additional misclassification arising from unobserved variation in search effort, I define non-employment broadly as any month not attached to a job—that is, any gap between two consecutive jobs—irrespective of contemporaneous self-reports about search or availability. Non-employment observed at the final interview is right-censored. Given the sample's youth (maximum age 43), retirement is assumed not to occur in the sample.

An important limitation is that the non-employment state combines unemployment and inactivity. As a result, differences in non-employment duration across parental-wealth groups should not be interpreted purely as differences in unemployment duration. For example, some of the lower re-entry hazards among workers from wealthier families may reflect delayed re-entry for reasons unrelated to job search.

2.3.2.2 Labor market transitions

I track three types of labor market transitions: (1) employment to non-employment, (2) non-employment to employment, and (3) job-to-job transitions. I identify an employment-to-non-employment transition ($E \to N$) when the respondent is employed on the first day of month $t-1$, non-employed on the first day of month t, and reports a separation in between the second day and the end date of month $t-1$. Conversely, a non-employment-to-employment transition ($N \to E$) occurs when the respondent is non-employed on the first day of month $t-1$, employed on the first day of month t, and reports a job finding in between the second day and the end date of month $t-1$. For a job-to-job transition, the respondent is employed in job j on the first day of month $t-1$ and in a different job j' on the first day of month t.

A move between distinct jobs that includes at least one interim non-employment

month is coded as the sequence $E \to N$ followed by $N \to E$, not as $E \to E$; only direct switches with zero non-employment months are coded as $E \to E$.[16]

2.3.2.3 Parental Wealth

Parental wealth is net worth, calculated as the total value of assets minus total liabilities, which is the standard measure linking wealth to labor market behavior (e.g., Lise, 2013; Saez and Zucman, 2016; Carroll et al., 2019; Barth et al., 2020). I construct net worth from three components using KLIPS: financial assets, housing assets, and liabilities. Financial assets include bank deposits; stocks, bonds, and trusts; insurance holdings; gye (a rotating savings and credit association); private lending; and other financial instruments. Housing and property assets are measured as the market value of owner-occupied housing—or rental deposits for renters—plus the market value of non-residential real estate. Liabilities cover all outstanding debts, including loans from bank and non-bank institutions as well as private borrowing. All monetary amounts are deflated to 2020 CPI.

I implement a rank-based construction over all years. First, for each survey year I form annual net worth from its components. I then map parental net worth into percentile ranks within (year $\times$ child birth-cohort) cells. Next, I average these within-cell ranks over all observed years for each child and, based on the resulting time-averaged rank, define quartile indicators (Q1–Q4). Averaging annual ranks preserves ordinal information while smoothing the level shifts due to asset-price cycles and aligning families by the child's stage of the life cycle; the quartile coding provides a simple, nonparametric partition for estimation.

[16] An alternative would be to use self-reported job search activity from the questions for the employed workers in the individual survey and to classify job changes with no reported search as job-to-job transitions, interpreting them as unsolicited offers or headhunting. However, these search questions are observed only at the interview date for a short reference period and do not provide a reliable month-by-month history of search intensity. In addition, such a definition would correspond more closely to a hire without an ILO unemployment spell than to a job change without any non-employment period in my monthly panel. For these reasons, I do not adopt this alternative.

I measure parental wealth as a time-averaged percentile rank with quartile indicators for three reasons. First, a rank-based measure is comparable across cohorts and years, is robust to asset-price cycles, zeros/negatives, and heavy tails, and it aligns with the intergenerational wealth literature that analyzes mobility in terms of relative position in the wealth distribution (e.g., rank–rank approaches). Second, time-averaging smooths transitory shocks and measurement noise, yielding a more stable proxy for the family's persistent capacity to provide private insurance, which is the mechanism of interest here. Third, using quartile dummies allows flexible nonlinearity and an intuitive "Q1 vs Q4" interpretation without committing to a functional form. This design is consistent with recent work that models the channels of wealth in levels (Levander, 2019; Fontaine et al., 2024) but uses the distributional position when studying parental wealth and early-career outcomes (Holmberg et al., 2024).

2.3.3 Descriptive Analysis

2.3.3.1 Summary statistics

Table 2.2 reports summary statistics for the analysis sample of young workers and their parents. The sample includes 4,396 young workers (48% women) who entered the labor market after completing their education and 2,886 linked parents. The average age observed in the panel is 25.3 years. The average age at labor market entry, defined as the month of completing the highest qualification, is 22.0 years.[17] For the hazard models, I use four categories: below or equal to high school graduate, associate degree, bachelor's degree, and postgraduate.

All monetary variables are expressed in real 2020 KRW, using the consumer price

[17] This average aligns with typical graduation ages in Korea, where individuals finish high school at around 18 years, two-year college at about 20 years, and four-year university at about 23–24 years for women and 25–26 years for men.

index as the deflator. For paid employees, "monthly wage" denotes post-tax labor income. For the self-employed, it denotes net monthly business income.[18] "Average wage" is the within-spell mean across all months of a given employment spell, whereas "labor market entry wage" is the first observed wage in the first job after entry.

I distinguish between non-employment spells that occur before the first job and those that occur between jobs. Entry non-employment spells are longer on average and more dispersed than between-job non-employment spells. This pattern reflects the higher share of individuals who are out of the labor force immediately after graduation and the fact that new graduates are typically ineligible for unemployment insurance and have no prior wage savings. As a result, entry non-employment spells are expected to be more strongly affected by parental wealth.

Employment spells last on average 32.3 months, which is slightly less than three years in observed duration.[19] The standard deviation is 38.0 months, larger than the dispersion for both types of non-employment spells. This is expected because employment durations vary widely across contract types, occupations, and firms, and some spells are right-censored within the observation window.

Parental wealth is summarized by net worth, defined as financial assets plus real estate assets minus financial liabilities. I decompose net worth into these three components and report the quartile means of each component and of net worth (units: 10,000 KRW; deflated to 2020 prices). Quartiles are constructed from parental net worth for the analysis period. The distribution is highly skewed. The bottom quartile has low or negative net worth, while both financial and real estate assets rise

[18] Although intergenerational mobility studies typically use pre-tax wages, I use disposable income because this study focuses on the role of parental assets as a private form of insurance against labor income risk.

[19] Employment-spell duration is measured as the observed duration within the panel. Spells that are still ongoing at the last observation contribute their observed duration up to the censoring date.

Table 2.2: Summary statistics for children and parents[1)]

Children		Parent Household	
	Mean		Mean
Female (%)	48.0	Average age of household head	50.7
Observation age	25.3		
Labor market entry age	22.0	Average total assets (10,000 KRW)	
Educational attainment (%)		- 1st quartile	1,094.5
- Below high school graduate	1.9	- 2nd quartile	4,872.6
- High school graduate	35.3	- 3rd quartile	10,157.0
- Associate degree	23.2	- 4th quartile	23,055.2
- Bachelor's degree	35.1		
- Master's/Doctoral	4.4	Average financial assets (10,000 KRW)	
Health status: Poor (%)	2.6	- 1st quartile	500.0
Region of residence (%)		- 2nd quartile	1,407.7
- Seoul	22.6	- 3rd quartile	3,094.2
- Gyeonggi province	24.7	- 4th quartile	7,525.7
- Other metropolitan cities	27.1		
Birth cohort (%)		Average real estate assets (10,000 KRW)	
- 1981–1990	69.5	- 1st quartile	2,335.7
- 1991–2000	27.9	- 2nd quartile	5,954.3
- 2001–2010	2.5	- 3rd quartile	11,809.3
Labor income (10,000 KRW)	200.6	- 4th quartile	24,026.3
	(0.478)		
Share of self-employed (%)	8.1	Average financial liabilities (10,000 KRW)	
Share of non-regular workers (%)	26.3	- 1st quartile	1,472.9
Share of part-time workers (%)	7.2	- 2nd quartile	3,656.3
Entry non-employment spells (months)	15.1	- 3rd quartile	7,906.7
	(24.7)	- 4th quartile	13,428.0
Re-employment spells (months)	12.7		
	(22.5)	Number of households	2,886
Employment spells (months)	32.3		
	(38.0)		
Number of workers	4,396		

Notes: 1) Numbers in parentheses are standard deviations.

steeply across quartiles. Liabilities also increase with quartiles but less than assets.

2.3.3.2 Distribution of transitions and raw hazard probabilities

Table 2.3 reports monthly counts of transitions up to month 12 for non-employment spells preceding the first job and for spells preceding re-employment after a separation. The time window is set to 12 months because more than ninety percent of spells remain under observation within this window, so the risk set at each duration is sufficiently large. By month 12, 58.51 percent of spells end in a job, 8.78 percent are right-censored before month 12 because respondents are lost to follow-up within the window, and the remaining 32.71 percent are right-censored at month 12 because the non-employment spell is still ongoing at the window's end. For first-job spells, I exclude individuals whose date of schooling completion cannot be identified; they enter the re-employment sample only if they later experience a separation, in which case their subsequent non-employment spells are observed.

To describe the distribution, I use the raw job-finding hazard.[20]Raw hazards are mostly higher for re-employment spells than for first-job spells throughout the first year of non-employment spells, except for month 3. A plausible explanation is that first-job spells include preparation for market entry, such as examinations and credential acquisition, and may also include time spent out of the labor force immediately after graduation, both of which lower transition rates. In contrast, attrition within twelve months, defined as loss to follow-up before month 12 or administrative truncation in the final survey wave, is more frequent among re-employment spells, at 12.45%, whereas it is at 4.87% among first-job spells. Consistent with these patterns, a smaller share of workers remain non-employed at month 12 for re-employment spells, about 23.37%, compared with 42.68% for first-job spells.

[20] For duration t, the raw job finding hazard is $h_t = \frac{\sum_i d_{it}}{\sum_i y_{it}}$, where $d_{it} = 1$ if worker i finds a job during month t and $d_{it} = 0$ otherwise, and $y_{it} = 1$ if worker i is still non-employed and observed at the start of month t and $y_{it} = 0$ otherwise. Right-censored spells contribute to the risk set y_{it} until the censoring time and never to the event count d_{it}.

Table 2.3: Distribution of non-employment-to-employment transitions

Transitions	All		First jobs[1)]		Subsequent jobs	
Non-employment-to-employment	Number	Raw hazard[2)]	Number	Raw hazard[2)]	Number	Raw hazard[2)]
In month 1	2,154	26.42	939	23.81	1,215	28.86
2	544	9.14	244	8.13	300	10.17
3	518	9.68	302	10.95	216	8.32
4	286	6.00	131	5.36	155	6.66
5	267	6.07	105	4.62	162	7.62
6	196	4.84	75	3.53	121	6.30
7	167	4.45	65	3.24	102	5.84
8	169	4.83	71	3.74	98	6.11
9	135	4.13	38	2.11	97	6.61
10	117	3.81	45	2.57	72	5.44
11	123	4.22	33	1.95	90	7.35
12	94	3.40	20	1.21	74	6.69
Censored	3,383		1,875		1,508	
Total	8,153		3,943		4,210	
	Number	Percent	Number	Percent	Number	Percent
Transitions within 12 months	4,770	58.51	2,068	52.45	2,702	64.18
Censored within 12 months[3)]	716	8.78	192	4.87	524	12.45
Censored at month 12[4)]	2,667	32.71	1,683	42.68	984	23.37
Total	8,153		3,943		4,210	

Notes: 1) Workers for whom the date of schooling completion cannot be identified are excluded from the first-job analysis.

2) For duration t, the raw monthly job finding hazard is $h_t = \frac{\sum_i d_{it}}{\sum_i y_{it}}$, where $d_{it} = 1$ if worker i finds a job during month t and $d_{it} = 0$ otherwise, and $y_{it} = 1$ if worker i is still non-employed and observed at the start of month t and $y_{it} = 0$ otherwise.

3) Spells that become unobservable before month 12, either because respondents drop out of the survey or because observation ends at the final survey wave (wave 26).

4) Spells that remain ongoing at month 12; they are right-censored at the 12-month observation horizon.

Table 2.4 documents quarterly separations from current jobs over a 12-quarter (36-month) window, distinguishing transitions into non-employment and direct job-to-job switches.[21] Unlike the 12-month horizon used for non-employment spells, I adopt a 12-quarter (36-month) observation window for employment spells because the observed mean duration including right-censored spells is about 36 months; extending the horizon increases exposure time and the number of failures. Spells that persist to quarter 12 are therefore treated as right-censored. For the descriptive route-specific raw hazards in Table 2.4, the alternative observed exit route is recorded as a competing event that terminates the spell after the event quarter. Thus, a job-to-job transition is not counted as an employment-to-non-employment event, and an employment-to-non-employment transition is not counted as a job-to-job event. This descriptive convention should be distinguished from survey attrition or administrative right-censoring. In the regression specification below, both exit types are retained in a single competing-risk event indicator and estimated as route-specific discrete-time hazards.

The bottom panel summarizes outcomes within the 12-quarter window. Considering all types of separations, just under one half of employment spells (44.84%) end in a transition within 12 quarters, about one fifth (21.15%) are lost to follow-up before quarter 12, and roughly one third (34.01%) remain employed and are censored at quarter 12. Among the 3,532 observed separations, 2,512—or 71.1%—are employment-to-non-employment transitions, and 1,020—or 28.9%—are direct job-to-job transitions. Expressed relative to all employment spells, these correspond to 31.89% and 12.95%, respectively. Consistent with this composition, separation hazards into non-employment exceed job-to-job hazards at every quarter from 1 to 12, and both hazards generally increase with duration over the first several quarters,

[21] For duration t, the raw quarterly separation hazard is defined as $h_t = \frac{\sum_i d_{it}}{\sum_i y_{it}}$, where $d_{it} = 1$ if worker i separates from the current job during quarter t and $d_{it} = 0$ otherwise, and $y_{it} = 1$ if worker i is still employed and observed at the start of quarter t and $y_{it} = 0$ otherwise. Cross-type transitions are handled as censoring in the opposite panel so that each hazard pertains to one exit route. Spells that persist to quarter 12 are right-censored.

and then decrease.

Supplementary Kaplan–Meier survival and hazard estimates by parental-wealth group are reported in Appendix 2.E. These estimates are descriptive and do not condition on the covariates used in the main duration models.

2.4 Empirical Model Specification

To examine the relationship between parental wealth and early-career job mobility, I use a discrete-time duration framework that follows three transition types: non-employment to employment (NE), employment to non-employment (EN), and job-to-job transitions (EE). Some spells are observed only for a finite period and end without an observed transition, either because the respondent leaves the survey or because the observation window closes. The spell data are therefore right-censored. I organize the data into discrete spell-periods and include flexible duration indicators, which allow the baseline hazard to vary nonparametrically with elapsed duration while matching the timing at which employment and non-employment spells are observed in the KLIPS.

The main analysis proceeds in two steps. First, I estimate discrete-time duration models with covariates—parental wealth, individual characteristics, and previous or current job information—to document parental-wealth gradients in job finding, job separation, and job switching.[22] Second, I estimate the relationship between parental wealth and accepted wages using linear regressions. Supplementary Kaplan–Meier survival and hazard estimates are reported in Appendix 2.E. These nonparametric estimates summarize raw duration patterns by parental-wealth group, while the main text focuses on covariate-adjusted duration models and wage regres-

[22] As discussed above, if family connections work in the opposite direction, the observed gradient may understate the insurance interpretation; however, the estimates themselves remain descriptive rather than causal.

Table 2.4: Distribution of employment-to-non-employment and job-to-job transitions

Transitions	All[1)]		E-to-N[1)]		Job-to-Job[1)]	
Employment exits from current job	Number	Raw hazard (%)[2)]	Number	Raw hazard (%)[2)]	Number	Raw hazard (%)[2)]
In quarter 1	231	2.93	182	2.31	49	0.62
2	393	5.30	298	4.02	95	1.28
3	454	6.68	335	4.93	119	1.75
4	478	7.76	344	5.59	134	2.18
5	411	7.45	278	5.04	133	2.41
6	335	6.76	232	4.68	103	2.08
7	296	6.62	211	4.72	85	1.90
8	255	6.32	169	4.19	86	2.13
9	216	5.92	143	3.92	73	2.00
10	165	4.94	110	3.29	55	1.65
11	150	4.89	107	3.49	43	1.40
12	148	5.24	103	3.64	45	1.60
Censored	4,345		5,365		6,857	
Total	7,877		7,877		7,877	
	Number	Percent	Number	Percent	Number	Percent
Transitions within 12 quarters	3,532	44.84	2,512	31.89	1,020	12.95
Censored within 12 quarters[3)]	1,666	21.15	2,686	34.10	4,178	53.04
Censored at quarter 12[4)]	2,679	34.01	2,679	34.01	2,679	34.01
Total	7,877		7,877		7,877	

Notes: 1) All (Column 1) counts separations from the current job, regardless of the status of next quarter. In the E-to-N panel, job-to-job transitions are treated as censoring events, while in the Job-to-Job panel, separations into non-employment are treated as censoring events. Job-to-job transitions include switches that occur within the same quarter.
2) For duration t, the raw quarterly separation hazard is $h_t = \frac{\sum_i d_{it}}{\sum_i y_{it}}$, where $d_{it} = 1$ if worker i separates from the current job during quarter t and $d_{it} = 0$ otherwise, and $y_{it} = 1$ if worker i is still employed and observed at the start of quarter t and $y_{it} = 0$ otherwise.
3) Censored within 12 quarters denotes spells that become unobservable before quarter 12 because respondents stop responding or because observation ends at the final survey wave (wave 26). In the route-specific descriptive columns, this row also includes observed exits through the competing route. These observed cross-type exits are not treated as ordinary survey attrition in the regression analysis; instead, they are retained as competing events in the employment-spell event indicator.
4) Censored at quarter 12 denotes spells that remain ongoing at quarter 12; the job is not separated and the spell is right-censored at the 12-quarter observation horizon.

sions.

A key empirical issue is censoring. I assume that right-censoring is conditionally independent: conditional on elapsed duration, observed individual and job covariates, and year effects, survey attrition and end-of-window censoring are unrelated to the underlying transition hazard. This assumption is analogous to a missing-at-random restriction in panel settings. For employment spells, exits into non-employment and job-to-job transitions are competing exit routes from the same employment spell. I therefore construct a competing-risk event indicator that distinguishes remaining in the current job or being censored, separation into non-employment, and job-to-job transition. The two exit routes are then estimated as route-specific, cause-specific discrete-time hazards. Thus, the alternative exit route is not treated as ordinary survey attrition; instead, it is retained as a competing event that terminates the employment spell after the event quarter.

I estimate a discrete-time duration model for job finding and competing-risks discrete-time duration models for exits from employment. The model estimates the likelihood of each transition occurring over time, conditional on the worker remaining at risk at the start of the period. The discrete-time hazard rate for worker i in period t for transition category z is defined as:

$$h_{it}^{z} = Pr(T_i = t,\ E_i = z \mid T_i > t-1), \qquad z \in \{NE, EN, EE\}.$$

where h_{it}^{z} is the discrete-time hazard, and $z \in \{NE,\ EN,\ EE\}$ indexes the category: non-employment-to-employment (NE), employment-to-non-employment (EN), and job-to-job (EE). For non-employment spells, the model reduces to a binary hazard for NE. For employment spells, EN and EE are competing exit routes from the same spell. I estimate separate binary logit hazards for each exit route, rather than a multinomial logit model. In each cause-specific equation, the denominator is the probability of not experiencing that particular exit route in the current

period, which includes both remaining in the current job and exiting through the competing route.

The key distinction from a single-risk duration model is that observed cross-type exits are not removed from the data as if they were unobserved censoring events. In the EN equation, a direct job-to-job transition contributes a zero to the EN outcome in the quarter in which it occurs; in the EE equation, a separation into non-employment contributes a zero to the EE outcome in the quarter in which it occurs. In both cases, the spell leaves the risk set only after the observed competing event. Therefore, the competing route remains part of the at-risk denominator for the cause-specific hazard in the event quarter. The conditionally independent censoring assumption is required only for survey attrition and administrative end-of-window censoring, not for the observed competing exit route. This specification estimates route-specific hazards rather than a joint multinomial likelihood.

Duration dependence is modeled by including dummy variables D_{it}^{z} for each time point so that the baseline hazard is left unrestricted and the association between parental wealth and transition hazards is estimated conditional on elapsed non-employment or employment duration. Accordingly, the parental-wealth coefficients are interpreted as conditional associations between parental wealth and transition hazards, while the duration dummy variables flexibly absorb duration dependence. I estimate the job finding and the employment-exit models with worker-specific random effects to capture unobserved heterogeneity. The random effects are specified as individual-specific random intercepts and are intended to capture persistent, time-invariant differences across workers in their baseline transition propensities that are not fully observed in the data, such as search ability, preferences for job stability, risk tolerance, work attachment, health or family constraints not captured by the observed controls, and other persistent components of employability. The identifying assumption is that, conditional on the included covariates, duration indicators, and year effects, these individual-specific effects are independent of the

observed regressors, including parental-wealth quartiles. This is a random-effects assumption rather than a fixed-effects strategy. Because parental wealth is time-invariant in the main specification, individual fixed effects would absorb the main variable of interest. The estimates should therefore be interpreted as conditional associations net of modeled time-invariant unobserved heterogeneity, not as causal effects if unobserved traits correlated with parental wealth remain. Ignoring such heterogeneity can mimic duration dependence and attenuate covariate effects, so modeling it helps reduce these biases (Jenkins, 2005; see also Heckman and Singer, 1984; Lancaster, 1990).[23]

2.4.1 Job Finding: discrete time duration model

I estimate a discrete time duration model for the probability that a non-employed worker finds a job. Let T_i^{NE} denote the month in which worker i's non-employment spell ends in employment. The discrete time hazard in month t is

$$h_{it}^{NE} = Pr(T_i^{NE} = t \mid T_i^{NE} > t-1),$$

where

$$\log\left(\frac{h_{it}^{NE}}{1-h_{it}^{NE}}\right) = \beta_0^{NE} + \sum_{d=2}^{k} \beta_{1d}^{NE} D_{it}^{NE}(d) + \sum_{j=1}^{J} \gamma_{1j}^{NE} PWD_{ji} + \beta_2^{NE} x_{it}^{NE} + u_i^{NE},$$

$$u_i^{NE} \sim N(0, \sigma_{NE}^2).$$

Duration dependence in non-employment is modeled with month indicators $D_{it}^{NE}(d)$ for $d = 2, ..., k$ (month 1 is the base), rather than with a parametric function of t, so the baseline hazard is left unrestricted. The specification includes duration dummies

[23] In discrete-time duration models, omitted individual heterogeneity can generate spurious duration dependence because high-risk individuals exit the risk set earlier, leaving a progressively selected lower-risk population. Following Jenkins (2005, Lesson 7), I include individual-level random intercepts. The NE, EN, and EE equations each allow for a separate random-intercept variance.

and parental-wealth indicators without their interactions. The resulting modeling assumption is a time-invariant, proportional-odds effect of parental wealth: the indicators $D_{it}^{NE}(d)$ nonparametrically capture the baseline hazard profile, allowing the hazard to rise or fall with tenure, while each parental wealth coefficient shifts the log-odds of transition by a constant amount in every month. Equivalently, for any two workers who differ only in their parental-wealth quartile, the odds ratio of transitioning in month t is the same for all t.

To capture parental-wealth gradients in transition hazards, I include PWD_{ji}, an indicator that worker i's parents fall in quartile j of a rank-based, time-averaged wealth distribution. Quartiles are defined from this time-averaged rank $\overline{r_i}$, so PWD_{ji} = 1 when $\overline{r_i} \in [\underline{r_j},\ \overline{r_j})$, and zero otherwise.[24] By using wealth quartile dummy variables PWD_{ji} rather than the size of asset holdings, I allow parental wealth to have a non-linear effect on children's job search and labor market outcomes. The reference group is the richest quartile ($Q4$).

The vector x_{it}^{NE} includes individual covariates (i.e., age entered as a quadratic function, gender (i.e., female), completed education level, birth cohort indicators, health status, marital status), region and year indicators, and job covariates (i.e., non-regular employment, part-time jobs, self-employment, industry [four sectors], occupation [five categories], and the log of CPI-deflated average wages in the prior spell). The worker-specific random intercept u_i^{NE} captures persistent unobserved differences in workers' baseline job finding propensities. These differences may include unobserved search ability, reservation-wage preferences, work attachment, or other stable characteristics that affect the probability of leaving non-employment. The coefficient γ_{1j}^{NE} is therefore interpreted as the association between parental-wealth quartile j and the log-odds of job finding relative to $Q4$, conditional on observed covariates, elapsed duration, and the modeled individual-level unobserved

[24] $\overline{r_i}$ denotes the time-averaged percentile rank of parental wealth for worker i, and $[\underline{r_j},\ \overline{r_j})$ denotes the interval that defines quartile j of the rank distribution, therefore, Q1: [0, 25), Q2: [25, 50), Q3: [50, 75), Q4: [75, 100].

heterogeneity. Under this specification, γ_{1j}^{NE} measures the conditional association between parental-wealth quartile j and the log-odds of finding a job relative to $Q4$, rather than a causal effect of parental wealth. If the observed patterns are consistent with the self-insurance mechanism, then, holding other characteristics fixed, workers from quartiles below $Q4$ should have higher job finding hazards and shorter non-employment spells.

Table 2.5: Variables controlled for in the model

Variables		
Parental wealth	Bottom three quartiles (Q1–Q3) dummy variables to the reference group (Q4)	Time×cohort-averaged percentile rank
Duration dependence	Duration dummy variables	
Unobserved heterogeneity	Worker-specific random intercepts	Separate random effects for NE, EN, and EE; assumed conditionally independent of observed covariates
Individual covariates	Age	Quadratic function
	Gender	Female
	Completed education level	Less than high school/high school/colleges and universities/post graduate
	Birth cohort	1980s/1990s/2000s
	Health status	Poor health
	Marital status	
(Previous/current) Job information	Log wages	Average during the prior spell (previous) /Current wages (current)
	Non-regular jobs	
	Part-time jobs	
	Self-employment	
	Industry	Manufacturing/Construction/Service/etc
	Occupation	Manager/Office workers/Production workers/Unskilled labor/etc
Labor market	Region indicator	Seoul/Gyeonggi province/Other metropolitan cities
	Year indicator	

2.4.2 Job separation and job switching: a competing-risks discrete-time duration model

I also examine how parental wealth relates to outcomes in the subsequent job. Let T_i^E denote the quarter in which worker i's current employment spell first ends through either separation into non-employment or a job-to-job transition, and let $E_i \in \{EN, EE\}$ denote the exit type, where EN is a transition from employment to non-employment and EE is a direct job-to-job transition. Because these are competing exit routes from the same employment spell, I retain both routes in the employment-spell risk set and estimate route-specific hazards. Administrative end-of-window censoring and survey attrition are treated as right-censoring and are assumed to be conditionally independent of the latent transition hazards, conditional on elapsed duration and observed covariates.

The employment-spell data are organized at the quarterly frequency. Starting from the monthly spell data, I restrict employment spells to the first 36 months after job start, convert elapsed duration into quarters, and keep one observation per person–quarter. Thus, the employment-exit risk set covers up to twelve quarters. For each worker i and quarter q, define the competing-risk event indicator

$$y_{iq} \in \{0, EN, EE\},$$

where $y_{iq} = 0$ if the worker remains in the current job through quarter q or is administratively censored, $y_{iq} = EN$ if the worker separates into non-employment in quarter q, and $y_{iq} = EE$ if the worker moves directly to another employer in quarter q. After the first observed exit, the worker leaves the risk set; the event quarter itself is retained, but subsequent spell-quarter observations are excluded.

Conditional on remaining in the current job up to the start of quarter q, the cause-

specific discrete-time hazard for exit route e is defined as

$$h_{iq}^{e} = Pr(T_i^E = q,\ E_i = e \mid T_i^E > q-1), \qquad e \in \{EN, EE\}.$$

Equivalently, I define two binary outcomes,

$$y_{iq}^{EN} = 1\{y_{iq} = EN\}, \qquad y_{iq}^{EE} = 1\{y_{iq} = EE\},$$

and estimate separate binary logit hazards for EN and EE. In the EN equation, a direct job-to-job transition is coded as not being an EN event in the event quarter and the spell exits the risk set thereafter. Symmetrically, in the EE equation, a separation into non-employment is coded as not being an EE event in the event quarter and the spell exits the risk set thereafter. This implementation treats the alternative route as a competing event rather than as ordinary survey attrition.

For each exit route $e \in \{EN, EE\}$, I estimate the following random-effects discrete-time logit model:

$$\log\left(\frac{h_{iq}^{e}}{1-h_{iq}^{e}}\right) = \beta_0^e + \sum_{d=2}^{12} \beta_{1d}^e D_{iq}^e(d) + \sum_{j=1}^{J} \gamma_{1j}^e PWD_{ji} + \beta_2^e x_{iq}^e + u_i^e, \qquad e \in \{EN, EE\}.$$

Here, $D_{iq}^e(d)$ are quarter-duration indicators for time in the current employment spell, with quarter 1 as the omitted category. These indicators capture duration dependence without imposing a parametric functional form. The worker-specific random intercept u_i^e captures persistent unobserved differences in workers' baseline propensity to exit through route e, after conditioning on observed worker characteristics, current job characteristics, year effects, and elapsed employment duration. For example, u_i^{EN} may reflect unobserved differences in employment stability or attachment to work, while u_i^{EE} may reflect unobserved mobility preferences, search ability while employed, or career-upgrading propensity. I estimate separate random-effects cause-specific logit models for EN and EE; hence, the unobserved heterogeneity

terms are route-specific and are not estimated as a jointly correlated pair in a single multinomial likelihood.

I estimate two cause-specific binary logit models on the employment-spell risk set: one for separation into non-employment and one for direct job-to-job transitions.[25] Therefore, $1 - h_{iq}^{e}$ should be interpreted as the probability of not exiting through route e in quarter q, conditional on being at risk at the start of the quarter. It includes both remaining in the current job and exiting through the competing route.

Parental wealth enters through quartiles of the time-averaged rank measure described above, with the richest quartile $Q4$ as the reference group. Thus, γ_{1j}^{e} measures how the log-odds of exiting through route e differ for workers from quartile j relative to $Q4$, conditional on elapsed employment duration, observed characteristics, and unobserved worker heterogeneity. The vector x_{iq}^{e} includes the worker characteristics used in the job finding model and current job information, including current wages, non-regular and part-time status, industry, occupation, year indicators, and cohort indicators.

The main expectation regarding the employment spell is that limited parental insurance pushes workers from poorer families to accept lower-quality, less stable matches more quickly, making subsequent exits into non-employment more likely. This implies $\gamma_{1j}^{EN} > 0$ for $j = 1, 2, 3$ after conditioning on duration and observable characteristics. Effects on job-to-job transitions, γ_{1j}^{EE}, are a priori ambiguous because job-to-job mobility may reflect upgrading out of initial mismatches as well as movement out of unstable matches.

[25] This specification is not a multinomial logit model. The two exit routes are not estimated in a single likelihood with remaining in the current job as the base outcome.

2.5 Estimation Results

Appendix 2.E reports supplementary Kaplan–Meier survival and hazard estimates. The raw patterns suggest that parental wealth is associated with slower exits from non-employment, especially for re-employment spells, and with greater subsequent job stability. The main results below move beyond these descriptive patterns by estimating discrete-time logistic hazard models that condition on parental wealth, individual characteristics, job characteristics, duration dependence, and region and year effects.

2.5.1 Job Finding

Table 2.6 reports the main results from a discrete-time logit model of the monthly hazard of job finding. Throughout all columns, the coefficients of interest are indicators for belonging to the bottom three parental-wealth quartiles (Q1–Q3), relative to the top quartile (Q4, reference). The estimation window is the first 12 months after labor market entry (entry spells) and job loss (re-employment spells); spells that remain non-employed beyond month 12 are right-censored. The dependent variable equals one if a worker finds a job in month t, conditional on remaining non-employed at the start of t. The baseline hazard is flexibly captured by monthly duration dummies. In the first column ("All"), I regress the monthly job-finding indicator on parental-wealth quartiles, including the duration dummies and individual covariates, as well as region and calendar-year fixed effects to absorb local and aggregate shocks.

Because labor market entry spells differ systematically from re-employment spells, in the second column, I re-estimate the model restricting it to the period from labor market entry until the first job is found. On the other hand, the third and fourth columns use re-employment spells, which are post-separation non-employment spells.

In the third column, I add previous job covariates to address potential selection into occupations, industries, and dual labor markets with different search technologies or offer distributions, while retaining region and year fixed effects.

Across specifications, there is a clear negative association between parental wealth and the job finding hazard: relative to Q4, the Q1 and Q2 indicators are positive and statistically significant in all models, and all three (Q1–Q3) are positive and significant for first-job spells. The magnitudes increase monotonically as parental wealth declines, consistent with lower reservation wages and more intensive/less selective search among workers from low-wealth families. For post-separation spells, Q1 and Q2 remain significantly positive, and the coefficients increase once previous-job controls are included, indicating that differences in occupation, industry, or labor-market segment do not account for the gradient.

For entry spells, age displays a positive concave profile, but the education coefficients are mixed: associate degree holders have a higher job finding hazard, bachelor's degree holders have a lower hazard, and the postgraduate coefficient is close to zero relative to the omitted education group. After separation, age effects attenuate and become statistically small. Education gradients in re-employment depend on whether previous-job controls are included: with previous-job controls, only the associate coefficient is weakly significant, whereas without those controls all post-secondary categories are positive and statistically significant. Among previous-job controls, indicators for non-regular and part-time employment contribute little, whereas higher prior wages predict faster re-employment. The self-employed indicator is omitted from the final table because transitions out of self-employment in these samples occur very rarely with another covariate pattern.

To interpret the log-odds, let the estimates of j's quartiles of parental wealth be $\gamma_j,\ j = 1, 2, 3$. Then, each γ_j is a log-odds shift relative to $Q4$, and the corresponding odds ratio$\left(\frac{h_{it}}{1-h_{it}}\right)$ is $exp(\gamma_j)$. Because duration indicators enter only via

Table 2.6: Discrete time duration model for job finding [1) 2) 3)]

Independent Variables		**Sample**			
		All	First job	Subsequent jobs	
Parental Wealth (Net Worth)	1st quartile (Poorest)	**0.399*** ** (0.054)	**0.597*** ** (0.142)	**0.396*** ** (0.080)	**0.364** ** (0.078)
	2nd quartile	**0.164*** ** (0.056)	**0.260** ** (0.117)	**0.199** ** (0.083)	**0.138*** (0.082)
	3rd quartile	**0.117** ** (0.055)	**0.203*** (0.111)	0.098 (0.083)	0.073 (0.082)
Worker Characteristics	Age	**0.200*** ** (0.033)	**0.522*** ** (0.156)	0.029 (0.052)	**0.086*** (0.049)
	Age squared	**-0.003*** ** (0.001)	**-0.007** ** (0.003)	-0.000 (0.001)	-0.001 (0.001)
	Female	0.008 (0.038)	**0.677*** ** (0.124)	**-0.357*** ** (0.056)	**-0.377*** ** (0.051)
	Associate	**0.228*** ** (0.050)	**0.225*** (0.117)	**0.126*** (0.067)	**0.188*** ** (0.065)
	Bachelor	0.025 (0.051)	**-0.474*** ** (0.158)	0.101 (0.072)	**0.191*** ** (0.068)
	Postgraduate	**0.333*** ** (0.102)	-0.003 (0.232)	0.157 (0.158)	**0.317** ** (0.152)
Previous Job Info.	Log post-tax wages			**0.399*** ** (0.071)	
	Non-regular jobs			0.023 (0.056)	
	Part-time jobs			-0.064 (0.089)	
Number of Workers		4,138	3,920	2,020	2,115

Notes: 1) Standard errors are in parentheses. A constant term was not reported for brevity.
2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
3) All regressions include duration dummy variables, and controls for cohort, health condition, marriage, region of residence (Seoul, Gyeonggi province, or other metropolitan cities), and year fixed effects. The third column includes information on previous jobs: monthly labor income, job type (self, part-time/full-time, regular/non-regular), occupation and industry.

dummy-coded month variables, these wealth effects are time-invariant and therefore, proportional in odds across durations.

Relative to the richest quartile (Q4), the coefficients for Q1–Q3 are positive and precisely estimated: 0.399 (Q1), 0.164 (Q2), and 0.117 (Q3). Converting to odds ratios gives about 1.49 $\approx$ $exp(0.399)$, 1.18 $\approx$ $exp(0.164)$, and 1.12 $\approx$ $exp(0.117)$. Thus, workers from poorer families have higher job finding odds at a given month, consistent with lower reservation wages and intensive search leading to quicker acceptances.

The pattern is very similar when restricting to the first post-school search: 0.597 (Q1), 0.260 (Q2), and 0.203 (Q3), which correspond to odds ratios of roughly 1.82, 1.30, and 1.23, respectively. Hence, during initial labor market entry, job finding is fastest among those from the lowest wealth families.

When prior job controls are included (column 3), the wealth gradient remains: 0.396 (Q1, odds ratio $\approx$ 1.49), and 0.199 (Q2, odds ratio $\approx$ 1.22) are positive and significant; the Q3 estimate 0.098 (odds ratio $\approx$ 1.10) is smaller and not statistically significant. Dropping previous job controls (column 4) yields slightly lower magnitudes: 0.364 (Q1, odds ratio $\approx$ 1.44), 0.138 (Q2, odds ratio $\approx$ 1.15), and 0.073 (Q3, odds ratio $\approx$ 1.08). However, the basic pattern of the significant effects of the Q1 and Q2 quartiles and the insignificant effect of the Q3 quartile persists. The reemployment results also support the interpretation that limited access to parental assets makes non-employed workers from poorer families less selective and therefore quicker to accept offers. Moreover, once we control for the influence of the preceding job, this pattern becomes even more pronounced.

In the third column, among previous job controls, log wages from the previous job are significant: 0.399. Because wages are in logs, a 1% increase in prior wages changes the current month's job finding hazard by roughly 0.4% increase, indicating that

individuals with higher previous wages tend to find the next job faster. [26] Indicators for non-regular (0.023) and part-time (−0.064) status are small and not statistically significant in this specification.

Coefficients in Table 2.6 are estimated on the log-odds scale and are therefore not directly interpretable in probability units. In the discrete time logit specification above, the change in probability (the marginal effect) is as follows:

$$\frac{\partial h_{it}}{\partial Asset} = h_{it}(1 - h_{it})\gamma_{asset},$$

where, for simplicity, $Asset$ denotes the parental wealth quartile indicators relative to the reference group. The coefficient γ_{asset} is a constant log-odds shift across months, and the baseline hazard rate term $h_{it}(1 - h_{it})$ makes the probability changes by month t. By reporting average marginal effects (AMEs), I clarify how a time-invariant wealth effect in log-odds translates into time-varying probability impacts as the baseline hazard evolves over the spell. Figures 2.1 reports AMEs by non-employment duration for (i) the first job after labor market entry and (ii) re-employment after a separation.

In Figure 2.1, for each parental wealth quartile $q \in \{Q1, Q2, Q3\}$ the AME at duration t is the average change (in percentage points) in the probability of leaving non-employment in month t when moving from the reference quartile Q4 to q, holding all other covariates at their observed values and averaging over individuals at that duration.

In the left panel (entry spells), AMEs are positive for all three lower parental wealth quartiles at every duration, implying higher job finding probabilities for young

[26] Because wages are in logarithm, the coefficients $\gamma_j^n,\ j \in 1, 2, 3$ are described as 0.01 times γ_j^n change in the log-odds $\left(\log\left(\frac{p}{1-p}\right)\right)$ for a change to j's quartile wealth parents from the richest fourth quartile parents. Therefore, $exp(0.01 \cdot \gamma_j^n)$ can be interpreted as the change in the odds ratio $\left(\frac{p}{1-p}\right)$. In this case, a 1 percent higher previous wage ($\approx$ 0.01 in logs) raises the current month's job finding odds by about $exp(0.399 \times 0.01) - 1 \approx 0.4\%$.

adults from less wealthy families than for otherwise similar peers from the richest quartile Q4. After one month of non-employment, moving from Q4 to Q3, Q2, or Q1 increases the probability of entering the first job by about 2-3, 3-4, and 7-8 percentage points, respectively; these differences then steadily decline over the spell, reaching around 1 percentage point or less for Q2 and Q3 and about 2 percentage points for Q1 by month 12. The AMEs for Q1 remain statistically significant for most durations in the first year, whereas the AMEs for Q2 and especially for Q3 are clearly different from zero mainly in the early months.[27]

The right panel (re-employment spells) shows similar patterns for transitions back into work after a separation. Immediately after job loss (month 1), switching from Q4 to Q3, Q2, or Q1 raises the re-employment probability by roughly 2, 3-4, and 7-8 percentage points, respectively; by month 12, the corresponding effects for all three quartiles have fallen to around 1-2 percentage points. Because these are non-employment-to-employment transitions, "month 1" refers to exiting after one completed month of non-employment, so that, for example, months 5 and 11 correspond to the 6th and 12th months of non-employment; the AMEs at those durations show a modest uptick, mirroring slightly higher exit rates in those months. As with entry spells, the re-employment AMEs for Q1 are clearly significant for most of the first year, while estimates for the remaining quartiles become imprecise at longer durations.[28]

2.5.2 Job separation and job switching

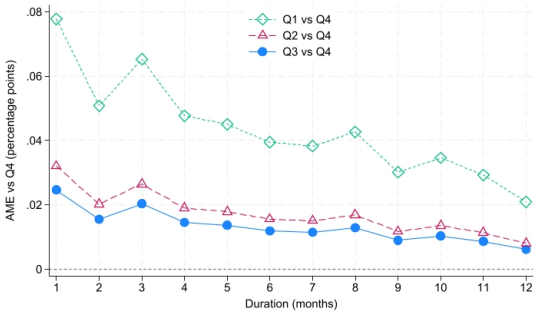
Table 2.7 reports estimates for employment spells that follow job finding using random-effects, cause-specific competing-risks discrete-time logit models of quarterly exits from the current job. The time window is the first 36 months after a job

[27] Confidence intervals and formal significance tests for entry-spell AMEs by parental wealth quartile and duration are reported in Appendix 2.F.

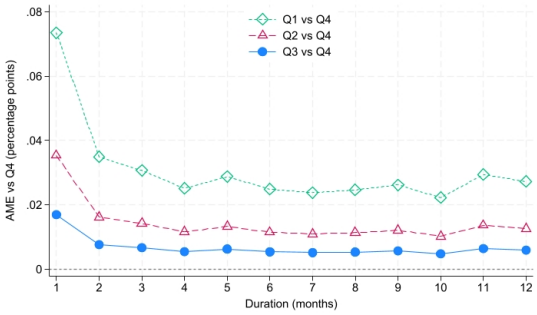
[28] Confidence intervals and significance patterns for re-employment AMEs are discussed in Appendix 2.F.

Figure 2.1: Average marginal effects of parental wealth on job finding hazards

(a) Entry spells



(b) Re-employment spells



Source: Author's calculation using KLIPS 2-26

starts; spells that remain ongoing beyond month 36 are right-censored. The unit of analysis is the person–quarter. Columns (1) and (2) report transitions from employment to non-employment, E→N, and job-to-job transitions, J→J, respectively. The baseline hazard is modeled nonparametrically with a full set of quarter duration dummy variables ($q = 1, ..., 12$). The specification includes individual covariates and current job information, and it absorbs local and aggregate shocks via region and calendar-year fixed effects.

For job separation, there is a clear negative relationship between parental wealth and the quarterly separation hazard. Relative to the top quartile (Q4), the indicators for Q1, Q2, and Q3 are positive and statistically significant, with the largest coefficient for the poorest quartile. This pattern is consistent with workers from low-wealth families accepting jobs under lower reservation wages or engaging in less selective search, which comes at the cost of poorer match quality or less stable employment.

By contrast, for job switching, there is no systematic association with parental wealth. The coefficients for Q1–Q3 are all negative and similar in magnitude, but none are statistically significant. This pattern suggests workers from poorer quartiles may be somewhat less likely to move directly to another employer within 36 months, yet the differences are too imprecise to be conclusive. A weak relationship is plausible because the job-to-job hazard aggregates distinct mechanisms, such as early "job

shopping" that upgrades matches and very short, less selective moves, whose effects need not align.[29]

The age profile is flat: neither the linear nor the quadratic age terms are statistically significant in either separation or switching. Female workers show a modestly higher separation hazard but no significant difference in switching. Education predicts lower separation risk across all levels: the associate, bachelor, and postgraduate levels are each negative and significant. For switching, however, the education coefficients are negative but not statistically significant. Turning to current job characteristics, higher log wages are associated with lower quarterly separation hazards, although the coefficient for switching is negative but not statistically significant. Non-regular jobs carry substantially and statistically higher hazards for both separation and job-to-job transitions, whereas part-time status is not statistically distinguishable from zero in either case.

In the first column, for job separation, the bottom three quartiles all have positive coefficients relative to Q4, and all are statistically significant. For the poorest quartile (Q1), the coefficient 0.219 implies an odds ratio of $exp(0.219) \approx 1.24$. Holding other covariates fixed, workers from Q1 face separation odds about 24% higher than otherwise similar workers from Q4. For Q2 and Q3, the odds ratios are $exp(0.149) \approx 1.16$ and $exp(0.146) \approx 1.16$, respectively. This pattern is consistent with a negative gradient in job stability with parental wealth: workers from less-wealthy families are more likely to have employment spells that end in non-employment, with the strongest association observed for the poorest quartile.

In the second column, for job switching, all three quartile coefficients are negative, but none are statistically significant. The coefficients for Q1, Q2, and Q3 are -0.066,

[29] In the simple search framework in Section 2.7, job separation and job switching roughly map into involuntary and voluntary exits. In the data, however, the classification is based on observed monthly job status, where some transitions coded as job switching may still reflect involuntary changes (for example, moves following non-employment spells of less than one month). Hence, job switching here likely combines both voluntary and involuntary transitions, and the empirical distinction does not perfectly coincide with the theoretical voluntary/involuntary dichotomy.

Table 2.7: Competing-risks discrete-time duration model for job separation and job switching [1) 2) 3)]

Independent Variables		Dependent Variable	
		Job Separation	Job Switching
Parental Wealth (Net Worth)	1st quartile (Poorest)	**0.219*** **	-0.066
		(0.075)	(0.070)
	2nd quartile	**0.149***	-0.058
		(0.079)	(0.074)
	3rd quartile	**0.146***	-0.054
		(0.078)	(0.074)
Worker Characteristics	Age	-0.057	0.041
		(0.049)	(0.047)
	Age squared	0.001	-0.000
		(0.001)	(0.001)
	Female	**0.137****	0.017
		(0.055)	(0.053)
	Associate	**-0.257*****	-0.054
		(0.064)	(0.064)
	Bachelor	**-0.384*****	-0.046
		(0.071)	(0.068)
	Postgraduate	**-0.828*****	-0.130
		(0.171)	(0.133)
Job Info.	Log wages	**-0.151****	-0.103
		(0.061)	(0.065)
	Non-regular jobs	**0.476*****	**0.237*****
		(0.054)	(0.060)
	Part-time jobs	0.092	0.075
		(0.083)	(0.091)
Number of Workers		3,510	3,510

Notes: 1) Standard errors are in parentheses. A constant term was not reported for brevity.
2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
3) Columns (1) and (2) report coefficients from competing-risks discrete-time duration models of quarterly exits from employment. Column (1) reports transitions from employment to non-employment, and column (2) reports job-to-job transitions. All specifications include quarter-duration dummy variables and controls for cohort, health condition, marriage, region of residence, occupation, industry, and year fixed effects. The omitted parental wealth category is the 4th quartile, i.e. the richest parental-wealth group.

-0.058, and -0.054, which correspond to odds ratios of $exp(-0.066) \approx 0.94$, $exp(-0.058) \approx 0.94$, and $exp(-0.054) \approx 0.95$, respectively. Hence, workers from poorer backgrounds appear somewhat less likely to move directly to another employer, though the differences are small and statistically indistinguishable from zero. This contrast implies that, compared with their wealthier counterparts, workers from lower-wealth families are relatively more prone to exit into non-employment than to switch jobs. One possible interpretation is that limited financial buffers lead some individuals to accept initial jobs more quickly and with less screening, resulting in weaker job matches that are more likely to end in non-employment rather than to be upgraded through job-to-job transitions.

Figure 2.2 shows average marginal effects (AMEs) of parental wealth on job separation and job-to-job transitions over job tenure in quarters. For each tenure and for each parental wealth quartile Q1, Q2, and Q3, the AME indicates by how many probability points the predicted probability of the corresponding transition differs relative to otherwise similar workers from the top quartile Q4.[30]

In the left panel (job separation), AMEs are positive for all three lower parental wealth quartiles at every tenure, implying systematically higher separation risks for workers from less wealthy families. In the first quarter, moving from Q4 to Q1 raises the separation probability by roughly 0.4–0.5 percentage points, while the corresponding differences for Q2 and Q3 are about 0.3 percentage points. These differences increase with tenure and peak around the fourth quarter, reaching about 1.1 percentage points for Q1 and about 0.7 percentage points for Q2 and Q3, before gradually declining and flattening at longer tenures. The Q1 profile remains consistently above the Q2 and Q3 profiles throughout the observed tenure range, indi-

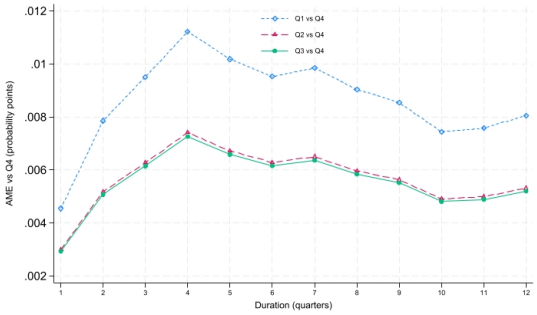
[30]In the competing-risks discrete-time duration setting, the AME is a cause-specific difference in predicted quarterly transition probabilities. For a given duration quarter, the AME for Q1, Q2, or Q3 compares the predicted probability of a specific transition—either job separation or job switching—with the predicted probability for Q4, averaging over the individuals at risk in that quarter and holding other covariates at their observed values. Thus, an AME of 0.010 for job separation means that workers in that parental-wealth quartile have a quarterly separation probability about one percentage point higher than comparable workers in Q4 at the same tenure.

cating that the separation-risk gap is largest for workers from the poorest parental-wealth quartile.[31]

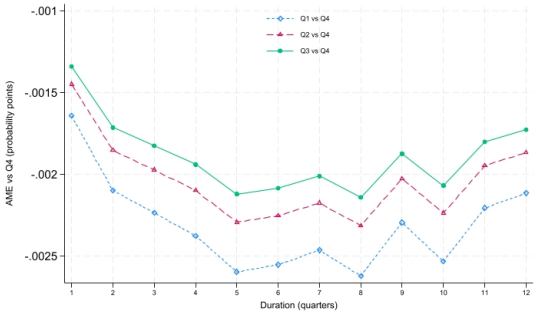
In the right panel (job-to-job transitions), AMEs are negative throughout but very small in magnitude, indicating slightly lower job-to-job mobility for workers from lower parental-wealth backgrounds relative to Q4. The negative AMEs are generally largest in absolute value for Q1, followed by Q2 and Q3, but the differences across quartiles remain small and fluctuate over tenure. This pattern is consistent with the coefficient estimates in Table 2.7: parental wealth is strongly associated with exits into non-employment, but its relationship with direct job-to-job switching is weak and statistically imprecise.[32]

Figure 2.2: Average marginal effects of parental wealth on job separation and job switching hazards

(a) Job separation



(b) Job switching



Source: Author's calculation using KLIPS 2-26

2.5.3 First and re-employment wages and parental wealth

Table 2.8 shows how starting wages in the first job and at re-employment vary with parental wealth and prior wages. The first–job regression keeps only individuals who report a starting wage for their first job. The re-employment regression uses the starting wage of the next job as the dependent variable and includes the

[31] Confidence intervals and formal significance tests for separation AMEs by parental wealth quartile and tenure are reported in Appendix 2.F.

[32] Confidence intervals and significance patterns for job-to-job AMEs are discussed in Appendix 2.F.

last observed wage from the previous job measured within one year prior to non-employment as a key explanatory variable. In both specifications, parental wealth quartiles (Q1–Q3, with Q4 as the reference) are included as central covariates. Both also control for current job information, worker characteristics, and region and calendar-year fixed effects.[33]

Parental wealth is strongly associated with entry wages but largely irrelevant for the wage set upon re-employment. In the first–job regressions, relative to Q4, Q1 workers earn about -7.7%, Q2 about -6.6%, and Q3 about -2.8% at the starting wage, with the first two effects statistically significant and the third statistically indistinguishable from zero. In the re-employment regressions, the corresponding wealth coefficients are small—approximately -2.1% for Q1, -1.8% for Q2, and -0.8% for Q3—and imprecisely estimated. This pattern runs counter to the mechanism that would predict higher re-employment wages for youth with greater parental liquidity during non-employment. Instead, re-employment wage setting responds primarily to wage history: the elasticity of the next job's starting wage with respect to the last wage in the previous job is about 0.209, so a 10% higher previous wage is associated with roughly a 2.1% higher re-employment starting wage.

Other covariates follow familiar labor market patterns. Age enters with a concave profile in both samples; women earn less than men in both cases, with a wider gap upon re-employment; educational attainment carries positive premia that are modest at the first job and larger at re-employment; and non-regular and part-time contracts are associated with substantial wage penalties throughout. These patterns, together with the weak wealth effects upon re-entry and the strong wage-history elasticity, indicate that parental wealth shifts reservation behavior at labor market entry but does not raise re-employment wages. Once workers return from non-employment, wage offers are shaped chiefly by information embedded in prior

[33] Percentage effects for dummies and categorical indicators are computed as $100[exp(\beta) - 1]$. Log–log coefficients are read as elasticities: a 1% increase in x changes y by $\beta\%$.

pay, so early-career wage dynamics are governed by accumulated wage history rather than ongoing parental liquidity.

Table 2.8: First and re-employment wages and parental wealth [1) 2) 3)]

Independent Variables		**Log Wages**	
		first job	re-employment
Parental Wealth (Net Worth)	1st quartile (Poorest)	**-0.080*** **	-0.021
		(0.020)	(0.017)
	2nd quartile	**-0.068*** **	-0.018
		(0.019)	(0.017)
	3rd quartile	-0.028	-0.009
		(0.019)	(0.017)
Worker Characteristics	Age	**0.080*** **	**0.031** **
		(0.018)	(0.013)
	Age squared	**-0.001** **	**-0.001** **
		(0.000)	(0.000)
	Female	**-0.082*** **	**-0.149*** **
		(0.015)	(0.013)
	Associate	0.022	**0.034** **
		(0.019)	(0.015)
	Bachelor	**0.036***	**0.112*** **
		(0.021)	(0.016)
	Postgraduate	**0.172*** **	**0.223** **
		(0.039)	(0.040)
Current Job Info.	Log wages of the previous job		**0.209*** **
			(0.013)
	Non-regular jobs	**-0.242*** **	**-0.154*** **
		(0.016)	(0.014)
	Part-time jobs	**-0.547*** **	**-0.575*** **
		(0.022)	(0.026)
Number of wage observations		3,119	4,898

Notes: 1) Robust standard errors are in parentheses. A constant term was not reported for brevity.
2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
3) All regressions include duration dummy variables, and controls for cohort, health condition, marriage, region of residence (Seoul, Gyeonggi Province, or other metropolitan cities), year fixed effects, and information of jobs: occupation and industry.

2.6 Robustness

All robustness checks in this section retain the empirical specifications used in Section 2.4: the random-effects discrete-time logit model for job finding and the random-effects cause-specific discrete-time logit models for exits from employment. The only change is the construction of the parental-wealth measure. The coefficients are therefore interpreted as conditional associations relative to the richest parental-wealth quartile, rather than as causal effects.

2.6.1 Wealth quartile variables

I first re-estimate the models using two alternative constructions of parental-wealth quartiles. The first alternative is a pure mean wealth-level measure, where CPI-deflated parental net wealth is averaged over the years in which parental wealth is observed and children are assigned to quartiles based on this mean. The second alternative is a year-rank-average measure, where parental wealth is first converted into a percentile rank within each survey year among households with observed wealth, and these annual percentile ranks are then averaged over time before assigning children to quartiles. These exercises examine whether the main results are specific to the baseline rank-based normalization of parental wealth, or whether they persist when parental resources are measured either directly in wealth levels or through a less cohort-specific measure of relative wealth position. The level-based measure captures absolute long-run parental wealth, while the year-rank-average measure captures the household's persistent relative position in the wealth distribution.

2.6.1.1 Mean wealth level quartile

In this robustness check, parental wealth quartiles are constructed using a pure mean wealth-level measure. For each parental household, CPI-deflated net wealth is first measured in each survey year in which wealth information is available, and then averaged over time. Children are subsequently assigned to quartiles based on this mean wealth.

Using this mean wealth-level measure, the parental-wealth relationship remains visible but is weaker than in the baseline rank-based specification. For job finding, children from lower-wealth households continue to have higher transition rates into employment relative to the richest quartile, although the coefficients are smaller than those obtained from the rank-based wealth measure. For job separation, the corrected ordering shows that the poorest quartile has the largest positive coefficient, followed by the 2nd and 3rd quartiles, suggesting a higher separation risk among children from lower-wealth families. By contrast, the estimates for job switching are negative and generally weaker, with only the poorest quartile marginally significant. This attenuation is plausible because absolute wealth levels are more sensitive to measurement error, extreme values, and asset-price fluctuations than rank-based measures of persistent relative parental wealth.

Table 2.9: Robustness check: discrete-time duration model for job finding using mean parental wealth level quartiles [1) 2) 3) 4)]

Independent Variables		**Dependent Variable**			
		All	First job	Subsequent jobs	
Parental Wealth (Mean Wealth Level)	1st quartile (Poorest)	**0.190*** **	**0.252** **	**0.196** **	**0.169** **
		(0.056)	(0.117)	(0.079)	(0.078)
	2nd quartile	**0.128** **	**0.235** **	0.123	0.083
		(0.056)	(0.115)	(0.079)	(0.078)
	3rd quartile	0.065	0.153	0.015	-0.004
		(0.055)	(0.108)	(0.079)	(0.078)
Worker Characteristics	Age	**0.199*** **	**0.471*** **	0.028	**0.089** *
		(0.034)	(0.152)	(0.052)	(0.049)
	Age squared	**-0.003*** **	**-0.006** **	-0.000	-0.001
		(0.001)	(0.003)	(0.001)	(0.001)
	Female	0.008	**0.661*** **	**-0.366*** **	**-0.387*** **
		(0.038)	(0.124)	(0.056)	(0.052)
	Associate	**0.201*** **	0.201*	0.103	**0.169** **
		(0.050)	(0.115)	(0.067)	(0.066)
	Bachelor	-0.023	**-0.499*** **	0.065	**0.157** **
		(0.051)	(0.161)	(0.073)	(0.070)
	Postgraduate	**0.301*** **	-0.021	0.141	**0.305** **
		(0.103)	(0.230)	(0.159)	(0.154)
Previous Job Info.	Log wages			**0.398*** **	
				(0.072)	
	Non-regular jobs			0.028	
				(0.056)	
	Part-time jobs			-0.081	
				(0.089)	
Number of Workers		4,138	3,920	2,020	2,115

Notes: 1) Standard errors are in parentheses. A constant term was not reported for brevity.
2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
3) All regressions include duration dummy variables, and controls for cohort, health condition, marriage, region of residence (Seoul, Gyeonggi province, or other metropolitan cities), and year fixed effects. The first subsequent-jobs specification additionally includes information on previous jobs: monthly labor income, job type (self, part-time/full-time, regular/non-regular), occupation and industry.
4) The parental wealth variable is based on pure mean net-wealth-level quartiles. For each parental household, CPI-deflated net wealth is averaged over all years in which parental wealth is observed, and children are assigned to quartiles of this mean net wealth.

Table 2.10: Robustness check: competing-risks discrete-time duration model for job separation and job switching using mean parental wealth-level quartiles [1) 2) 3) 4)]

Independent Variables		Dependent Variable	
		Job Separation	Job Switching
Parental Wealth (Mean Wealth Level)	1st quartile (Poorest)	**0.181****	**-0.127***
		(0.076)	(0.071)
	2nd quartile	**0.145***	-0.065
		(0.076)	(0.070)
	3rd quartile	0.117	-0.041
		(0.078)	(0.071)
Worker Characteristics	Age	-0.059	0.041
		(0.049)	(0.047)
	Age squared	0.001	-0.000
		(0.001)	(0.001)
	Female	**0.133****	0.019
		(0.055)	(0.053)
	Associate	**-0.261*****	-0.068
		(0.064)	(0.064)
	Bachelor	**-0.387*****	-0.065
		(0.071)	(0.069)
	Postgraduate	**-0.824*****	-0.152
		(0.171)	(0.133)
Job Info.	Log wages	**-0.150****	-0.104
		(0.061)	(0.065)
	Non-regular jobs	**0.476*****	**0.242*****
		(0.054)	(0.060)
	Part-time jobs	0.091	0.072
		(0.083)	(0.091)
Number of Workers		3,510	3,510

Notes: 1) Standard errors are in parentheses. A constant term was not reported for brevity.
2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
3) All regressions include duration dummy variables, and controls for cohort, health condition, marriage, region of residence (Seoul, Gyeonggi province, or other metropolitan cities), year fixed effects, and information on current or previous jobs: monthly labor income, job type (self, part-time/full-time, regular/non-regular), occupation and industry.
4) The parental wealth variable is based on pure mean net-wealth-level quartiles. For each parental household, CPI-deflated net wealth is averaged over all years in which parental wealth is observed, and children are assigned to quartiles of this mean net wealth.

2.6.1.2 Time-averaged wealth-rank quartiles

In this robustness check, parental wealth quartiles are constructed using a time-averaged annual wealth-rank measure. For each parental household, CPI-deflated net wealth is first converted into a percentile rank within each survey year among households with observed wealth. These annual wealth ranks are then averaged over time, and children are assigned to quartiles based on this household-level average annual rank. This differs from the baseline measure in the main analysis, which ranks parental wealth within survey-year-by-child-birth-cohort cells; here, the ranking is based only on the annual wealth distribution and does not apply cohort-specific normalization.

Using this year-rank-based measure, the parental wealth relationship is strong and closely aligned with the main specification. For job finding, children from lower-ranked parental-wealth households have higher transition rates into employment relative to the richest quartile, with the largest coefficients for the 1st quartile across all specifications: 0.457 in the full sample, 0.676 for first jobs, and around 0.4 for subsequent jobs. The 2nd quartile also shows positive and statistically significant coefficients, while the 3rd quartile is smaller and less consistently significant, suggesting a clear wealth gradient. For job separation, the poorest quartile has a large positive coefficient, indicating a higher separation risk relative to the richest group, while the 3rd quartile is also positive and significant. By contrast, the estimates for job switching are negative and statistically insignificant.

Table 2.11: Robustness check: discrete-time duration model for job finding using time-averaged wealth rank [1) 2) 3) 4)]

Independent Variables		**Dependent Variable**			
		All	First job	Subsequent jobs	
Parental Wealth (Wealth Rank)	1st quartile (Poorest)	**0.457*** **	**0.676*** **	**0.429*** **	**0.409*** **
		(0.061)	(0.160)	(0.089)	(0.087)
	2nd quartile	**0.275*** **	**0.421*** **	**0.285*** **	**0.250*** **
		(0.056)	(0.129)	(0.084)	(0.083)
	3rd quartile	**0.135** **	**0.240** **	0.097	0.087
		(0.055)	(0.110)	(0.085)	(0.083)
Worker Characteristics	Age	**0.200*** **	**0.505*** **	0.030	0.086*
		(0.033)	(0.154)	(0.052)	(0.049)
	Age squared	**-0.003*** **	**-0.006** **	-0.000	-0.001
		(0.001)	(0.003)	(0.001)	(0.001)
	Female	0.011	**0.674*** **	**-0.353*** **	**-0.373*** **
		(0.037)	(0.123)	(0.056)	(0.051)
	Associate	**0.227*** **	0.225*	0.128*	**0.188*** **
		(0.050)	(0.116)	(0.067)	(0.065)
	Bachelor	0.027	**-0.460*** **	0.104	**0.192*** **
		(0.051)	(0.156)	(0.072)	(0.068)
	Postgraduate	**0.351*** **	0.022	0.172	**0.333** **
		(0.102)	(0.230)	(0.158)	(0.152)
Previous Job Info.	Log wages			**0.395*** **	
				(0.071)	
	Non-regular jobs			0.024	
				(0.056)	
	Part-time jobs			-0.065	
				(0.089)	
Number of Workers		4,138	3,920	2,020	2,115

Notes: 1) Standard errors are in parentheses. A constant term was not reported for brevity.
2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
3) All regressions include duration dummy variables, and controls for cohort, health condition, marriage, region of residence (Seoul, Gyeonggi province, or other metropolitan cities), and year fixed effects. The third column includes information on previous jobs: monthly labor income, job type (self, part-time/full-time, regular/non-regular), occupation and industry.
4) The parental wealth variable is based on time-averaged annual wealth-rank quartiles. For each parental household, CPI-deflated net wealth is first converted into a percentile rank within each survey year. These annual wealth ranks are then averaged over time, and children are assigned to quartiles based on this average annual rank.

Table 2.12: Competing-risks discrete-time duration model for job separation and job switching using time-averaged wealth rank [1) 2) 3) 4)]

Independent Variables		**Dependent Variable**	
		Job Separation	Job Switching
Parental Wealth (Wealth Rank)	1st quartile (Poorest)	**0.343*** **	-0.060
		(0.085)	(0.078)
	2nd quartile	0.122	-0.117
		(0.079)	(0.073)
	3rd quartile	**0.186** **	-0.075
		(0.079)	(0.073)
Worker Characteristics	Age	-0.055	0.040
		(0.049)	(0.047)
	Age squared	0.001	-0.000
		(0.001)	(0.001)
	Female	**0.140** **	0.018
		(0.055)	(0.053)
	Associate	**-0.241*** **	-0.050
		(0.064)	(0.064)
	Bachelor	**-0.371*** **	-0.044
		(0.071)	(0.068)
	Postgraduate	**-0.819*** **	-0.132
		(0.170)	(0.133)
Job Info.	Log wages	**-0.158*** **	-0.105
		(0.061)	(0.065)
	Non-regular jobs	**0.474*** **	**0.236*** **
		(0.054)	(0.060)
	Part-time jobs	0.090	0.075
		(0.083)	(0.091)
Number of Workers		3,510	3,510

Notes: 1) Standard errors are in parentheses. A constant term was not reported for brevity.
2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
3) All regressions include duration dummy variables, and controls for cohort, health condition, marriage, region of residence (Seoul, Gyeonggi province, or other metropolitan cities), year fixed effects, and information on previous jobs: monthly labor income, job type (self, part-time/full-time, regular/non-regular), occupation and industry.
4) The parental wealth variable is based on time-averaged annual wealth-rank quartiles. For each parental household, CPI-deflated net wealth is first converted into a percentile rank within each survey year. These annual wealth ranks are then averaged over time, and children are assigned to quartiles based on this average annual rank.

2.6.2 Liquid Assets

I measure parental wealth using net worth—financial assets plus real-estate assets minus financial liabilities—and use net-worth quartiles as the main regressors. This choice follows search models with precautionary saving, where net wealth is the state variable linking saving behavior to search effort, reservation wages, and transition hazards (e.g., Rendon, 2006; Lentz, 2009; Lise, 2013; Chaumont and Shi, 2022).

In studies of parental wealth, researchers typically use net worth and analyze distributional position, such as percentile ranks or quantiles, to capture relative status and improve comparability across cohorts (Adermon et al., 2018; Boserup et al., 2018; Pfeffer and Killewald, 2018; Holmberg et al., 2024). By contrast, papers on own-wealth channels during job search often disaggregate portfolios into liquid assets, illiquid assets, and liabilities in order to isolate liquidity mechanisms (Levander, 2019; Fontaine et al., 2024).

This distinction is also practically important in the Korean context. Housing dominates household balance sheets and is often mortgage-financed, yet KLIPS does not allow mortgage liabilities to be cleanly separated from other financial debt. Treating assets and liabilities separately would therefore classify some households as simultaneously high-asset and high-debt, even when their net buffer capacity is more limited. Accordingly, the baseline specification uses net-worth quartiles.

As a robustness check, I re-estimate the baseline models by replacing net worth with parental financial assets, which capture a more liquid component of parental resources.[34] Tables 2.13 and 2.14 report these results.

For job finding hazards (Table 2.13), the coefficients on the 1st and 2nd financial-

[34]Fontaine et al. (2024) emphasize that decomposing workers' own wealth into its components is empirically important, since the effects of liquid assets, illiquid assets, and liabilities on job search may differ, while Oh and Lee (2022) similarly analyze disaggregated parental assets in the Korean context.

asset quartiles are positive and statistically significant in the full sample, indicating that youths from households with lower parental liquid assets have higher job finding hazards relative to those in the richest quartile. In the first-job specification, only the 1st quartile is statistically significant. For subsequent jobs, the 1st quartile remains positive and significant across specifications, while the 2nd quartile is significant only when previous job characteristics are included. The 3rd quartile is not statistically significant in any column. Overall, the financial-asset results preserve the direction of the baseline net-worth findings, but the coefficients are smaller and the gradient is less systematic.

For post-entry hazards (Table 2.14), parental financial assets are positively associated with job separation for the 1st and 2nd quartiles, significant at the 1% and 10% levels, respectively, while the 3rd quartile is not statistically significant. This is consistent with the baseline pattern that youths from poorer parental backgrounds face higher job separation risks. For job switching, however, the pattern differs: the 1st quartile is not statistically significant, while the 2nd and 3rd quartiles are negative and statistically significant. This suggests that lower-intermediate parental financial-asset groups are less likely to switch jobs than the richest group, although the non-monotonic pattern means that this result should be interpreted cautiously.

Replacing net worth with parental financial assets therefore yields partially consistent but weaker evidence. The results suggest that parental liquid assets contribute to the relationship between parental resources and early labor-market transitions, especially for job finding and job separation, but they do not show that financial assets exert a stronger or more systematic influence than net worth. Since the regressor is parental wealth rather than the worker's own wealth, the relevant form of "self-insurance" likely extends beyond direct liquidity. Net worth may better capture the broader environment parents provide, including housing stability, neighborhood quality, shared tangible resources, job search guidance, and risk tolerance at career entry. Accordingly, the financial-asset specification can be interpreted as isolating

the liquidity component, whereas the net-worth specification captures the combined effect of liquidity and broader parental support.

2.7 Theoretical Framework

I study a continuous-time incomplete-markets model with on-the-job search to generate predictions for how parental wealth affects young workers' job search and early-career transitions. The framework builds on the random-search/on-the-job search structure in Lise (2013) and the search–savings literature (Chaumont and Shi, 2022; Kaas et al., 2023), and extends the worker's problem developed in Chapter 1. The modeling choices are similar to those in Lammers (2014) and Holmberg et al. (2024), who allow search efficiency to differ between unemployment and employment and therefore allow reservation wages to vary with assets. To simplify the analysis, I solve the model in partial equilibrium with an exogenous wage-offer distribution and a fixed risk-free interest rate. The purpose of the model is not to identify causal effects of parental wealth, but to organize the conditional empirical associations documented in Sections 2.5 and 2.6. After deriving the model predictions, I return to the estimates and discuss where the data align with, and depart from, the model.

2.7.1 Environment

Agents and uncertainty

Time is continuous. There is a continuum of workers who are identical in preferences and technology, but who differ in their exogenous parental wealth. Upon entering the labor market, each worker draws parental wealth p from an exogenous cross-sectional distribution $G(p)$; this draw is fixed over the worker's lifetime and is not affected

Table 2.13: Robustness check: discrete-time duration model for job finding using parental financial assets [1) 2) 3)]

Independent Variables		**Dependent Variable**			
		All	First job	Subsequent jobs	
Parental Wealth (Financial Asset)	1st quartile (Poorest)	**0.218*** **	**0.288***	**0.291****	**0.209***
		(0.081)	(0.166)	(0.125)	(0.122)
	2nd quartile	**0.149****	0.133	**0.207***	0.152
		(0.071)	(0.133)	(0.116)	(0.112)
	3rd quartile	0.111	0.134	0.142	0.099
		(0.071)	(0.131)	(0.117)	(0.114)
Worker Characteristics	Age	**0.197*** **	**0.466*** **	0.031	**0.090***
		(0.033)	(0.154)	(0.053)	(0.049)
	Age squared	**-0.003*** **	**-0.006***	-0.000	-0.001
		(0.001)	(0.003)	(0.001)	(0.001)
	Female	0.010	**0.680*** **	**-0.368*** **	**-0.386*** **
		(0.038)	(0.128)	(0.056)	(0.052)
	Associate	**0.181*** **	0.184	0.084	**0.145****
		(0.050)	(0.117)	(0.067)	(0.065)
	Bachelor	-0.047	**-0.547*** **	0.044	**0.133***
		(0.051)	(0.168)	(0.072)	(0.069)
	Postgraduate	**0.287*** **	-0.045	0.128	**0.291***
		(0.103)	(0.233)	(0.159)	(0.154)
Previous Job Info.	Log wages			**0.402*** **	
				(0.072)	
	Non-regular jobs			0.037	
				(0.056)	
	Part-time jobs			-0.088	
				(0.090)	
Number of Workers		4,097	3,885	2,004	2,097

Notes: 1) Standard errors are in parentheses. A constant term was not reported for brevity.
2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
3) All regressions include duration dummy variables, and controls for cohort, health condition, marriage, region of residence (Seoul, Gyeonggi province, or other metropolitan cities), and year fixed effects. The third column includes information on previous jobs: monthly labor income, job type (self, part-time/full-time, regular/non-regular), occupation and industry.

Table 2.14: Robustness check: competing-risks discrete-time duration model for job separation and job switching using financial asset[1) 2) 3)]

Independent Variables		Dependent Variable	
		Job Separation	Job Switching
Parental Wealth (Financial Asset)	1st quartile (Poorest)	**0.355*** ** (0.118)	-0.006 (0.101)
	2nd quartile	**0.205*** (0.109)	**-0.185**** (0.091)
	3rd quartile	0.120 (0.110)	**-0.152*** (0.092)
Worker Characteristics	Age	-0.060 (0.049)	0.045 (0.047)
	Age squared	0.001 (0.001)	-0.000 (0.001)
	Female	**0.137**** (0.055)	0.021 (0.053)
	Associate	**-0.248***** (0.064)	-0.033 (0.064)
	Bachelor	**-0.379***** (0.070)	-0.031 (0.068)
	Postgraduate	**-0.818***** (0.170)	-0.124 (0.133)
Job Info.	Log wages	**-0.152**** (0.061)	-0.107 (0.066)
	Non-regular jobs	**0.474***** (0.054)	**0.232***** (0.060)
	Part-time jobs	0.079 (0.083)	0.087 (0.092)
Number of Workers		3,477	3,477

Notes: 1) Standard errors are in parentheses. A constant term was not reported for brevity.
2) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.
3) All regressions include duration dummy variables, and controls for cohort, health condition, marriage, region of residence (Seoul, Gyeonggi Province, or other metropolitan cities), job occupation, job industry, and year fixed effects.

by any of the worker's choices. Workers discount the future at rate $\rho > 0$.

State variables and ex-post heterogeneity

Conditional on their parental wealth draw p, workers become endogenously heterogeneous ex post in their own assets $a \in [\underline{a},\ \infty)$, wages $w \in [w^*(\underline{a}),\ \overline{w}]$, and search effort $\sigma \in [\underline{\sigma},\ \infty)$.[35] The lowest income state is home production b when workers are unemployed. Because markets are incomplete, own assets evolve endogenously with the history of search outcomes and employment spells, starting from an initial level that is itself determined by parental wealth.

Specifically, at the time of labor market entry, parents commit to provide a level of support $a_0(p) \leq p$, interpreted as the portion of parental wealth that is directly accessible to the young worker. This accessible parental wealth $a_0(p)$ is the worker's initial asset position in the model and is therefore more exogenous than subsequent asset holdings: $a_0(p)$ is pinned down by the parental-wealth draw p, whereas a_t for $t > 0$ evolves endogenously through the worker's savings and search decisions.

Preferences

Workers derive utility from consumption of a composite good c and disutility from job search effort σ. The utility function $u(c)$ and the search cost function $\psi(\sigma)$ are continuously differentiable with standard curvature: $u'(\cdot) > 0, u''(\cdot) < 0, \psi'(\cdot) > 0$, and $\psi''(\cdot) > 0$.

[35] $w^*(\underline{a})$ is the lowest reservation wage accepted by the worker with the least parental wealth. Let $\underline{p}$ denote the lowest parental wealth in the support of $G(p)$. The corresponding lowest accessible initial asset level is $\underline{a} \equiv a_0(\underline{p})$, where $a_0(p) \leq p$ is defined below. $\underline{\sigma}$ is free search, which is the effort level that has no disutility costs. See Section 2 of Chapter 1 for details.

Search technology and wage ladder

Search is random both off and on the job. An unemployed worker with asset level a and home production b chooses search effort $\sigma^u(a,b) = \sigma^u(a)$ and receives offers according to a Poisson process with intensity $\lambda^u\sigma^u(a)$. An employed worker with asset level a and labor income w chooses $\sigma^e(a,w)$ and receives offers at rate $\lambda^e\sigma^e(a,w)$. I assume that the unemployed and employed workers do not share the same search technology, and the unemployed workers' job search is more efficient than on-the-job search ($\lambda^u > \lambda^e$). This gap raises the option value of waiting in unemployment and implies a reservation wage strictly above b, with the reservation rule varying with assets and thus, indirectly, with parental wealth through the initial condition $a_0(p)$. Wage offers $\tilde{w}$ are drawn from an exogenous wage offer distribution $F(w)$. When a worker accepts the wage offer, the match is formed and output is produced and shared between the worker and the firm. Matches are separated in one of two ways. First, a worker could be laid off exogenously at the job destruction rate $\delta > 0$. The worker subsequently becomes unemployed with home production value b. Second, a worker may quit their job for any offer $\tilde{w} > w$ as a result of successful on-the-job search. Thus, for a worker earning wage w with asset holdings a, job-to-job transitions endogenously occur at rate $\lambda^e\sigma^e(a,w)\overline{F}(w)$, where $\overline{F}(w) = 1 - F(w)$, and the employment-to-non-employment hazard is δ.

Similarities and differences from the Chapter 1 model

This section simplifies and extends the worker's problem in Chapter 1 to isolate the role of parental wealth in early-career search:

(i). The Chapter 1 model endowed workers directly with their own initial wealth. In contrast, in the current model, parental wealth p is an exogenous, time-invariant characteristic. Upon entering the labor market, each worker draws p from a fixed

distribution $G(p)$ and parents commit to provide an initial level of support $a_0(p) \leq p$ (interpreted as the portion of parental wealth accessible to the child). This accessible parental wealth becomes the worker's initial asset position. Thereafter, own assets evolve endogenously through saving and dissaving out of wages.

(ii). In Chapter 1, both unemployed and employed workers use the same search technology, leading to a single job offer arrival rate. Additionally, in a general equilibrium setting, the job offer arrival rate is endogenously determined by the free entry condition of the labor market. Here, the search efficiency is state-specific and exogenous: $\lambda^u > \lambda^e$. This assumption generates heterogeneity of reservation wages, because the reservation wage of the unemployed is higher than the home production value b, leading to the additional amount above b varying with assets, and therefore with parental wealth via $a_0(p)$.

(iii). Chapter 1 solved the model in general equilibrium, endogenizing firms' wage policies and risk-free interest rates. Here, this model remains in partial equilibrium with the exogenous wage offer distribution and a fixed risk-free interest rate to focus on the direct effects of parental wealth on hazards and search policies.

(iv). This model does not introduce progressive redistribution policies, such as progressive labor income taxation or unemployment benefits, even though such policies significantly impact labor market transitions and earnings dynamics. Incorporating these policies is left for future research.

2.7.2 Workers' Problem

There is a continuum of workers who are risk averse. They save using a riskless interest rate r in incomplete asset markets, where a worker can only partially insure against idiosyncratic unemployment risk. Throughout, parental wealth p is treated as exogenous and fixed; the problem below is written conditional on a given parental-

wealth type p, and I suppress p in the value-function notation for brevity. Workers maximize the expected present discounted value of utility from consumption flows c_t and disutility from search effort flows σ_t, discounted at rate ρ as follows:

$$E_0 \int_0^\infty e^{-\rho t}[u(c_t) - \psi(\sigma_t)]dt.$$

A worker is paid gross labor wages w_t from a job, and can consume or save them. Conditional on parental wealth p, the worker enters the labor market with initial assets $a_0(p) \leq p$, representing the portion of parental wealth that is directly accessible. Thereafter, the worker's own wealth evolves according to

$$\dot{a}_t = w_t + ra_t - c_t, \qquad a_0 = a_0(p) \leq p.$$

The risk-free interest rate r is assumed to be less than the discount rate ρ, so as to prevent workers from being too patient and accumulating unlimited assets due to the precautionary savings motive. A worker also faces the borrowing limit at zero:

$$a_t \geq 0,$$

meaning borrowing is not permitted. Finally, workers' gross labor income evolves stochastically over time. Here, we assume that the home production value of an unemployed worker b is also taxable. The changes in the gross labor income are as follows:

$$dw_t = \begin{cases} dq_{\lambda^u \sigma^u} 1(v^e(a_t, \tilde{w}_t) \geq v^u(a_t, b))[\tilde{w}_t - b] & \text{when unemployed,} \\ dq_{\lambda^e \sigma^e} 1(v^e(a_t, \tilde{w}_t) \geq v^e(a_t, w_t))[\tilde{w}_t - w_t] + dq_\delta[w_t - b] & \text{when employed,} \end{cases}$$

where $1(\cdot)$ is the indicator function, $v^e(a, w)$ is the value of being employed with labor income w and assets a, $v^u(a, b)$ is the value of being unemployed with home production value b and assets a, and wage offers $\tilde{w} \in [\underline{w},\ \overline{w}]$ are drawn from the

exogenous wage offer distribution $F(w)$.

Suppose that there is an unemployed worker with income b and assets a. Job offers arrive according to a Poisson process with intensity $\lambda^u\sigma^u$, where λ^u is the baseline arrival rate and the search intensity is increasing in the worker's search effort σ^u. Upon the arrival of an offer with wage $\tilde{w}$, the worker accepts the offer if the value of being employed with $\tilde{w}$ is greater than remaining unemployed. Let $dq_{\lambda^u\sigma^u}$ denote whether the event of a job offer occurs or not. Therefore, $dq_{\lambda^u\sigma^u} = 1$ if a job offer arrives and 0 otherwise. This also applies to an employed worker with current wage w and assets a. When employed, there is an additional risk of job separation. Let dq_δ indicate whether a job separation occurs or not. Therefore, $dq_\delta = 1$ if a job is exogenously destroyed and 0 otherwise. Facing uncertainty regarding the time when a job offer arrives and job separation, as well as the wages offered, workers decide how much to consume and how much effort to expend in searching for a job.

The workers' problem is represented as a Hamilton-Jacobi-Bellman (HJB) equation that solves for the optimal savings and search effort policies, given prices and the distribution of workers. The HJB equations for the unemployed and the employed are as follows, respectively:

$$\rho v^u(a) = \max_{c\in[0,a],\sigma\geq\underline{\sigma}} \left\{ u(c) + \lambda^u\sigma^u \int \max\left(v^e(a,\tilde{w}) - v^u(a), 0\right) dF(\tilde{w}) \right.$$
$$\left. + v^u_a(a)\left(b + ra - c\right) - \psi(\sigma^u) \right\} \quad \text{when unemployed,} \tag{2.1}$$

$$\rho v^e(a,w) = \max_{c\in[0,a],\sigma\geq\underline{\sigma}} \left\{ u(c) + \lambda^e\sigma^e \int \max\left(v^e(a,\tilde{w}) - v^e(a,w), 0\right) dF(\tilde{w}) + \delta\left(v^u(a) - v^e(a,w)\right) \right.$$
$$\left. + v^e_a(a,w)\left(w + ra - c\right) - \psi(\sigma^e) \right\} \quad \text{when employed.} \tag{2.2}$$

Here, $v^u(a)$ denotes the value of unemployment of a worker with asset holdings a, and $v^e(a,w)$ denotes the value of employment of a worker working at wage w with asset holdings a. During unemployment, the value of unemployment is discounted at

rate ρ on the left-hand side. The right-hand side of equation (2.1) maximizes the flow utility (disutility) from consumption and search effort. The value of unemployment changes in expectation in one of two ways. First, there is an expected increase in future labor income when a worker succeeds in finding a job, which is represented by the second term on the right-hand side. Second, workers also consider how the value changes along their law of motion of assets in the third term. For the employed, workers have the additional route of expected decrease in labor income, which is associated with job destruction rate δ.

Workers' decisions are threefold: how much to consume, how much search effort to expend in looking for a job, and which job offers to accept. The first two decisions are determined by the first-order conditions given as follows:

when employed,

$$u'(c^e) = v^e_a(a, w), \tag{2.3}$$

$$\psi'(\sigma^e) = \lambda^e \int \max\left(v^e(a, \tilde{w}) - v^e(a, w), 0\right) dF(\tilde{w}). \tag{2.4}$$

when unemployed,

$$u'(c^u) = v^u_a(a, b), \tag{2.5}$$

$$\psi'(\sigma^u) = \lambda^u \int \max\left(v^e(a, \tilde{w}) - v^u(a, b), 0\right) dF(\tilde{w}). \tag{2.6}$$

Looking at employed workers, equation (2.3) is the Euler equation that solves for the standard consumption-savings problem. It chooses the optimal consumption such that the marginal utility of consumption is equal to the marginal value of assets. Equation (2.4) requires the marginal cost of search effort to be equal to the marginal expected return from on-the-job search. This condition determines how fast the employed workers move up the wage ladder, affecting their asset accumulation. Similarly, unemployed workers optimally choose their consumption using equation

(2.5), and their search effort using equation (2.6).

Lastly, workers choose which job offers to accept conditional on their current wages. Given the difference in search technology represented by the job offer arrival rates λ^u and λ^e, the reservation wage of unemployed workers is greater than the home production value b, and depends on their current assets. Because higher search efficiency in unemployment ($\lambda^u > \lambda^e$) raises the value of remaining unemployed relative to accepting low wages, the associated reservation wage schedule varies systematically with parental wealth through its effect on the initial asset position $a_0(p)$.

2.7.3 Predictions on Labor Market Transitions across Parental Wealth Distribution

2.7.3.1 Job Finding: Non-employment-to-Employment Transitions

Reservation Wage. The reservation wage $w^*(a)$ for an unemployed worker with assets a solves

$$\upsilon^u(a) = \upsilon^e(a, w^*(a)). \tag{2.7}$$

Differentiating both sides with respect to a and using the first order conditions $\upsilon^u_a(a) = u'(c^u(a))$ and $\upsilon^e_a(a, w) = u'(c^e(a, w))$, the derivative of the reservation wage with respect to asset holdings a is obtained as follows:

$$\frac{dw^*(a)}{da} = \frac{\upsilon^u_a(a) - \upsilon^e_a(a, w^*(a))}{\upsilon^e_w(a, w^*(a))} = \frac{u'(c^u(a)) - u'(c^e(a, w^*(a)))}{\upsilon^e_w(a, w^*(a))}. \tag{2.8}$$

As shown in Lemma 1 and the proof in Appendix 1.C in Chapter 1, the value function $\upsilon^e(a, w)$ is strictly increasing in wages w, so the denominator is positive. Under the assumption of $u'(\cdot) > 0$, if consumption while unemployed $c^u(a)$ is less than the consumption when employed at the reservation wage $c^e(a, w^*(a))$, the

numerator is positive. Hence the reservation wage increases with assets a. This implies that unemployed workers with wealthier parents can afford to wait and therefore set higher reservation wages.

Search Effort. Unemployed search effort solves the first order condition in equation (2.6):

$$\psi'(\sigma^u) = \lambda^u \int \max\left(v^e(a,\tilde{w}) - v^u(a), 0\right) dF(\tilde{w}) =: \lambda^u J^u(a),$$

where $J^u(a)$ denotes the expected gains from search of the unemployed. Rewriting as $H^u(\sigma^u, a) := \psi'(\sigma^u) - \lambda^u J^u(a) = 0$ and applying the Implicit Function —Theorem gives

$$\psi''(\sigma^u)\frac{\partial \sigma^u}{\partial a} = \lambda^u \frac{\partial J^u}{\partial a}. \tag{2.9}$$

Differentiating $J^u(a)$ with respect to a yields

$$\begin{aligned}\frac{\partial J^u}{\partial a} &= \int 1\{v^e(a,\tilde{w}) \geq v^u(a)\}\left(v^e_a(a,\tilde{w}) - v^u_a(a)\right) dF(\tilde{w}) \\ &= \int 1\{v^e(a,\tilde{w}) \geq v^u(a)\}\left(u'(c^e(a,\tilde{w})) - u'(c^u(a))\right) dF(\tilde{w}) \leq 0,\end{aligned}$$

with strict inequality if $c^e > c^u$. Since $\psi''(\cdot) > 0$, it follows that the sign of $\frac{\partial \sigma^u}{\partial a}$ is equal to the sign of $\frac{\partial J^u}{\partial a}$ and consequently, $\frac{\partial \sigma^u}{\partial a} < 0$.

Combining the higher reservation wage $\left(\frac{\partial w^*}{\partial a} > 0\right)$ and lower search effort $\left(\frac{\partial \sigma^u}{\partial a} < 0\right)$ of the unemployed workers with higher parental wealth, the job finding hazard,

$$h_{NtE} = \lambda^u \sigma^u(a)[1 - F(w^*(a))]$$

declines with parental wealth through a higher reservation wage and lower search effort, which shrinks the acceptance region. Consequently, workers with wealthier parents are less likely to accept job offers, resulting in lower job finding rates and

longer durations of non-employment. Conversely, low-wealth workers are less selective and search harder.

2.7.3.2 Job Switching: Job-to-Job Transitions

Search Effort. Employment values are strictly increasing in the current wage (Chapter 1, Lemma 1).[36] Hence an employed worker will accept any wage offer that is higher than the current wage ($\tilde{w} > w$). The job switching hazard is therefore

$$h_{JtJ} = \lambda^e \sigma^e(a, w)(1 - F(w)),$$

given the current state of (a, w).

On-the-job search effort solves the first order condition in equation (2.4):

$$\psi'(\sigma^e) = \lambda^e \int_w^{\bar{w}} (v^e(a, \tilde{w}) - v^e(a, w))\, dF(\tilde{w}) =: \lambda^e J^e(a, w).$$

Let $H^e(\sigma^e, a) := \psi'(\sigma^e) - \lambda^e J^e(a, w) = 0$. By the Implicit Function Theorem,

$$\psi''(\sigma^e)\frac{\partial \sigma^e}{\partial a} = \lambda^e \frac{\partial J^e}{\partial a}, \quad \psi''(\sigma^e)\frac{\partial \sigma^e}{\partial w} = \lambda^e \frac{\partial J^e}{\partial w}.$$

Differentiating J^e with respect to a and using the first order conditions,

$$\begin{aligned}\frac{\partial J^e}{\partial a} &= \int_{\tilde{w}>w} (v_a^e(a, \tilde{w}) - v_a^e(a, w))\, dF(\tilde{w}) \\ &= \int_{\tilde{w}>w} (u'(c^e(a, \tilde{w})) - u'(c^e(a, w)))\, dF(\tilde{w}) \leq 0,\end{aligned}$$

because accepted offers satisfy $\tilde{w} > w$ and, upon acceptance, $c^e(a, \tilde{w}) \geq c^e(a, w)$ so

[36] For the formal derivation, see Appendix 1.C in Chapter 1.

that $u'(c^e(a,\tilde{w})) \leq u'(c^e(a,w))$. This implies

$$\frac{\partial \sigma^e}{\partial a} < 0,$$

meaning higher assets reduce on-the-job search effort.

Differentiating J^e with respect to the current wage w, and applying Leibniz' rule,

$$\frac{\partial J^e}{\partial w} = \int_w^{\bar{w}} [-\upsilon_w^e(a,w)] f(\tilde{w}) d\tilde{w} = -\upsilon_w^e(a,w)[1-F(w)] < 0,$$

since the lower-limit term vanishes because the bracket is zero at $\tilde{w} = w$, and $\upsilon^e(a,w)$ is strictly increasing in wages w (Chapter 1, Lemma 1). Then, using $\psi''(\sigma^e)\frac{\partial \sigma^e}{\partial w} = \lambda^e \frac{\partial J^e}{\partial w}$, and $\psi''(\cdot) > 0$, it follows that

$$\frac{\partial \sigma^e}{\partial w} < 0.$$

Intuitively, the option value of moving up the wage ladder is smaller when already at a higher rung, so on-the-job search effort declines with the current wage. Upon $\sigma_w^e < 0$ and $\sigma_a^e < 0$, as young workers earn more, accumulating their own wealth more quickly, this reduces the intensity of on-the-job search and job switching.

A way to summarize the channels is to differentiate the log hazard $ln(h_{JtJ})$:

$$\frac{\partial ln(h_{JtJ})}{\partial a} = \frac{1}{\sigma^e}\frac{\partial \sigma^e}{\partial a} + \frac{\partial ln[1-F(w)]}{\partial w} \cdot \frac{\partial w}{\partial a}.$$

The first term is negative because $\frac{\partial \sigma^e}{\partial a} < 0$. If the job is the worker's first job, then $\frac{\partial w}{\partial a} \geq 0$through a higher entry wage from a higher $w^*(a)$, while $\frac{\partial ln[1-F(w)]}{\partial w} = -\frac{f(w)}{1-F(w)} < 0$. Both terms therefore reduce the job-to-job mobility as parental wealth rises: search effort is lower, and the acceptance region $[1-F(w)]$ is smaller at higher w. This predicts higher early-career job-to-job transitions among workers from low-wealth families.

Early in the career, low-wealth workers start at lower wages and choose higher on-the-job search effort, so the job switching hazard is relatively high. Then, as they move up the wage ladder and accumulate assets more quickly, both w (higher rung) and a (higher asset holdings) put downward pressure on on-the-job search effort and on the acceptance region, implying a decline in job-to-job transitions with tenure.

2.7.3.3 Job Separation: Employment-to-Non-employment transitions

In the baseline specification, the separation rate δ is constant, so job separation hazard does not directly vary with parental wealth. The model is therefore silent about heterogeneity in job stability across wealth groups. The frictional markets literature often emphasizes that higher-wage matches are more stable either due to match-quality or firm-type heterogeneity. If one were to allow the job separation rate δ to depend on wage w negatively ($\delta'(w) < 0$), the mechanism above would imply that higher parental wealth raises the entry wage $w^*(a)$ and, in turn, lowers early-career separations. I keep δ constant in the core model to isolate search effort and the reservation wage effects; the wage-dependent separation can be considered as a robustness extension.

2.7.4 Interpreting the Empirical Results through the Model

The model is useful not as an additional source of identification, but as a disciplined way to interpret the conditional associations documented in the empirical analysis. It highlights three ways through which parental wealth can matter for early-career labor market outcomes: the reservation wage and search effort during non-employment, the wage and match-quality consequences of accepting offers quickly, and the job upgrading through on-the-job search.

First, the job finding estimates in Table 2.6 align closely with the model's cen-

tral prediction. In the model, parental resources raise the value of remaining non-employed and allow young workers to be more selective. Lower parental wealth is therefore associated with a higher non-employment-to-employment hazard. The positive coefficients for the lower parental-wealth quartiles, especially $Q1$ and $Q2$, in both first-job and re-employment specifications are consistent with this search-selectivity margin. Because the first-job and re-employment risk sets differ in observable composition, I interpret these estimates as within-risk-set associations rather than as directly comparable effect sizes across columns.

Second, the wage estimates in Table 2.8 are consistent with the model mainly at labor market entry. If workers from low-wealth families accept offers more quickly and under lower reservation wages, their first accepted jobs should pay less. This is what the first-job wage estimates show: workers from poorer parental-wealth quartiles enter their first jobs at lower starting wages than workers from the richest quartile. By contrast, the re-employment wage coefficients for parental wealth are small and imprecisely estimated once previous wages are controlled for. This suggests that, after the first job, accepted wages are more closely associated with accumulated wage history than with contemporaneous parental liquidity.

Third, the employment-exit estimates in Table 2.7 both support and qualify the model. The baseline model treats separations into non-employment as exogenous and therefore does not directly generate a parental-wealth relationship in such separations. However, the search-selectivity mechanism suggests a natural extension: if lower reservation wages lead low-wealth workers into lower-quality or less stable matches, then these workers should be more likely to exit employment into non-employment. The positive coefficients for lower parental-wealth quartiles in the separation equation are consistent with this broader match-quality interpretation. I therefore read the separation results as evidence on a margin suggested by the model's search-selectivity logic, but not formally generated by the baseline model.

Fourth, the job-to-job estimates reveal an important tension with a simple job-ladder prediction. If low-wealth workers accept lower initial wages, the model would suggest that they have stronger incentives to search on the job and climb the wage ladder through direct job-to-job transitions. The data do not support this prediction. The job-to-job coefficients for the lower parental-wealth groups are negative and statistically indistinguishable from zero, providing no evidence that low-wealth workers engage in more direct upgrading mobility. Instead, their excess mobility is concentrated in exits into non-employment. One interpretation is that poor initial matches are more likely to break down before workers can climb the job ladder. Another is that observed job-to-job mobility includes non-wage job attributes, constrained mobility, and involuntary moves that are outside the simple upward-only wage ladder in the model.

Finally, the model clarifies why the composition of the risk sets matters. If workers from lower-wealth families leave non-employment more quickly and are more likely to return to non-employment after accepting less stable jobs, then the observed pools of non-employed and employed workers are selected by parental wealth, elapsed duration, and previous job history. Appendix 2.D documents these observable composition differences across the transition-specific risk sets and shows why coefficient magnitudes across the pooled, first-job, and subsequent-job specifications should be interpreted within each risk set rather than compared mechanically across columns. The empirical specifications condition on duration dependence, observed worker characteristics, job characteristics, and previous-job controls, but the estimates should still be interpreted as conditional associations rather than structural causal effects. The theoretical framework therefore contributes by explaining why such selection arises, organizing the signs and tensions in the empirical results, and clarifying which patterns are inside the model and which point to mechanisms beyond the baseline framework.

2.8 Conclusion

This study has examined how the early careers of young workers differ systematically by parental wealth, in patterns consistent with a "private insurance" channel. Motivated by the Korean "spoon-class" discourse, I asked whether and how parental assets, rather than only education or innate ability, are associated with job search behavior, labor market transitions, and early wage profiles. Building on search-and-savings models in incomplete markets, I interpreted parental liquidity as a possible buffer stock that may relax borrowing constraints for young workers who enter the market with little wealth of their own and often limited access to unemployment insurance. In such an environment, parental wealth can substitute for own assets, potentially altering reservation wages, search selectivity, and the stability of accepted jobs. Because the empirical analysis is observational, these patterns should be interpreted as conditional associations rather than causal effects of parental wealth.

The empirical analysis using KLIPS waves 2–26 shows a consistent pattern along these lines. Young workers from poorer families leave non-employment faster than those from wealthier families, both at initial entry and after a separation, even after conditioning on rich sets of individual and job characteristics. Because the first-job and re-employment samples differ in composition, I interpret these gradients within each transition-specific risk set rather than as directly comparable effect sizes. This is consistent with lower reservation wages and less selective search among low-wealth youth. At the same time, children from poorer households are more likely to experience separations into non-employment, while direct job-to-job transitions show no statistically clear relationship with parental wealth. By contrast, parental wealth plays little role in explaining wages at re-employment once previous pay is taken into account: subsequent offers largely track wage history rather than current parental liquidity. Together, these findings suggest that parental wealth is closely

associated with the initial sorting of young workers into jobs and with the stability of early matches, but that later wage offers are governed more by accumulated labor market signals than by ongoing parental support.

Comparing these facts with a search-and-savings model highlights both alignments and tensions. The model predicts that higher parental wealth lowers job finding hazards by raising reservation wages, which is in line with the empirical gradient in non-employment durations. It also predicts that low-wealth youth, who accept lower-wage jobs more quickly, should subsequently engage in more job-to-job mobility in order to climb the wage ladder. In the data, however, job switching hazards show no clear positive relationship for low-wealth workers and, if anything, appear slightly lower for workers from poorer families. Rather than compensating for early lower wages via more frequent upgrading moves, poorer youth seem more exposed to separations into non-employment.

Several limitations point to avenues for future research. First, the insurance role of family background is proxied by parental net worth in a linked parent–child panel, without direct information on intra-family transfers, informal support, or student loan borrowing; in addition, the non-employment state combines unemployment and inactivity, so the estimated gradients should not be interpreted as pure unemployment-duration effects. Linking survey data to administrative records on transfers, debt, and student-aid or income-support programs would allow a clearer decomposition of private and public insurance and a fuller view of how parental resources buffer early-career risks. Second, the discrete-time hazard models assume conditionally independent right-censoring and impose proportional wealth effects over duration, constraining the impact of parental assets on job-finding hazards to be time-invariant; yet in an environment with unemployment insurance and a finite benefit period, liquidity constraints are likely to evolve over the spell of non-employment, so relaxing the proportional hazards assumption and allowing the wealth effect to vary with elapsed duration would be a natural extension.

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Appendix

2.A Empirical context of South Korea: educational expansion and social mobility

As this study uses Korean data and the analysis relies on the socio-economic context of South Korea, below I summarize empirical evidence on labor market mobility, social mobility, and educational expansion in South Korea.

2.A.1 Educational expansion

(i) South Korea experienced a great expansion of higher education within a short period.

The college system in South Korea rapidly expanded during the 1990s. Before 1992, fewer than 35% of high school graduates enrolled in higher education, but by 2004, the figure had surged to 80% (Choi, 2015). As a result of this, by 2023, South Korea's tertiary attainment rate among 25–34-year-olds reached 69.7%, ranking the first among 46 OECD countries (OECD, 2024a). For individuals, tertiary education was a rational and attractive choice, considering differences in labor market outcomes by educational attainment and the social aspiration of achieving a higher education than their parents. However, as nearly 70% of young adults now hold a tertiary degree, the overall labor market has experienced increasing overqualification. The share of workers employed in jobs below their level of education stands at 31%, well above the OECD average of 23% (OECD, 2024b). Moreover, the returns to higher education in Korea vary by socioeconomic background. Lee (2022) examined workers who graduated high school in 2005 and subsequently pursued tertiary education, and found that among men from lower-income families, the wage premium for a 2-year college degree exceeded that for a 4-year degree. This suggests a reduced

effect of higher education on labor market outcomes.

Labor market mobility of young workers

Before the 1997 Asian economic crisis, Korea was known for high job stability represented by seniority pay and long-term employment. Since the crisis, job mobility increased and has subsequently remained high.[37] Three factors are suggested by empirical studies:

(i) Over-education and job mismatch

Korea's education-job mismatch is well documented and is associated with high job mobility. The supply of Bachelor's degree holders exceeds labor market demand, leading to a large skills mismatch (Nam and Kim, 2014). Over-educated young workers are significantly more likely to change jobs in search of better matches (Park and Shahiri, 2015). Relatedly, even doctorate holders face over-education with wage penalties, which raises on-the-job search intensity and mobility (Park et al., 2018).

(ii) Labor market duality (regular vs. non-regular jobs, large-firm vs SME)

Since the 1997 Asian economic crisis, firms have chosen the strategies of outsourcing and the expansion of non-regular employment. This has persisted for two decades, widening gaps between dual labor markets (permanent *vs* outsourced contracts, large corporations *vs* SME) and therefore reducing mobility between them (Song, 2020). Compared with relatively protected regular jobs in large firms, non-regular segments and SMEs (small and medium enterprises) feature poorer working conditions and greater instability. Due to the barrier to mobility between the dual markets, workers in the secondary labor market (low wage, low stability) strug-

[37] Multiple sources show Korea stands out for short job tenure and high worker turnover. In 2018, 30.4% of employees in Korea had been in their job for less than one year (OECD average of 19.4%) (OECD, 2020). Working Korea 2022 also reports that 31.7% of workers had under one year of tenure.

gle to transition into the primary market (high wage, stable employment).[38] Consequently, frequent job changes among young workers are associated with higher unemployment rather than career progression.

(iii) Greater search intensity associated with wage gains

By contrast, some research argues that after the 1997 economic crisis, frequent job-to-job transitions have expanded opportunities for upward earning mobility among low-wage workers (Choi, 2016; Lim and Lee, 2018). Some young workers' job mobility has been associated with improvements in wages and working conditions, consistent with the "job shopping" mechanism in which inter-firm transitions yield wage gains as workers sort into better matches (Mincer and Jovanovic, 1981). Despite Korea's dual labor market, young workers with Bachelor's degrees show the highest upward transitions from non-regular to regular employment; more than 60 percent report such trajectories (Keum and Yi, 2016).

2.A.2 Intergenerational mobility

(i) South Korea's intergenerational earnings mobility is similar to, or slightly higher than, that of already developed countries, while it remains lower than that of recently developed or developing economies.

In South Korea, economic mobility is primarily measured using Intergenerational income elasticity (IGE). It is defined as the percentage change in a child's income associated with a 1% change in their parents' income.[39] A higher IGE means a stronger

[38] In South Korea, it is widely perceived that the labor market is sharply segmented into a small core of stable, well-paid "insider" jobs (typically large firms and the public sector) and a much larger periphery of precarious, low-paid positions (small firms, temporary and subcontracted work), with substantial institutional and social barriers that make upward mobility from the secondary to the primary sector both rare and difficult.

[39] The basic approach of IGE is provided by Solon (1992), where the elasticity is estimated as the coefficient in an OLS regression of children's log income on that of their parents. However, estimates based on short-term or current income generate downward bias (Haider and Solon, 2006). To avoid these biases, several methodologies have been developed by adjusting family size (Nam, 2018), minimizing life-cycle bias through averaging earnings over time (Haider and Solon, 2006;

impact of parental income on children's income, implying lower intergenerational earnings mobility. In other words, IGE is negatively associated with economic mobility. From the literature, there have been several estimates of the IGE of South Korea, which mostly lie between 0.2 and 0.3 since the 2000s (Kim et. al., 2012; Nam, 2018; Lee, 2022). However, these estimates are not directly comparable with those of other countries, as they are computed using post-tax labor income. Since labor income taxation plays a key role in earnings inequality, post-tax IGEs tend to be smaller than their pre-tax counterparts (Mitnik et al., 2015). As most international comparisons rely on pre-tax income, South Korea's IGE estimates must be interpreted with caution in cross-country contexts.

Kim (2017) provides South Korea's IGE using pre-tax income and a two-sample estimation strategy, yielding a value of 0.39. When compared with other countries using the same methodology, South Korea's IGE is similar to, or slightly higher than, that of developed countries (e.g., 0.29 in the UK, 0.34 in Japan, and 0.42 in the US), but significantly lower than that of recently developed or developing countries (e.g., 0.69 in Brazil, 0.63 in China, and 0.52 in Chile). Additionally, the World Economic Forum's Global Social Mobility Index ranks South Korea 25th among 82 countries. This places it below Germany (11th), Japan (15th), and the UK (21st), but ahead of the US (27th), China (45th), and Brazil (60th), offering a similar relative position in cross-country comparison.

(ii) Social mobility in South Korea has declined since the late 2000s compared to earlier periods.

Empirical research on long-term trends in intergenerational mobility in South Korea remains limited. A few studies find no consistent long-term trend in the IGE, and apparent spikes in particular years are usually attributed to sampling variability rather than genuine changes in intergenerational persistence (Kim, Seok, and Hyun,

Grawe, 2006), and applying two-sample estimation to approximate permanent parental income (Ueda, 2013; Kim, 2017).

2012; Lee, 2022). On the other hand, such studies report that the average IGE after the late 2000s is higher than that of earlier periods. For example, (Nam, 2018) estimated annual IGE values from 2007 to 2012, finding no systematic trend aside from a spike in 2008. Yet, the relatively short period of six years limits the ability to identify long-term patterns. In contrast, (Lee, 2022) estimated the IGE for each year from 1998 to 2019, providing a broader time window. Although no consistent upward or downward trend was observed, IGE values fluctuated between 0.20 and 0.32 before the late 2000s and then stabilized at a higher range thereafter (around 0.27 to 0.30), suggesting a potential decline in mobility. Supporting this view, Kim, Seok, and Hyun (2012) estimated an average IGE of 0.30 for the period 1999–2010, and found that income elasticity was higher after 2006 than before 2005, indicating reduced mobility in the latter period.

2.B Sample Construction

The sample is restricted only to the children who are initially matched to their parents at age 15-18, and whose job histories can be tracked through the interviews. The limited time span of the KLIPS results in the sample of young workers, where the oldest group of workers was observed at Wave 1 at their age of 18. Table 2.B.1 shows the number of observations by ages and gender from each Wave. More than 85% of observations are those of workers under 35.

Table 2.B.1: Ages and Gender by Waves

	Ages					Gender	
Wave	19-24	25-29	30-34	35-39	40-43	Male	Female
26	531	675	661	513	604	1,570	1,414
25	592	710	583	556	477	1,533	1,385
24	601	690	516	604	325	1,412	1,324
23	686	701	488	659	168	1,390	1,312
22	721	705	518	721	0	1,361	1,304
21	719	707	523	603	0	1,325	1,227
20	798	648	564	469	0	1,282	1,197
19	785	562	577	330	0	1,155	1,099
18	787	518	646	173	0	1,083	1,041
17	613	465	664	0	0	864	878
16	740	516	602	0	0	952	906
15	725	561	491	0	0	897	880
14	682	639	352	0	0	838	835
13	675	758	194	0	0	828	799
12	655	874	0	0	0	752	777
11	700	700	0	0	0	691	709
10	758	600	0	0	0	671	687
9	816	412	0	0	0	569	659
8	856	218	0	0	0	471	603
7	1,003	0	0	0	0	447	556
6	865	0	0	0	0	381	484
5	686	0	0	0	0	297	389
4	582	0	0	0	0	254	328
3	438	0	0	0	0	210	228
2	266	0	0	0	0	139	127
Total (%)	40.6	27.4	17.4	10.9	3.7	50.3	49.7

2.C KLIPS Parents–Children linked sample and external benchmarks for the Korean working-age population

The KLIPS Parents–Children linked sample used in Chapter 2 is a monthly panel constructed from KLIPS waves 2–26, covering 1999–2023. The parent–child linked data are restricted to children who are initially observed with their parents at ages 15–18, observations from age 18 onward, and post-schooling labor market histories after completion of the worker's final educational degree. I then retain employment and non-employment spells of young post-schooling workers linked to parental households, rather than a representative sample of all Korean working-age individ-

uals. To benchmark this selected sample, I use external official statistics aligned to 2023, the final year of the KLIPS sample window.

Relative to these external benchmarks, the KLIPS Parents–Children linked sample has a broadly similar gender composition, with a female share of 48.0% compared with 48.6% in the Korean working-age benchmark. The sample is more highly educated than the broader benchmark population: 62.7% of the sample have tertiary education, compared with 55.0% in the external benchmark, while the share below high school is much lower in the KLIPS sample. The sample is also more strongly attached to employment, with a higher employment share (78.5% versus 69.2%) and a lower non-employment share (21.5% versus 30.8%). This is consistent with the construction of the sample, which focuses on young individuals after labor market entry. The full-time share among employed workers is also higher in the Parents–Children linked sample than in the external benchmark. Overall, these comparisons should therefore be read as a descriptive check on sample selection rather than as a strict definition-identical comparison; in particular, the education and full-time benchmarks use different official age and population bases from the KLIPS analysis sample.

Table 2.C.2: KLIPS Parents–Children linked sample and external benchmarks for the Korean working-age population[1)]

Variable	KLIPS Parents–Children linked sample	Korean working-age benchmark
Female[2)] (%)	48.0	48.6
Educational attainment[3)]		
Below high school (%)	1.9	7.0
High school graduate (%)	35.3	38.0
Tertiary / college or higher (%)	62.7	55.0
Labor market states[4)]		
Share of employment (%)	78.5	69.2
Share of non-employment (%)	21.5	30.8
Employment composition[5)]		
Full-time share among employed (%)	92.8	82.4

Sources: KLIPS Parents–Children linked sample statistics are from Table 2.2 in Chapter 2. External benchmark statistics are from official Statistics Korea labor market indicators, official education attainment statistics, and the 2023 Economically Active Population Survey Supplementary Survey.

Notes: 1) External benchmark statistics are reported using 2023 figures, aligned to the final year of the KLIPS sample window.
2) KOSIS population projections by sex and age, resident population aged 15–64.
3) Educational-attainment benchmarks use official 2023 education-attainment statistics for adults aged 25–64.
4) The shares of employment/non-employment for KLIPS analysis sample are from additional calculations from monthly employment and non-employment states in the constructed KLIPS waves 2–26 person-month panel. Labor market state benchmarks use official 2023 Statistics Korea indicators for the population aged 15–64.
5) The external full-time benchmark is calculated for wage employees aged 15 and over using the 2023 Economically Active Population Survey Supplementary Survey.

2.D Sample composition by transition sample

Table 2.D.3 compares the observed composition of the first job and subsequent job risk sets. The two samples differ substantially along several dimensions. Subsequent job spells are observed at older ages, and individuals in this sample are more likely to be female, in poor health, and married. They are also less likely to hold a university or postgraduate degree and more likely to have a high-school-or-lower qualification. This is because workers with a high-school-or-lower qualification, for whom the timing of degree completion is not precisely observed, are excluded from the first-job spell sample but enter the analysis from subsequent job spells after their first job. In addition, university graduates are more likely to obtain more stable jobs,

and are therefore observed less frequently in subsequent job spells. By contrast, regional composition is broadly similar across the two samples, with no statistically significant differences in the shares living in Seoul, metropolitan cities, or other cities. Cohort composition differs more strongly: the subsequent-job sample contains a larger share of workers born in the 1980s and a smaller share born in the 1990s. These differences confirm that the first job and subsequent job specifications are estimated on distinct risk sets with different observable characteristics. Accordingly, I do not interpret differences in coefficient magnitudes across the two specifications as directly comparable effects; instead, the estimates are interpreted as conditional associations within each transition-specific sample.

Table 2.D.3: Sample composition by transition sample[1)]

Covariate	First job spells	Subsequent job spells	Difference (Sub - First)	p-value
Number of Workers	3,943	4,207		
Panel A. Demographics				
Age (years)	22.249 (3.255)	27.278 (5.288)	5.029	<0.001
Female	0.486 (0.500)	0.528 (0.499)	0.042	<0.001
Poor health	0.019 (0.135)	0.035 (0.184)	0.016	<0.001
Married	0.026 (0.159)	0.232 (0.422)	0.206	<0.001
Panel B. Education				
High school or less	0.338 (0.473)	0.439 (0.496)	0.101	<0.001
College	0.244 (0.430)	0.272 (0.445)	0.028	0.005
University	0.369 (0.482)	0.261 (0.439)	-0.107	<0.001
Postgraduate	0.049 (0.216)	0.027 (0.162)	-0.022	<0.001
Panel C. Region and cohort				
Seoul	0.216 (0.412)	0.209 (0.407)	-0.007	0.419
Metropolitan city	0.237 (0.426)	0.228 (0.419)	-0.010	0.311
Other city	0.289 (0.453)	0.295 (0.456)	0.006	0.563
Born in 1980s	0.487 (0.500)	0.703 (0.457)	0.216	<0.001
Born in 1990s	0.416 (0.493)	0.266 (0.442)	-0.150	<0.001

Notes: 1) The table reports means for continuous variables and shares for indicator variables. Age is measured in years. All indicator variables are reported as shares. The difference is computed as the value for subsequent-job spells minus the value for first-job spells. The p-values are from regressions of each covariate on an indicator for the subsequent-job sample.

2.E Kaplan–Meier survival analysis

This appendix reports supplementary nonparametric evidence on the timing of labor-market transitions. Because some workers are observed only for a limited period and leave the survey before experiencing a transition, the spell data are right-censored. The Kaplan–Meier estimator is therefore useful as a descriptive tool because it uses information from both completed and censored spells without imposing a parametric duration distribution. I estimate raw survival and hazard probabilities for the three transition types studied in the main text: non-employment to employment (NE), employment to non-employment (EN), and direct job-to-job transitions (EE). These estimates describe how transition risks evolve with elapsed duration and how the raw duration profiles differ by parental-wealth group.

The Kaplan–Meier analysis is not intended to estimate the conditional effect of parental wealth. It does not control for observed differences in worker characteristics, previous or current job characteristics, region, year effects, or unobserved heterogeneity. For this reason, the main text focuses on discrete-time duration models, which condition on these covariates and flexibly control for duration dependence. The results in this appendix should instead be interpreted as descriptive evidence that motivates and complements the regression analysis.

For non-employment spells, I report separate estimates for entry into the first job after labor-market entry and re-employment after a separation, since these two processes differ in both timing and institutional context. Entry spells begin around school completion and may include preparation for labor-market entry, whereas re-employment spells start from a more clearly defined post-separation non-employment spell and may be affected by unemployment-insurance incentives. I use a 12-month window for non-employment spells and a 12-quarter (36-month) window for employment spells, treating spells that continue beyond these windows as right-censored. This restriction keeps the analysis focused on durations where

the risk sets remain sufficiently large and avoids unstable estimates in the tails of the duration distribution.

The descriptive patterns are broadly consistent with the private-insurance interpretation developed in the main text. Workers from higher-wealth families tend to remain non-employed for longer, especially in re-employment spells, suggesting more selective search or a higher reservation wage. Conditional on employment, higher parental wealth is associated with greater subsequent job stability, while raw differences in direct job-to-job transitions are comparatively small. These patterns are only descriptive, but they provide useful background for the covariate-adjusted hazard estimates reported in the main results.

2.E.1 Kaplan–Meier survival and hazard probabilities

Kaplan and Meier (1958) provide a nonparametric estimator of the survival and hazard functions that requires only the observed duration and an event indicator at each time t. Using this estimator, I trace survival and hazard over time for each transition type. The survival function $S(t)$, represents the probability that the event has not occurred by time t, and is defined as follows:

$$S^z(t) = Pr(T_i^z > t), \qquad z \in \{NE, EN, EE\}$$

where z indexes the type of transition among non-employment-to-employment transition (NE), employment-to-non-employment transition (EN), and job-to-job transition (EE).

Let $S(T_i^z|T_{i-1}^z)$ be the probability that the transition has not occurred by T_{i-1}^z and also does not occur at T_i^z:

$$\hat{S}(T_i^z|T_{i-1}^z) = 1 - \frac{d_i^z}{n_i^z},$$

where d_i^z is the number of events of type z occurring at T_i and n_i^z is the number

of workers who remain at risk just before T_i. The Kaplan–Meier estimators of the survival and (raw) hazard functions are then

$$\hat{S}(t) = \prod_{T_i \leq t} \hat{S}(T_i^z | T_{i-1}^z) = \prod_{T_i \leq t} \left[1 - \frac{d_i^z}{n_i^z} \right],$$

$$\hat{h}(t) = \frac{d_i^z}{n_i^z}.$$

2.E.2 Kaplan–Meier survival results

I estimate Kaplan and Meier (1958) survival functions for all observed transition types—non-employment-to-employment (job finding), employment-to-non-employment (job separation), and employment-to-employment (job switching)—plotting the probability of remaining in the initial state over elapsed time.

For job finding, I report two separate curves: (i) entry into the first job after labor market entry and (ii) re-employment after a separation. This is because the two types of non-employment spells have distinct processes and potential confounding variables. First, entry spells originate from a pre-market state (mostly student), so the start of search is not precisely observed; even when I define labor market entry as the date of completing the highest qualification, search may begin earlier (e.g., during the final academic year). Re-employment spells start at a well-defined unemployment date. Second, re-employment spells are potentially shaped by unemployment insurance (UI) incentives, whereas first-job entry is generally not UI-covered for new graduates in Korea. A large amount of literature shows that UI generosity, through benefit levels or potential duration, affects exit hazards and thus unemployment duration (Schmieder et al., 2012; Farber and Valletta, 2015; Landais, 2015; Marinescu and Skandalis, 2021; Lichter and Schiprowski, 2021)

Several studies recommend reporting survival estimates only when a sufficient number of individuals remain at risk (e.g., Gebski et al., 2018). Therefore, I restrict the

plotted time windows to those that are substantively meaningful and empirically supported by the data. Specifically, I use a 12-month window for non-employment spells (entry and re-employment) and a 12-quarter (36-month) window for employment spells; observations exceeding the relevant window (i.e., $>$ 12 months for non-employment spells and $>$ 12 quarters for employment spells) are treated as right-censored. This focuses attention on durations where risk sets remain large enough for precise estimation and avoids unstable tails that appear beyond one year in this sample, while still allowing comparison with short and medium windows commonly used in the literature (Berg et al., 2012; Caliendo et al., 2013; Gebski et al., 2018).

Job Finding Figure 2.E.1 plots Kaplan–Meier survival functions for remaining in non-employment over spell duration, split by parental asset quartiles and separately for entry spells (first job search after labor market entry) and re-employment spells (search following a separation).

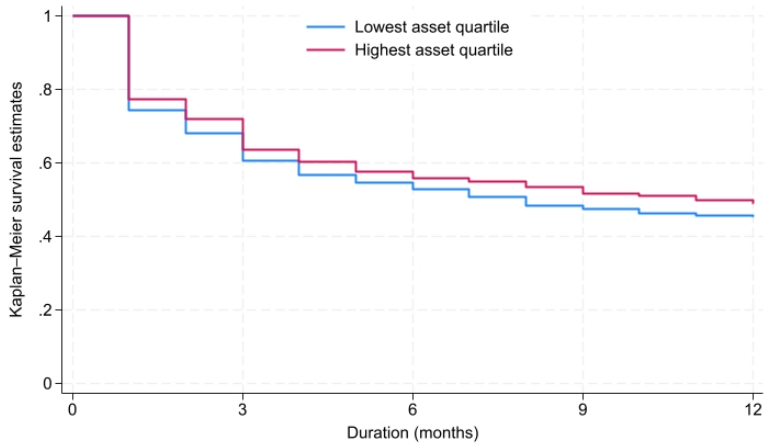
In entry spells (panel a), survival differs by parental assets. Across the 12-month window, the highest-asset quartile maintains a higher survival probability (slower exit) than that from the lowest quartile. The curves separate modestly in the first 1–2 months and stay roughly parallel through month 12, leaving a small but persistent gap.

In re-employment spells (panel b), the same ordering holds and the gap is more pronounced than in entry spells within the 12-month time window. The curves are close over months 1–6, then diverge from roughly month 7 onward; the lowest-asset quartile exits more rapidly between months 7 and 12, while the highest-asset quartile sustains a higher survival probability. This timing coincides with the exhaustion of unemployment-insurance entitlements in Korea—typically 120 to 270 benefit days (about four to nine months)—which is consistent with liquidity constraints

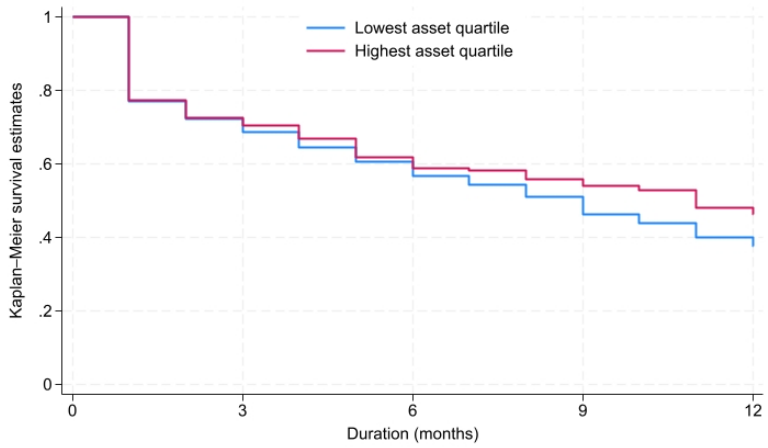
becoming particularly salient for workers from low-asset families as public benefits lapse. However, the discrete-time hazard model assumes proportional wealth effects over duration, so this interpretation should be viewed as suggestive rather than as evidence of a formally estimated change in the wealth gradient at benefit exhaustion. Overall, the descriptive evidence is consistent with a private insurance interpretation that smooths search and lengthens non-employment spells, especially in re-employment episodes.

Figure 2.E.1: Survival probabilities to stay in non-employment ($S^{NE}(t)$)

(a) Entry spells



(b) Re-employment spells



Source: Author's calculation using KLIPS 2-26

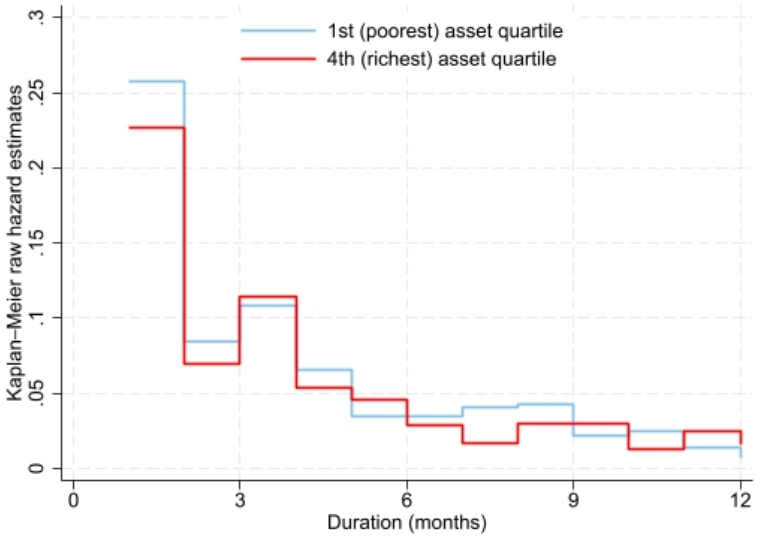
In Figure 2.E.2, the Kaplan–Meier raw hazard rates show a sharp decline over spell duration. In both panels, hazards start at very high levels (around 0.20–0.30) during the first month, then fall rapidly. In entry spells (panel a), the monthly hazard

stabilizes at relatively low levels (around 0.02–0.06) after three to four months. Compared with re-employment spells, the parental wealth effects appear weaker and not persistent in entry spells: during the first two months the lowest-asset quartile shows higher job finding hazards, but the two quartile traces often cross and the differences are small. Nonetheless, as first job hazards are likely driven more by other individual characteristics, such as education level, region of residence, or year-specific macro shocks, it is necessary to control for covariates when assessing the relationship. In re-employment spells (panel b), hazards are generally higher after three months and do not decline with additional elapsed time, remaining roughly in the 0.05–0.10 range. From about months 6–10, the lowest asset quartile's hazard stays above the highest asset quartile, and the two lines remain separated through month 12. The timing coincides with typical exhaustion of unemployment-insurance benefits in Korea (about 4–9 months), suggesting that once public support lapses, liquidity constraints bind more tightly for those from low-asset families, raising their job finding hazards.

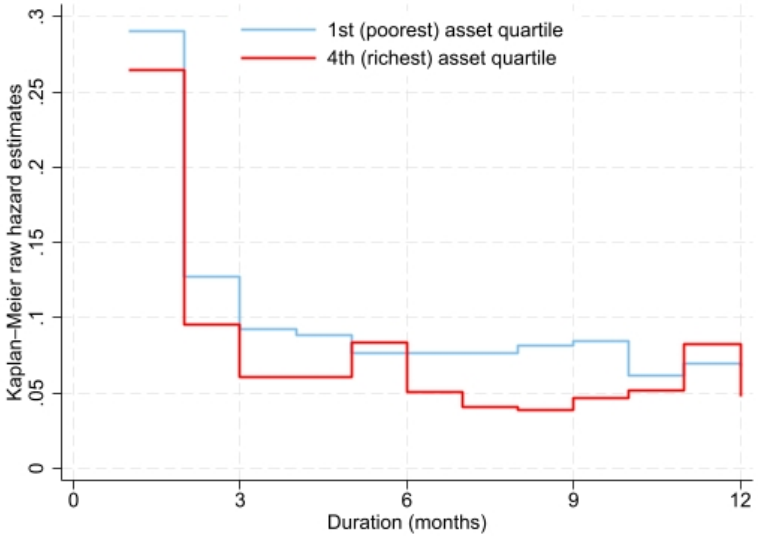
Job Separation and Job Switching Figure 2.E.3 reports quarterly Kaplan–Meier survival functions for remaining in the current job by parental-asset quartile. Panel (a) shows job separations into non-employment; panel (b) shows job-to-job transitions. In panel (a), the survival curve for the highest-asset quartile lies consistently above that for the lowest quartile over the full horizon (0–12 quarters). The gap opens early and widens to around 10 percentage points by quarter 12, indicating lower separation hazards among high-asset workers. By contrast, in panel (b) survival remains close to one and the two curves nearly overlap. The highest-asset group is only slightly higher—by just a few percentage points—suggesting that job-to-job transition rates are low overall and asset-related differences are limited over this window. Taken together, asset gaps are more pronounced for separations into non-employment than for job-to-job mobility.

Figure 2.E.2: Job finding hazard probabilities ($h^{NE}(t)$)

(a) Entry spells



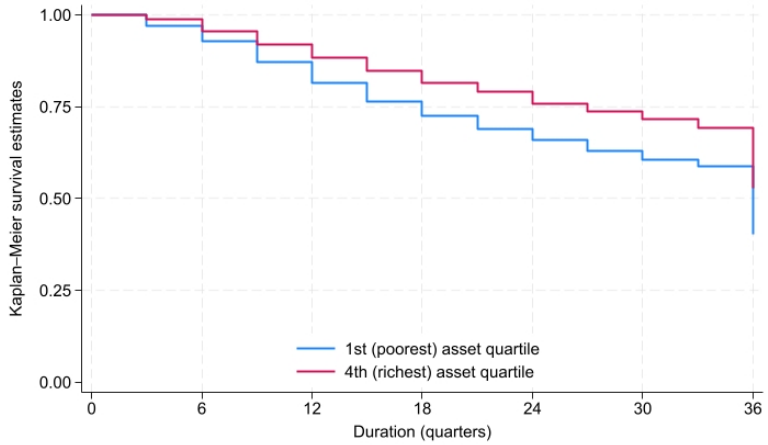
(b) Re-employment spells



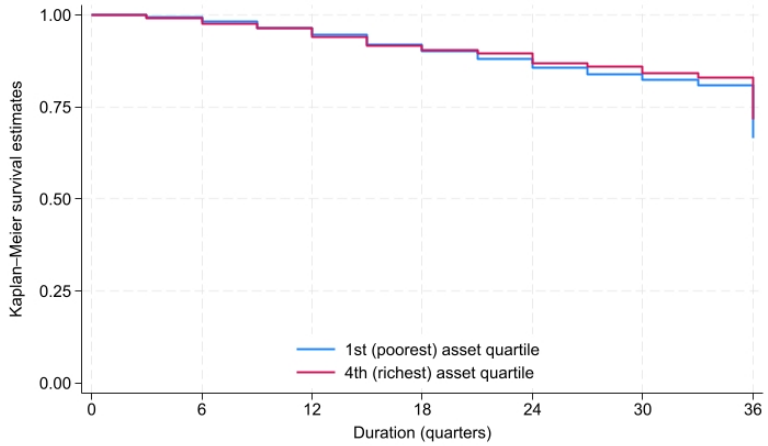
Source: Author's calculation using KLIPS 2-26

Figure 2.E.3: Survival probabilities to stay in current job ($S^e(t)$)

(a) Job separation ($S^{EN}(t)$)



(b) Job switching ($S^{EE}(t)$)

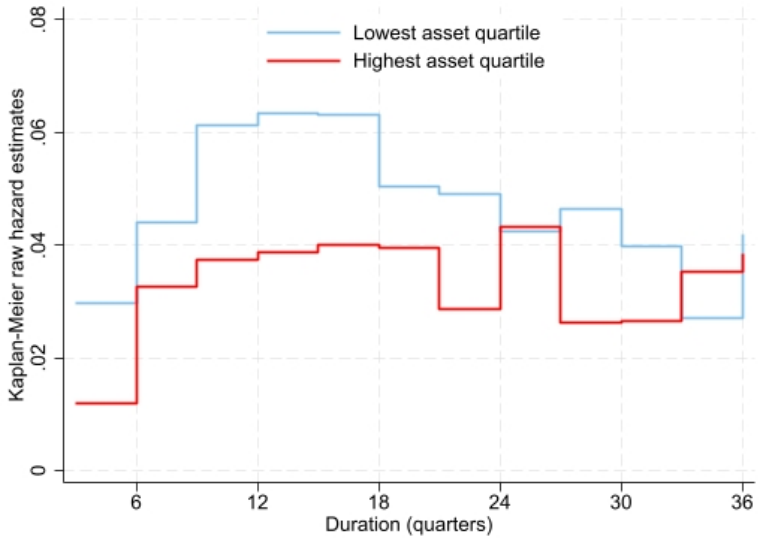


Source: Author's calculation using KLIPS 2-26

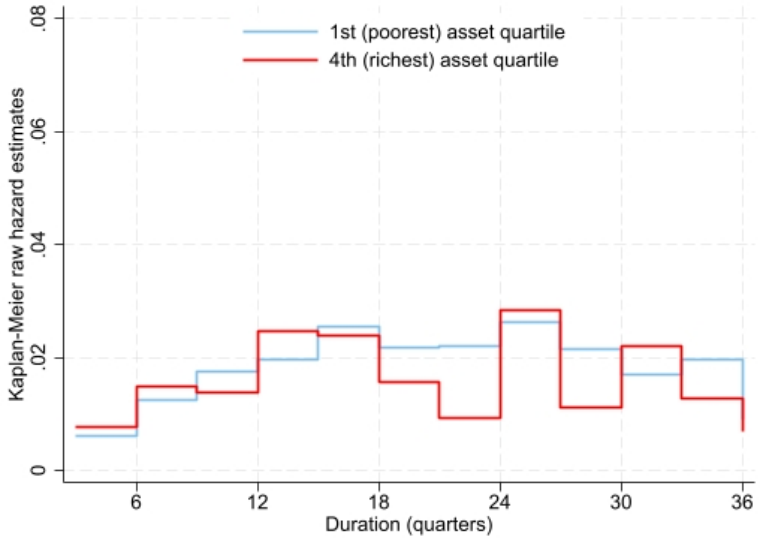
Figure 2.E.4 plots quarterly Kaplan–Meier raw hazard estimates for exits from the current job by parental-asset quartile: panel (a) shows separations into non-employment; panel (b) shows job-to-job transitions. In panel (a), separation hazards rise sharply over the first few quarters, peak around quarters 10–12 (0.05–0.07 for the lowest-asset quartile and 0.04 for the highest), and then taper to the 0.02–0.03 range with some quarter-to-quarter noise. The lowest-asset group lies above the highest-asset group for most of the window, with narrowing and occasional crossover near the end. This pattern is consistent with parental assets providing insurance that helps sustain matches or allows more selective quitting. In panel (b), job switching hazards are low and comparatively flat—generally below 0.03 each quarter for both groups. The two series track each other closely, with only small, transitory deviations, indicating limited short-run job-to-job mobility and little systematic heterogeneity by parental wealth.

Figure 2.E.4: Job separation and job switching hazard probabilities ($h^e(t)$)

(a) Job separation ($h^{EN}(t)$)



(b) Job switching ($h^{EE}(t)$)



Source: Author's calculation using KLIPS 2-26

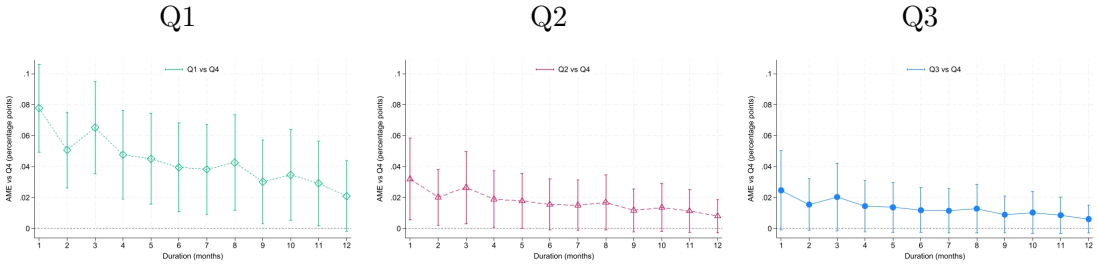
2.F Average marginal effects of parental wealth on transition probabilities and their statistical significance

2.F.5 plots, for each labor market transition, the average marginal effects of parental wealth by quartile together with 95% confidence intervals. The four rows correspond to job finding into the first job, job finding into re-employment, job separation, and job switching, while the three columns show effects for Q1–Q3 relative to the reference group Q4. The graphs therefore summarize, in probability units, both the magnitude of the parental wealth differentials and the statistical significance of these effects across the duration.

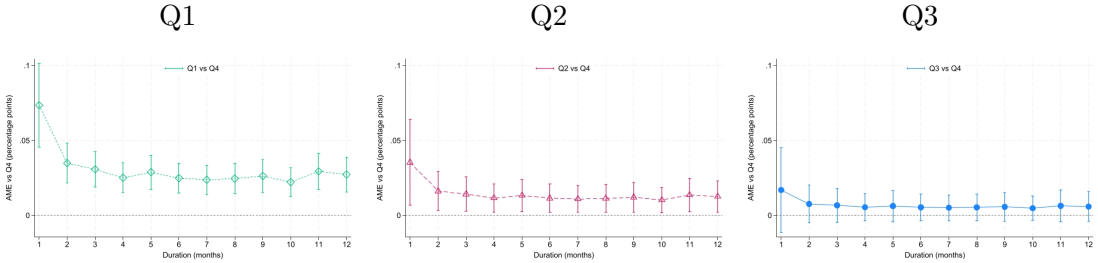
The confidence bands suggest that the wealth effects are statistically meaningful mainly for job finding and job separation. For job finding–both entry and re-employment–the AMEs for Q1 are significantly different from zero at the 5% level for most durations, with Q2 significant primarily in the first few months and Q3 only sporadically so. For job separations, the AMEs for Q1 are again clearly significant over a wide range of tenures, while those for Q2 and Q3 are significant at shorter and medium tenures but not at the end of the spell. By contrast, for job-to-job transitions the estimated AMEs are small, rarely statistically different from zero at conventional levels, and do not display a clear monotonic pattern across the wealth distribution.

Figure 2.F.5: Confidence intervals and Significance tests for AMEs by Parental Wealth and Duration

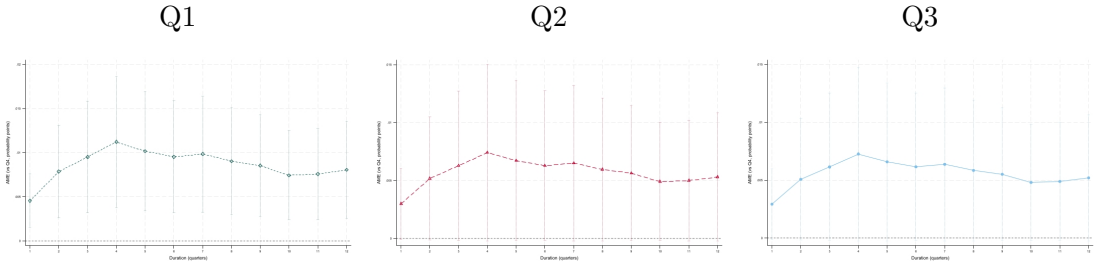
(a) Job finding – Entry



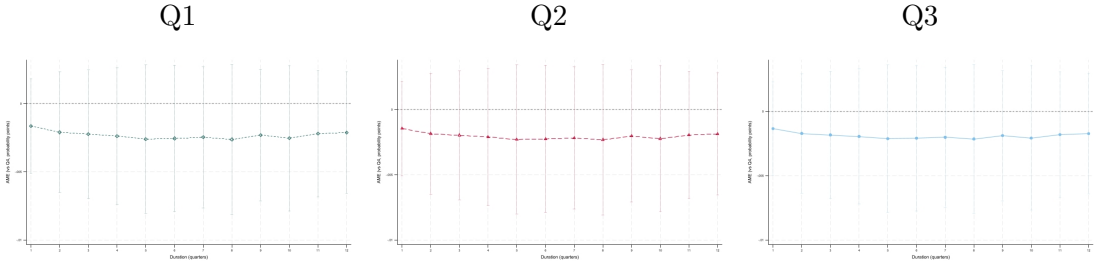
(b) Job finding – Re-employment



(c) Job Separation



(d) Job switching



Source: Author's calculation using KLIPS 2-26