Hiring with a Quantity-Skill Tradeoff*

Fil Babalievsky† Henry R. Hyatt‡ Lawrence Warren§

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Abstract

When firms expand their workforce, do they maintain their educational requirements? Using Longitudinal Employer-Household Dynamics (LEHD) data from 2005–2015, we document a strong inverse relationship between a firm's hiring rate and the average educational attainment of its hires. We develop a search and matching model with worker heterogeneity and decreasing returns to scale to explain this quantity-skill tradeoff. The model combines multi-worker firms, skill heterogeneity, skill-specific recruiting costs, and endogenous firm dynamics. College workers are more productive, but scaling up the high-skilled workforce quickly is costly, echoing the quasi-fixed factor model of Oi (1962). This tradeoff benefits established businesses, which have had more time to build out their college workforce, relative to entrants, creating a link between the skill composition of the labor force and business dynamism. In our counterfactual exercise, the increase in the college share of the workforce since the 1990s reduces employer startups per employed worker by 9.4 percent, accounting for about 44 percent of the observed decline in startup intensity.

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†Center for Economic Studies, U.S. Census Bureau. Email: filip.f.babalievsky@census.gov

‡Center for Economic Studies, U.S. Census Bureau. Email: henry.r.hyatt@gmail.com

§Center for Economic Studies, U.S. Census Bureau. Email: lawrence.fujio.warren@census.gov

1 Introduction

How do firm-level constraints on hiring affect the human capital composition of the workforce? A large literature in labor economics explores how search frictions and hiring costs influence the scale of the firm, yet we know far less about how these constraints alter the specific types of workers a firm recruits during periods of rapid growth. While aggregate "upskilling" and "downskilling" have been documented over the business cycle (Modestino, Shoag, and Ballance, 2016, 2020), less is known about whether firms face a systematic tradeoff between hiring rapidly and recruiting more educated workers. Understanding this relationship is critical for evaluating how worker composition can influence firm entry, growth, and the relative advantages of young and established firms.

In this paper, we document a systematic "quantity-skill tradeoff" at the micro-level: as firms increase their hiring intensity, the average educational attainment of their new hires falls.[1] We endogenize this in a novel multi-worker-firm search model that builds on the "quasi-fixity" insight of Oi (1962): skilled labor is harder to scale up quickly. Since differences in scaling costs affect young and mature firms differently, the same mechanism that generates a tradeoff between hiring quantity and skill also impacts business entry and aggregate business dynamics. We show that the increase in the college share of employment can account for about 44% of the observed decline in business startup rates since the 1990s.

Using linked employer-employee data from the Longitudinal Employer-Household Dynamics (LEHD) infrastructure files, we document a robust and persistent empirical relationship between a firm's hiring rate and the educational attainment of new hired workers. In the cross section, doubling of the hiring rate is associated with a roughly 3.5 percentage point reduction in the share of hires with a college degree. While a significant portion of this cross-sectional relationship is driven by sorting across different firm types, our results remain statistically significant when accounting for firm-level heterogeneity. Including firm fixed effects reveals a within-firm semi-elasticity of approximately minus one percentage point, indicating lower college shares of hires within firms in higher-hiring years. An instrumental variables estimation strategy motivated by firm needs for replacement hiring due to the effects of its age composition (separation rates) confirms the presence of a robust quantity-skill tradeoff. The magnitude and persistence of this relationship across both cross-sectional and longitudinal specifications are consistent with firm-level recruiting incentives shaping hiring composition, motivating a model in which recruiting incentives vary systematically by skill type.

[1] Following Katz and Murphy (1992) and numerous others, we link observed educational attainment with latent labor skill, using college degree completion as our empirical proxy and using the terms "skill" and "education" interchangeably.

To rationalize these findings, we develop a model in which firms choose both the scale and skill composition of recruitment in a frictional labor market setting. Firms produce with decreasing returns using college and non-college labor, and firm entry, growth, and exit respond endogenously. Following Bilal, Engbom, Mongey, and Violante (2022) and Herkenhoff, Lise, Menzio, and Phillips (2024), we characterize hiring, separations, and worker mobility using the joint value of a firm and its workers. Our model features discrete worker counts in continuous time, as in Trapeznikova (2017). A distinguishing feature of our model is that search costs for college and non-college workers have different curvature parameters. College workers are more productive, but recruiting effort for college workers is less responsive to increases in the return to hiring because recruiting costs are more convex.[2] This mechanism connects the quantity-skill tradeoff to the insight of Oi (1962) that differences in hiring and training costs affect the incidence of firm employment adjustments, and thus these are typically borne by non-college workers.

The calibrated model reproduces the declining college share of hires across the hiring-rate distribution and generates a higher college share of employment than of gross hires, consistent with differences in recruiting and separation rates. Our model also highlights how the same search cost mechanism which links hiring intensity and composition significantly affects firm dynamics and entry. New firms enter with no workers and face high marginal returns to expanding employment. Because college recruitment is more difficult to scale quickly, young firms rely relatively more on noncollege workers during periods of rapid expansion. Established firms, by contrast, have had more time to accumulate college workers and benefit from their higher productivity, shifting returns to established firms and away from entrants.

We use our model to study how changes in the educational composition of the workforce affect business formation and growth. Starting from a reconstructed 1990s economy, raising the college share of the worker population from 31.8 percent to its 2005–2015 level of 40.4 percent reduces employer startups per employed worker by 9.4 percent and gross hiring per employed worker by 4.2 percent, while increasing average employer size by 9.3 percent. Aggregate output, by contrast, rises by 3.7 percent. The decline in startup intensity is approximately 44 percent as large as the 21.5 percent decline observed over the same comparison period.

We also examine the separate contributions of changes in skill-biased productivity and entry costs to business dynamism. While an increase in college supply reduces entry, an increase in the relative productivity of college workers has the opposite effect. Raising

[2]We show that this differential curvature can, under certain assumptions, be reinterpreted as a tractable stand-in for differential training costs. Firms trying to scale up their skilled workforce need to spend increasingly more to train skilled workers who are increasingly "distant" from the firm's specialization. Lower-skilled workers are less differentiated, so scaling is easier for them.

college productivity to its later-period level increases startup intensity by 5.9 percent, as higher productivity increases the expected return to an entrant firm. By contrast, increasing goods-denominated entry costs to the level inferred from the historical calibration reduces startup intensity by about 18.0 percent. Interestingly, the inferred increase in entry costs is approximately proportional to the increase in average labor productivity, leaving their burden in output-equivalent worker-years roughly unchanged. These exercises suggest that changes in labor supply and skill-biased technological change can have opposing effects on business dynamism, even as both contribute to a more educated and productive workforce. Additional counterfactuals highlight the quantitative importance of skill-specific recruiting technologies for business dynamism, as equalizing recruiting technologies has a substantially larger effect on startup intensity than equalizing separation rates or productivity.

Our empirical findings contribute to a growing literature on how firms adjust their labor composition along differential margins. The classic quasi-fixity insight of Oi (1962) implies that workforce adjustment occurs disproportionately through lower-skill labor. More recently, evidence suggests that formal skill requirements are not static but instead rise and fall with aggregate labor market slack (Modestino et al., 2016, 2020; Hershbein and Kahn, 2018; Huckfeldt, 2022). Our findings also relate to Gulyas (2025), who studies skill sorting across expanding and contracting firms. We focus on the educational composition of gross hires and develop a mechanism in which skill-specific recruiting costs shape how firms adjust their hiring and entry decisions. Our approach also complements Sedláček (2014) and Carrillo-Tudela, Gartner, and Kaas (2023), who examine how endogenous hiring standards and recruitment policies shape matching outcomes.

This dynamic perspective complements a long-standing literature following Katz and Murphy (1992) that analyzes skill demand and firm composition. Recent advancements in this framework highlight how these allocations are shaped by the labor supply margin (Patel, 2025), skill-biased technological change (Lindner, Muraközy, Reizer, and Schreiner, 2026) and market structure (Deb, Eeckhout, Patel, and Warren, 2024). While these models often focus on steady-state allocations, our contribution highlights the dynamic process of how firms shape their composition, providing a microfoundation for cross-firm differences in hiring rates and composition in the presence of labor market frictions. We build on models of multi-worker firms with search frictions (Kaas and Kircher, 2015; Bilal et al., 2022; Herkenhoff et al., 2024), allowing recruiting costs to differ in curvature across skill groups. Combined with decreasing returns to scale and endogenous firm entry and exit, these differences connect the educational composition of gross hires to firm growth and business dynamism.

Our counterfactual exercises contribute to a literature examining the secular decline in job-to-job mobility, reallocation, and firm entry in the United States (Hyatt and Spletzer,

2013; Davis and Haltiwanger, 2014; Decker, Haltiwanger, Jarmin, and Miranda, 2014; Molloy, Smith, Trezzi, and Wozniak, 2016). A growing literature links demographic changes to business dynamism. Slower labor-force growth can reduce entry and shift the firm age distribution (Hopenhayn, Neira, and Singhania, 2022; Karahan, Pugsley, and Şahin, 2024; Peters and Walsh, 2026). Workforce composition also matters. The framework of Engbom (2019), subsequently developed in Engbom (2024), links aging to the accumulation of good incumbent jobs. Older workers in good matches become less willing to switch employers or start businesses, and entrants find it harder to attract workers, decreasing entry and mobility at a given workforce size. Most of these frameworks focus on the opportunity cost of entrepreneurship through a tradeoff between participating in the labor market or starting a firm. We study a complementary channel through which the differential cost of hiring links changes in educational composition to firms' returns to entry.[3]

More closely related to our counterfactual exercises, education and technology have also been linked to entrepreneurship through occupational choice. Salgado (2026) studies how technical change raises the return to skilled wage employment relative to entrepreneurship. Kozeniauskas (2025) finds that skill-biased technical change helps explain the relative decline in entrepreneurship among educated workers, while rising entry costs are central to the aggregate decline. Jiang and Sohail (2023) examine how changes in skill supply and technology alter the relative returns to wage work and entrepreneurship. Skills also affect firm scale through organizational choices: Engbom et al. (2025) show how educated workers enable delegation and larger firms. Our contribution is a recruiting channel connecting educational composition to business formation. We document a quantity-skill tradeoff in hiring and study how skill-specific recruiting costs shape workforce expansion and entry. College recruitment is harder to scale quickly, so a larger college share can favor incumbents that have had time to build their workforce relative to entrants. This channel operates through firms' hiring decisions and worker mobility in a frictional environment rather than the tradeoff between wage employment and entrepreneurship.

The remainder of the paper is organized as follows. Section 2 describes the LEHD infrastructure and our firm-level hiring and education measures. Section 3 presents the empirical findings. Sections 4 and 5 develop the model and its calibration. Section 6 presents the quantitative results, and Section 7 concludes.

[3]Other mechanisms include reduced opportunities for young workers to acquire entrepreneurial skills when older workers occupy senior positions (Liang, Wang, and Lazear, 2018), and greater consumer inertia as households age, which favors incumbents over entrants (Bornstein, 2026). Engbom, Malmberg, Porzio, Rossi, and Schoellman (2025) show how educated workers can support larger organizations through delegation. Lower dynamism can also accompany better static allocation: Bilal, Engbom, Mongey, and Violante (2021) show that slower technological imitation reduces entry and worker reallocation while giving productive incumbents more time to expand.

2 Data and Variable Construction

2.1 Data Sources

The empirical analysis in this paper utilizes the Longitudinal Employer-Household Dynamics (LEHD) infrastructure files from the U.S. Census Bureau. The LEHD program integrates administrative records from state unemployment insurance (UI) systems with Census Bureau surveys and other administrative data, as detailed in Abowd, Stephens, Vilhuber, Andersson, McKinney, Roemer, and Woodcock (2009).[4] This linked employer-employee framework allows us to observe the near-universe of private-sector employment in the United States, providing the scale necessary to analyze workforce composition across the entire distribution of firm growth. Specifically, we utilize the internal Census Bureau LEHD Snapshot, which contains the longitudinal histories of employer-employee matches and firm-level characteristics (U.S. Census Bureau, 2024). It also includes information on employer industry and location (geography). It also contains annual measures of firm age and size as described in Haltiwanger, Hyatt, McEntarfer, Sousa, and Tibbets (2014).

A critical feature of the LEHD infrastructure is its reliance on a voluntary partnership between state labor market information agencies and the U.S. Census Bureau. Because different LEHD state partners have provided data for different time periods, the available longitudinal depth varies significantly across jurisdictions. While some states provide records reaching back to the early 1990s, others joined the partnership much later. To ensure our results are nationally representative and not driven by the shifting geographic composition of reporting states, we restrict our primary analysis to the period from 2005 to 2015. This window represents the years in which the LEHD contains complete, continuous data from all fifty states plus the District of Columbia. By focusing on this consistent set of states, our primary sample covers a diverse set of economic conditions (including the 2007–2009 recession) while maintaining a consistent geographic scope. It is important to note that while the set of reporting states is constant, the underlying microdata is an unbalanced panel of firms; we do not restrict our analysis to continually-lived firms, which allows the sample to reflect the full impact of firm entry and exit during this period.

2.2 Firm Definitions

A primary challenge in using administrative data is the distinction between legal entities and economic firms. In our sample, firm identifiers are assigned following the methodology detailed in Haltiwanger et al. (2014). We aggregate federal Employer Identification Numbers

[4] We provide only an outline of our data here, for additional details, see Appendix A.1.

(EINs) to the firm level, often referred to as the "alpha" level in Census Bureau terminology, to ensure that we capture the activities of multi-establishment parent companies as single decision-making units.

Following Cao, Hyatt, Mukoyama, and Sager (2022, 2026), in instances where a firm-level identifier is unavailable, we utilize the EIN as the proxy for the firm identifier. This approach ensures maximum coverage of the employer universe while maintaining longitudinal consistency for both large enterprises and the recent surge of small, single-unit startups.

2.3 The Hiring Rate

Our primary measure of hiring intensity is the annual hiring rate. Because the underlying administrative records consist primarily of quarterly earnings totals, we apply the foundational definitions of employment and hiring established by Abowd et al. (2009). Individual hires are identified using quarterly longitudinal links—identifying a new hire when an employer-employee match transitions from zero earnings to positive earnings.

Our specific hiring rate is an annualized version of the quarterly flow measures, following the methodology used by Hyatt, Murray, and Sandusky (2021). Our hiring concept represents the total volume of recruitment over a four-quarter span. The annual hiring volume is the sum of these quarterly inflows, normalized by the average of beginning-of-year and end-of-year employment.[5] While net employment growth is bounded by the symmetric growth rate formula of Davis, Haltiwanger, and Schuh (1996), this hiring rate $h_{j,year}$ is not bounded above. This is particularly relevant for startups and high-churn firms where the total number of individuals cycling through the firm over a year can significantly exceed the average headcount.

2.4 Measuring Educational Composition

To measure workforce composition, we leverage the person-level educational attainment data available within the LEHD infrastructure. We rely on observed educational attainment for the subset of LEHD workers who can be matched to the Census 2000 Long Form or the American Community Survey (ACS). Because educational attainment is a relatively stable characteristic for the adult population, we utilize the education level reported by the individual in these surveys, regardless of whether the survey was conducted in the same year as the hiring event.

While this approach means we do not observe the education level for every worker at a given firm, the Census and ACS are both large-scale, random samples of the U.S. popula-

[5] Additional details on the construction of the hiring rate are provided in Appendix A.2.

tion. This "college share" serves as our empirical proxy for high-skilled labor, following the literature that begins with Katz and Murphy (1992). We calculate this share as the number of matched college-educated hires in the year divided by the total number of matched hires in the year, ensuring the composition estimate is consistent with the sampling frame of the underlying Census 2000 and ACS data.

2.5 Sample Selection

To ensure the stability of our annual measures, we restrict our primary analysis to firms that report positive employment in all four quarters of the focal year. For our primary outcome variable—the share of hires with a college degree—to be defined for a given firm-year, we impose the requirement that the firm must have hired at least one worker whose educational attainment is observed in either the Census 2000 Long Form or the ACS.[6] Crucially, this observation of educational attainment may occur at any point in the worker's longitudinal history within the Census records, not necessarily within the same calendar year as the hire. This restriction ensures that our measure of educational composition is based on observed data, while the aggregation into hiring rate deciles addresses potential sampling noise at the individual firm level.

3 Empirical Findings

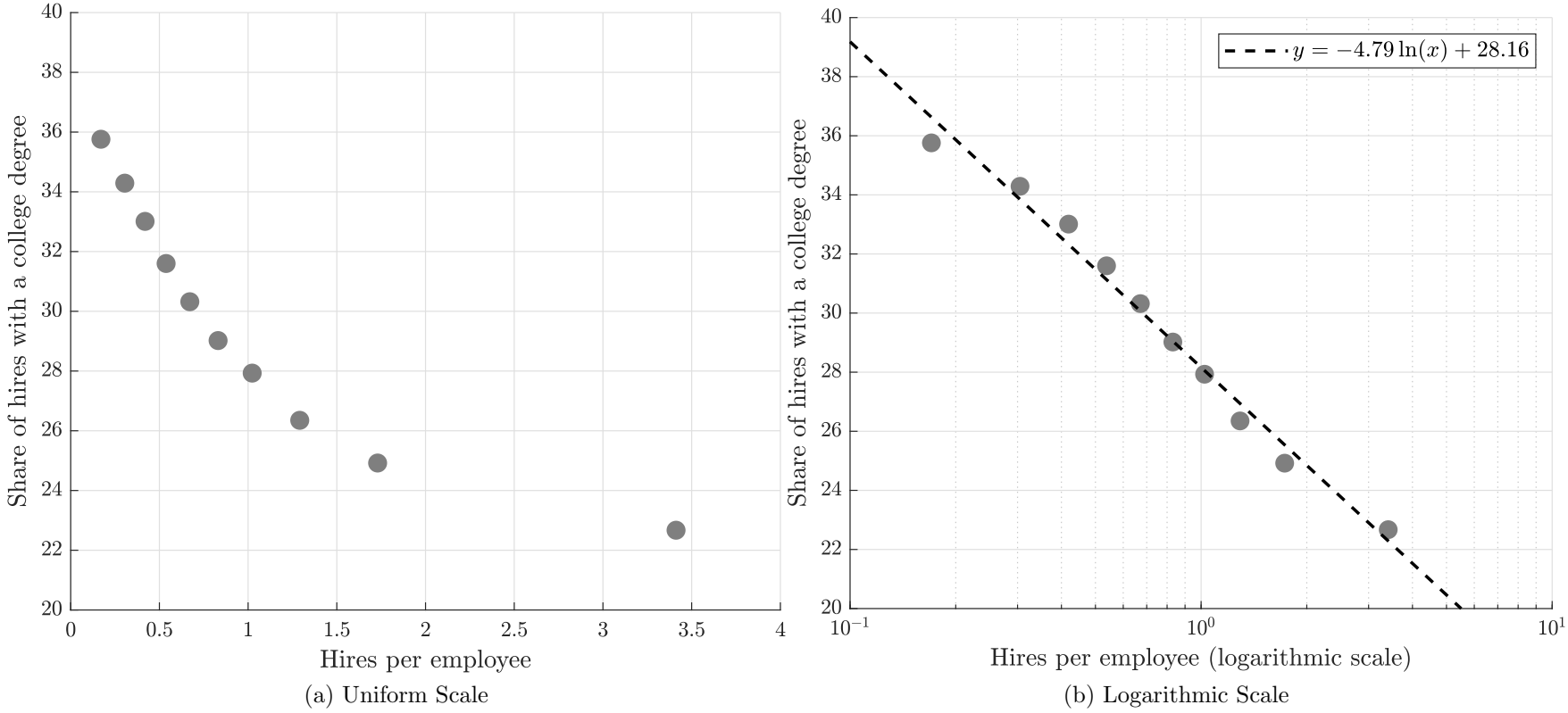
In this section, we present the core empirical regularities governing the relationship between firm hiring and workforce composition. Using the LEHD infrastructure files, we document a persistent "quantity-skill tradeoff" that characterizes the hiring behavior of firms across the U.S. economy. This relationship provides the empirical foundation for the model developed in Section 4.[7]

3.1 The Quantity-Skill Tradeoff

We begin by documenting a novel and stark empirical regularity: the inverse relationship between a firm's hiring intensity and the educational attainment of its new hires. Figure 1(a) presents the mean college-educated share of hires across ten deciles of the annual hiring rate. The horizontal axis measures hiring intensity as the total number of hires made over the

[6] Education coverage varies across workers, and requiring at least one hire with observed education may disproportionately exclude firm-years with few hires. Our estimates therefore describe the selected sample of eligible firm-years.

[7] We observe hires' education, not stated educational requirements. Causal interpretations of the IV estimates require the instruments' exclusion restrictions; firm fixed effects alone do not identify causal responses.



(a) Uniform Scale

(b) Logarithmic Scale

Figure 1: Average educational attainment for ten deciles of the hiring rate

Notes: Deciles are calculated based on the annual hiring rate. Educational attainment is measured as the share of new hires with at least a four-year college degree. The horizontal axis shows total hires in a calendar year, relative to average annual employment, as obtained from the Longitudinal Employer-Household Dynamics Employer Characteristics File, 2005-2015. College degree attainment is obtained from the Census 2000 long form and the American Community Survey (ACS). Firms must have positive employment in each quarter of the year and at least one hired worker who reported their educational attainment to either the Census 2000 long form or the ACS.

Table 1: Regression of College Share on Hiring Rates

Dependent Variable:	College Share (pp)			
	(1)	(2)	(3)	(4)
Log(Hiring Rate)	-4.664***	-5.048***	-1.007***	-1.041***
	(0.016)	(0.017)	(0.018)	(0.018)
Firm Age		-0.136***		-0.028*
		(0.001)		(0.015)
Log(Firm Size)		0.448***		-0.340***
		(0.013)		(0.021)
Fixed Effects	No	No	Yes	Yes
R-squared	0.010	0.012	0.567	0.567

Notes: Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the college share of hires multiplied by 100. Fixed effects allow a parameter estimate for every firm, as well as every year (not reported). Firm size is increased by one prior to taking logarithms.

course of a calendar year divided by the firm's average employment. This ratio represents the gross inflow of new workers relative to firm size, capturing both expansion-driven hiring and replacement hiring due to churn.

The horizontal axis captures a vast heterogeneity in recruitment intensity, ranging from firms engaged in minimal replacement hiring to those whose annual hiring volume is several times the size of their existing workforce. As shown in Figure 1(a), there is a monotonic and significant decline in skill composition as this intensity increases. Firms in the lowest decile of hiring intensity—which are typically mature, stable organizations engaged primarily in low-volume replacement hiring—maintain a college-educated hire share of 35.8%. As we move across the distribution, the hiring rate increases steadily. Notably, in the seventh decile, the hires per employee ratio is approximately equal to one, implying the firm makes approximately one hire for every existing employee over the course of the year. Because the seventh decile is the first to reach this parity, it follows that more than half of all firms in our sample operate with an annual hiring rate of less than one. In contrast, firms in the highest decile, representing those hiring most intensively, see the college-educated share fall to 22.7%. This represents a total 13.1 percentage point decline across the hiring distribution.

To better understand the functional form of this relationship, Figure 1(b) plots the same data on a logarithmic scale. This transformation reveals a strong log-linear relationship, which we estimate as $y = -4.79 \ln(x) + 28.16$. At $x = 1$, the regression predicts a college-educated hire share of approximately 28.2%, given the intercept of 28.16 and $\ln(1) = 0$.

The slope coefficient of -4.79 quantifies the severity of the tradeoff: for every doubling of the annual hiring rate, the share of hires with a college degree falls by approximately 3.32 percentage points ($4.79 \ln 2$). This semi-elasticity suggests that the "hiring penalty" on skill is substantial; higher recruitment intensity is associated with a lower college share of hires.[8]

Table 1 presents the results of regressing the college share of hires on the log hiring rate. Column (1) shows the unconditional tradeoff, where a 1% increase in the hiring rate is associated with an approximately 0.046 percentage point decline in the college share ($4.664 \ln 1.01$). In Column (2), we control for firm age and size; while older firms tend to hire a lower college share and larger firms a higher college share, the primary coefficient on the hiring rate remains stable at -5.048.

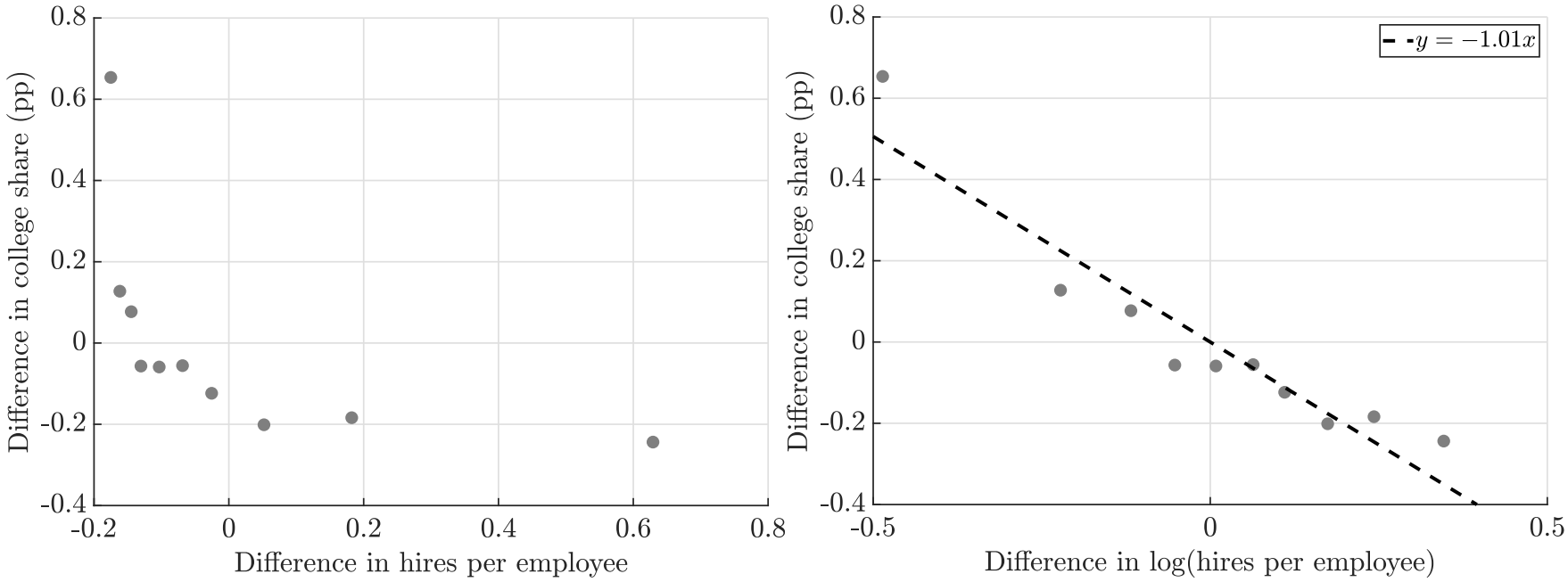
The relationship between the regression estimates in Columns (1) and (2) and the graphical evidence in Section 3.1 is direct. The slope of the regression line in Figure 1(b) is approximately equal to the estimate reported in Column (1) of Table 1 (-4.79 and -4.66, respectively). This similarity arises because Figure 1(b) is effectively a discretized visualization of the bivariate regression; while the plot bins the data into deciles for clarity and to limit disclosure, the decile fit and microdata OLS summarize the same unconditional relationship but are distinct estimators.

3.2 Within-Firm Variation

The baseline results in Section 3.1 establish a clear negative relationship between hiring intensity and the educational attainment of new hires across the broad distribution of firms. However, these unconditional correlations might be driven by persistent, unobserved heterogeneity across entities. For instance, certain industries may structurally require lower-skill workers while naturally maintaining higher turnover or hiring rates.[9] Alternatively, geographic location or local labor market conditions could simultaneously dictate both the available pool of college graduates and the typical hiring intensity of a firm.

[8] While this aggregate relationship is driven in part by the sorting of different firm types, we show in Appendix B that this log-linear tradeoff is remarkably consistent across the firm lifecycle and size distribution, although the slope of the relationship differs among these subgroups. Nevertheless whether examining small startups or large established incumbents, the negative relationship between hiring intensity and college share persists within every age, size, industry, growth, and time interval group we consider, confirming that the tradeoff is not merely an artifact of the composition of the firm population.

[9] As shown in Appendix Table B.1, the semi-elasticity of college share with respect to hiring varies by an order of magnitude across sectors—ranging from -0.74 in Leisure and Hospitality to -9.67 in Professional and Business Services. Because different industries operate with different long-run average hiring rates and educational requirements, a pooled OLS estimate risks conflating these structural sector-level differences with the functional tradeoff we seek to identify. By introducing entity fixed effects in Table 1, we effectively control for these persistent sectoral (and firm-specific) differences, ensuring the resulting coefficient captures the dynamic tradeoff within firms over time.



(a) Uniform Scale

(b) Logarithmic Scale

Figure 2: Average educational attainment for ten deciles of the hiring rate (difference from firm-level average)

Notes: Deciles are calculated based on the annual hiring rate. Educational attainment is measured as the share of new hires with at least a four-year college degree. The horizontal axis shows total hires in a calendar year, relative to average annual employment, as obtained from the Longitudinal Employer-Household Dynamics Employer Characteristics File, 2005-2015. College degree attainment is obtained from the Census 2000 long form and the American Community Survey (ACS). Firms must have positive employment in each quarter of the year and at least one hired worker who reported their educational attainment to either the Census 2000 long form or the ACS.

To distinguish within-firm variation from static cross-sectional differences, we move to a fixed-effects regression framework. By including entity-level fixed effects, we control for all time-invariant firm characteristics—such as industry, location, and technology.[10] This allows us to isolate the "within-firm" variation: when a specific firm hires more than its own historical average, does its college share of hires simultaneously fall?

The results of this within-entity analysis are presented in Columns (3) and (4) Table 1. While the coefficient magnitude decreases from the pooled OLS estimate of -4.66 in Column (1) to a within-firm estimate of -1.01 in Column (3), the relationship remains highly statistically significant. This confirms that the quantity-skill tradeoff is a robust feature of firm-level hiring dynamics that persists even when controlling for firm-specific heterogeneity.

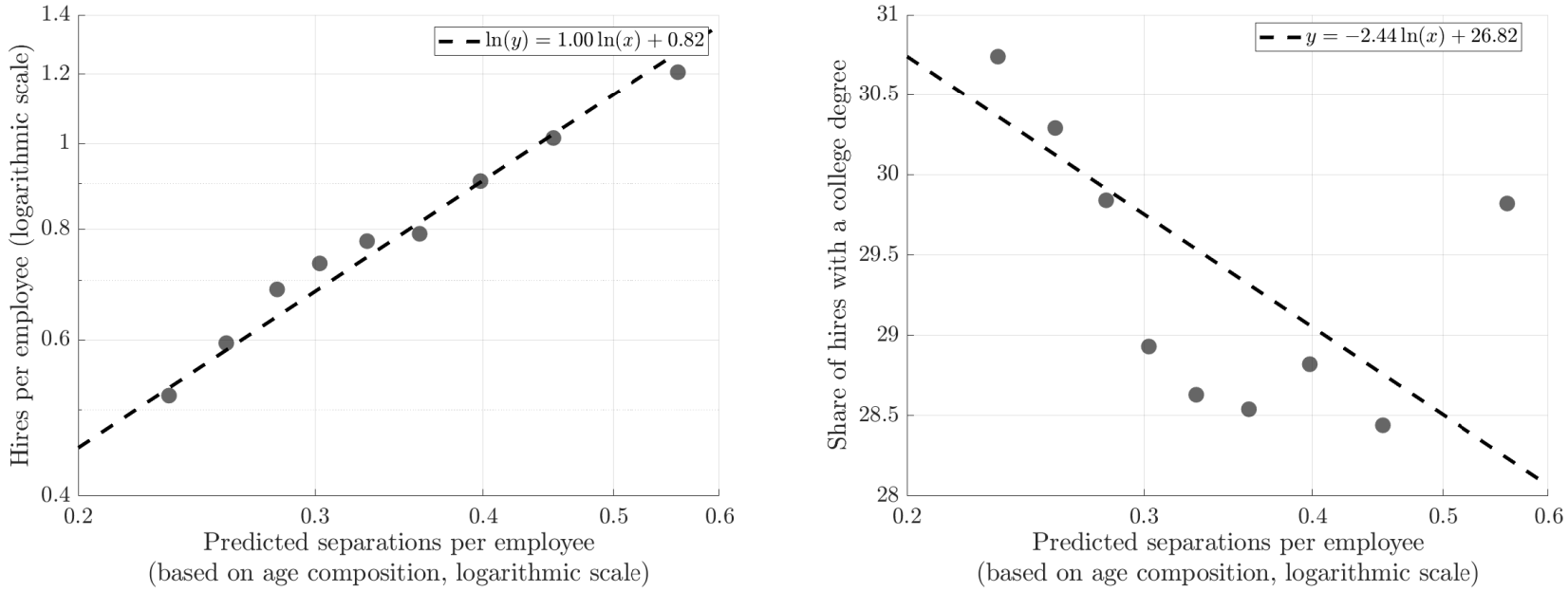
This within-firm relationship is visualized in Figure 2. By plotting the difference between each observation and its entity-level average, we remove the cross-sectional "level" effects. Figure 2b shows that the log-difference in hiring is negatively correlated with the difference in college share, with a regression line summarizing the relationship for these deciles that passes through the origin ($y = -1.01x$). The slope of this relationship is virtually identical to that which is reported in Column (3) of Table 1, which was run on the underlying microdata. This confirms that the quantity-skill tradeoff is a robust feature of firm-level hiring dynamics, persisting even when controlling for firm-specific heterogeneity.

3.3 Demographic Replacement Instrument

In this section, we expand our empirical analysis by introducing an instrumental variables (IV) strategy to further address potential endogeneity in the relationship between firm-level hiring and hire composition. While our previous fixed-effects specifications account for time-invariant firm characteristics, they may still be susceptible to time-varying idiosyncratic shocks that simultaneously affect both the scale and the selectivity of recruitment. To seek exogenous variation in hiring intensity, we use variation in "replacement hiring" needs. This instrument is grounded in the observation that a significant portion of firm-level hiring is driven by the necessity to backfill positions vacated by departing employees. Crucially, the rate at which workers separate from a firm is heavily influenced by the demographic composition of its existing workforce—specifically, the predictable lifecycle patterns of job mobility and retirement.

Our method builds upon the work of Murray (2019), who documented co-incident spikes

[10] Because our dataset is restricted to firm-year observations from 2005–2015, the estimation of these fixed effects is subject to left and right censoring. Specifically, firms that entered the market before 2005 or remained active after 2015 have their historical or subsequent hiring behavior excluded from the calculation of the firm-level average.



(a) First Stage (b) Reduced Form

Figure 3: Hiring rate and share of hires with a college degree for ten deciles of the age-predicted separation rate

Notes: Deciles are based on the age-predicted separation rate, a demographic-peer leave-out mean excluding the reference firm. The panels show hiring rates and college shares of hires, respectively, for 2005–2015. Education is observed in the Census 2000 Long Form or ACS. Firms must have positive employment in all four quarters and at least one hire with observed education.

in the separation and hiring rates among firms with only one employee around the age of retirement. To implement this strategy, we first characterize the beginning-of-year age distribution of each firm using the age categories from the LEHD Quarterly Workforce Indicators.[11] For each one-employee firm, the share of employees in any age group will be 100%. For each firm, we calculate the shares of the workforce falling into these categories and assign the firm to a discrete demographic peer group using a dyadic partition of these shares.[12] This strategy overcomes a difficulty when attempting to look at fine movements in the separation rate among firms. Very small firms have a high baseline rates of separation and hiring, and their demographic shares will settle among well-known fractions. A dyadic partition allows us to leverage the fact that e.g., five-employee firms are much more likely to have 20% of workers in a single age category rather than 80%, and so pays more attention to the former than the latter. This helps yield a smooth relationship between the demographic implied separation rates and firm-level hiring rates.

The instrument is then constructed as the leave-out mean separation rate of the firm's demographic peer group. By calculating the average separation rate of workers who were employed at the beginning of the year across all other firms in the group, we isolate the component of turnover that is common to firms with that specific age profile. This strategy effectively captures the "natural" turnover or replacement pressure inherent to the firm's demographic makeup, which is predetermined relative to contemporaneous hiring shocks. If the quantity-skill tradeoff is a structural feature of the recruitment process, we should find that firms compelled into higher hiring volumes simply to maintain their workforce size are similarly forced to lower their educational standards.

The results from our demographic-based IV strategy, presented in Table 2, reinforce the evidence of a quantity-skill tradeoff. By leveraging the predetermined age structure of the firm's workforce, we isolate a component of hiring that is driven by the predictable need to backfill positions rather than expansionary productivity shocks.

Panel A provides the first-stage estimates, regressing the firm's actual hiring rate on the age-predicted separation rate. Across all specifications, the instrument is a remarkably potent predictor of hiring intensity. In the most restrictive specification (Column 4), which accounts for both firm and year fixed effects, the coefficient of 0.086 is highly significant

[11] The eight QWI age groups are 14–18, 19–21, 22–24, 25–34, 35–44, 45–54, 55–64, and 65–99. We include a ninth category for workers with missing age identifiers (which are imputed for publication purposes) to ensure the sum of shares across categories equals unity.

[12] The dyadic partition uses bins $[2^{-(n+1)}, 2^{-n})$ for $n = 0, \ldots, k_{\max}$ and a residual bin $[0, 2^{-(k_{\max}+1)})$, with $s = 1$ included in the top bin. A firm is assigned to a unique demographic group based on the intersection of these indicators across all nine age categories. While whenever possible we utilize the most granular partition ($k_{\max} = 4$), coarser groupings at $k_{\max} = 2$ and $k_{\max} = 3$ provide a leave-out-mean group for firms without any second firm in that so-defined age distribution bin in a given year.

Table 2: IV Regression of College Share on Hiring Rates:
Age-Predicted Separation Rate Instrument

	(1)	(2)	(3)	(4)
Panel A: First Stage				
Dependent Variable:	Log(Hiring Rate)			
Log(Age-Predicted Sep. Rate)	0.984***	0.760***	0.083***	0.086***
	(0.001)	(0.001)	(0.001)	(0.001)
Firm Age		-0.012***		0.027***
		(3.429×10^{-5})		(0.000 407 7)
Log(Firm Size)		-0.113***		-0.186***
		(0.000 326 5)		(0.000 495 1)
R-squared	0.131	0.198	0.735	0.740
Panel B: Two-Stage Least Squares				
Dependent Variable:	College Share (pp)			
Log(Hiring Rate)	-2.279***	-2.981***	-1.925***	-1.843***
	(0.044)	(0.059)	(0.547)	(0.530)
Firm Age		-0.099***		-0.006
		(0.002)		(0.021)
Log(Firm Size)		0.709***		-0.489***
		(0.014)		(0.101)
First-stage F-stat	898,800†	538,900†	10,110†	11,110†
Fixed Effects	No	No	Yes	Yes

Notes: Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable in Panel B is the college share of hires multiplied by 100. The instrument in Panel A is the leave-out mean separation rate of the firm's demographic peer group, constructed via a dyadic partition of beginning-of-year workforce age shares. Fixed effects in columns (3) and (4) allow a parameter estimate for every firm and every year. Firm size is increased by one prior to taking logarithms. Following rounding requirements, all results have been rounded to four significant digits, including the first-stage F-statistic. †: Values beyond the fourth significant digit were rounded following Census Bureau requirements for the disclosure of estimates from confidential microdata.

($p < 0.01$) with a first-stage F-statistic of 11,110. This shows that a firm's demographic profile predicts hiring intensity.

The second-stage (2SLS) estimates in Panel B indicate a negative relationship between instrumented hiring intensity and the college share of hires. In our preferred specification with fixed effects (Column 4), the coefficient of -1.843 implies that a doubling of the hiring rate—when driven by demographic turnover—results in an approximately 1.28 percentage

point decline in the share of hires with a college degree ($1.843 \ln 2$).

Figure 3 provides a visual representation of the demographic identification strategy by plotting firm-level outcomes against deciles of the age-predicted separation rate. Panel (a) illustrates the first-stage relationship between the instrument and actual hiring intensity. There is a near-perfect monotonic relationship between a firm's demographic-driven turnover and its hiring rate, with a fitted slope of 1.00. This unit elasticity highlights the mechanical nature of replacement hiring: for firms in this sample, a 10% increase in predicted separations due to the workforce age profile is associated with approximately a 10% increase in the total hiring rate.

Panel (b) presents the reduced-form relationship, showing how these demographically-induced hiring spikes correlate with the college-educated share of new recruits. Consistent with the quantity-skill tradeoff, firms that are forced into higher hiring regimes to backfill vacancies see a steady decline in the educational attainment of their hires. The relationship has a slope of -2.44, indicating that even when hiring is driven by internal, predictable replacement needs rather than expansionary shocks, hiring composition shifts toward noncollege workers. Together, these panels are consistent with the replacement-hiring interpretation.

It is worth noting that while these magnitudes are somewhat smaller than the estimates derived from the industry-level instrument (which captures broader sectoral poaching shocks), they are significantly larger than the baseline within-firm OLS correlations. The consistency of this negative relationship across two distinct identification strategies—one based on external sectoral churn and the other on internal demographic structure—supports the quantity-skill tradeoff under different sources of hiring variation. Both replacement-hiring interpretations are consistent with lower college hiring shares at higher hiring rates.[13]

3.4 Taking Stock

The empirical evidence presented in this section establishes a robust inverse relationship between the quantity of workers a firm hires and the average skill level of those hires. Across the broad distribution of the U.S. economy, the baseline OLS estimates suggest a semi-elasticity of approximately -5.0: a firm operating at a hiring rate twice that of a peer typically hires a cohort with a college share approximately 3.5 percentage points lower ($5.0 \ln 2$).

The importance of this finding is twofold. First, the quantity-skill tradeoff is not confined to cross-sectional differences in industry, production technology, or lifecycle stage. As de-

[13] We find similar evidence of a structural tradeoff using an alternative instrumental variables strategy based on industry-level leave-out-mean separation rates. These results, which yield a larger semi-elasticity of -5.4 when controlling for firm-specific fixed effects, as well as firm age and firm size (and even larger semi-elasticities in other specifications), are detailed in Appendix C.

tailed in Appendix B, the tradeoff persists across diverse firm types, from nascent startups to established conglomerates. Crucially, the persistence of the effect after controlling for firm fixed effects—and using the demographic replacement instrument—is consistent with changes in hiring composition within individual firms, rather than only sorting across firms.

Second, this tradeoff defines the specific economic environments that serve as entry points for non-college labor. Our results suggest that the skill composition of hires varies with hiring intensity. The model must distinguish expansion from replacement hiring and poaching, and allow college workers to be both more productive and harder to recruit at scale. Changes in business dynamism can affect all these margins, so their aggregate employment consequences require an equilibrium analysis.

The persistence of the within-firm relationship motivates the model in Section 4. The framework combines skill-specific recruiting responsiveness with decreasing returns, heterogeneous turnover, on-the-job search, and endogenous firm survival. It asks whether these forces can reconcile a declining college share of gross hires with college workers' higher productivity and their greater representation in the employment stock.

4 A Hiring Model with a Quantity-Skill Tradeoff

We consider an economy with heterogeneous firms and two types of workers, college (indexed by H) and noncollege (indexed by L). College workers are more productive, but their recruiting costs have greater curvature. This provides a quasi-fixed-factor interpretation of skilled labor in the spirit of Oi (1962): firms can find college workers more valuable while expanding noncollege hiring more rapidly when the return to recruiting rises.

4.1 Environment

Time is continuous. Workers and firms are risk neutral and discount at rate ρ. The worker population has unit mass, with college share π_H and noncollege share $\pi_L = 1 - \pi_H$. Each worker holds at most one job or is nonemployed[14]. There is a mass ϕ of firms per worker, including firms that have not yet hired. This mass is determined endogenously: there is free entry with an entry cost of k_e^0. A firm's state is $x = (\theta, z, n_H, n_L)$: θ is the firm's permanent productivity type, z is its idiosyncratic productivity, and $n_s \in \mathbb{N}_0$ is the number of skill-s employees. Output is

$$y(x) = A_\theta z(a_H n_H + a_L n_L)^\alpha, \qquad 0 < \alpha < 1, \qquad a_H \geq a_L > 0. \tag{1}$$

[14]Nonemployment encompasses both unemployment and nonparticipation.

Skills are perfect substitutes in efficiency units, while decreasing returns make the marginal product of either skill decline as the firm grows. New firms start without employees and draw productivity from a common birth distribution. Firms meet both employed and nonemployed workers in a frictional environment, to be described in more detail in Section 4.3.

4.2 Worker values and bargaining

Let $J(x)$ denote the joint value of the firm and all its incumbent workers, as in Herkenhoff et al. (2024) or Bilal et al. (2022). As in these papers, decisions about hiring, mobility, and separations depend on the gains from trade between workers and firms, and wages distribute surplus without affecting real allocations. Write e_s for the addition of one skill-s worker. A firm's marginal value of a new hire and its marginal value of an incumbent depend on the change in its dynamic joint value $J(x)$ rather than on flow marginal product alone:

$$m_s(x) = J(x + e_s) - J(x), \qquad c_s(x) = J(x) - J(x - e_s). \tag{2}$$

The process for job mobility and bargaining over surplus follows Cahuc, Postel-Vinay, and Robin (2006). Workers have bargaining power β when negotiating with firms, regardless of whether they are coming from employment or nonemployment. This means that workers receive a fraction β of the surplus generated in a match, while the firm retains the remaining $1-\beta$. Let $\bar{U}_s$ denote the lifetime value of nonemployment for a worker of skill type $s \in \{H, L\}$. A nonemployed worker has reservation value $\bar{U}_s$. An employed worker at an incumbent firm of state x has reservation value in bargaining $r_s(x) = \max\{c_s(x), \bar{U}_s\}$, reflecting competition from the incumbent employer upon a poaching opportunity. A worker with reservation value $r_s(x)$ moves to a firm with state x' and marginal value $m_s(x')$ if and only if $m_s(x') > r_s(x)$. Conditional on a move, workers and firms bargain over wage according to the Nash bargaining solution, and the firm commits to delivering the promised lifetime payoff:

$$P_s(m_s(x'), r_s(x)) = r_s(x) + \beta(m_s(x') - r_s(x)), \tag{3}$$

leaving the hiring firm $(1 - \beta)(m_s(x') - r_s(x))$.

4.3 Search and recruiting

Firms recruit separately by skill and meet workers randomly within each skill market. Nonemployed workers search with intensity one; employed workers search with relative intensity ι. If E_s and N_s are employment and nonemployment, effective search supply is $S_s = N_s + \iota E_s$. Given aggregate vacancies V_s, meetings (M_s) and meetings per vacancy (η_s)

are determined by a Cobb-Douglas matching function with skill-specific meeting efficiency C_s and elasticity $\nu \in (0,1)$:

$$M_s = C_s S_s^{\nu} V_s^{1-\nu}, \qquad \eta_s = \frac{M_s}{V_s} = C_s (S_s/V_s)^{\nu}. \tag{4}$$

Firms are atomistic and take contact efficiency η_s as given, and do not internalize the fact that their vacancy posting causes congestion.

A firm chooses vacancies $v_s(x)$ per unit of scale $\ell(x) = 1 + n_H + n_L$. The additive constant allows empty entrants to recruit. Its contact intensity is $\eta_s \ell(x) v_s(x)$, and recruiting expenditure is

$$\mathcal{C}_s(v; x) = \ell(x) v^{\gamma_s}, \qquad \gamma_H \geq \gamma_L > 1. \tag{5}$$

Let $G_s(m)$ be the expected positive difference between marginal value m and the reservation value of a randomly encountered worker. Optimal effort is

$$v_s(x) = \left[\frac{\eta_s (1-\beta) G_s(m_s(x))}{\gamma_s} \right]^{1/(\gamma_s - 1)}. \tag{6}$$

The effort elasticity with respect to its return is $1/(\gamma_s - 1)$. Greater college cost curvature therefore makes college recruiting less responsive to expansion incentives.[15] Realized hiring also depends on acceptance and on the composition of the search pool, so this mechanism does not impose a downward-sloping college share of hires by construction.

Denoting $\mu(dx)$ as the share of firms with state x, aggregate recruiting effort is

$$V_s = \phi \int \ell(x) v_s(x) \mu(dx).$$

4.4 Nonemployed value

The value of nonemployment for a worker of skill type s therefore depends both on flow benefits b_s and on the expected gains from search. Its value satisfies

$$\rho \bar{U}_s = b_s + \beta \lambda_s^N \int (m - \bar{U}_s)_+ O_s(\mathrm{d}m), \tag{7}$$

where $\lambda_s^N = M_s/S_s$ and O_s is the recruiting-weighted distribution of destination bids. Thus $\rho \bar{U}_s$ includes search gains and is higher than the underlying nonemployment payoff.

[15] In Appendix D.2, we show that the same curvature can arise from training costs.

4.5 Separations and firm survival

Ordinary matches break exogenously at skill-specific rate δ_s. Each match also receives opportunities to break endogenously at rate ψ, akin to Adenbaum, Babalievsky, and Jungerman (2024), at which point the match ends if $c_s(x) < \bar{U}_s$. Workers can also leave for another employer.

At rate χ, a firm draws a one-time continuation cost $K \sim \text{Exp}(\text{mean } \kappa)$. The firm pays the full cost and continues whenever it is covered by organizational surplus $\mathcal{S}(x) = J(x) - n_H\bar{U}_H - n_L\bar{U}_L$. Otherwise, the firm closes and its employees return to nonemployment. The resulting closure hazard is

$$h(x) = \chi \exp[-\max\{\mathcal{S}(x), 0\}/\kappa]. \tag{8}$$

Higher surplus lowers the probability that the next cost draw causes exit. Continuation costs also use real resources when the firm stays open. They therefore affect recruiting incentives as well as firm lifetimes.

4.6 Free entry

Because entrants are empty, their organizational value is also the founder's value. The entry cost supporting the stationary allocation is

$$k_e^0 = \mathbb{E}_{\mathcal{B}} J(\theta, z, 0, 0), \tag{9}$$

where $\mathcal{B}$ is the birth distribution. We estimate firm mass ϕ in the calibration and recover this implied entry cost. With a given entry cost, free entry instead determines firm mass.

4.7 Stationary equilibrium

Let F_s denote the distribution of reservation values encountered by a recruiter and O_s the distribution of destination bids encountered by a worker. An employed worker receives offers at rate $\lambda_s^E = \iota\lambda_s^N$. Write $B(n) = n_H\bar{U}_H + n_L\bar{U}_L$ for the outside value of a firm's workforce, and let $x^{z'} = (\theta, z', n_H, n_L)$ denote the state following a productivity transition, which occurs at rate $q_{zz'}$.

Given contact rates, value distributions, and nonemployment values, joint organizational value satisfies the Hamilton–Jacobi–Bellman equation

$$\begin{aligned}\rho J(x) = y(x) &+ \sum_s \max_{v\geq 0} \ell(x) \left\{ \eta_s v(1-\beta) \int (m_s(x) - r)_+ F_s(\mathrm{d}r) - v^{\gamma_s} \right\} \\ &+ \sum_s n_s \left[\delta_s + \psi \mathbf{1}\{c_s(x) < \bar{U}_s\}\right] [\bar{U}_s - c_s(x)] \\ &+ \sum_{z' \neq z} q_{zz'} [J(x^{z'}) - J(x)] \\ &+ \sum_s \beta n_s \lambda_s^E \int (m - r_s(x))_+ O_s(\mathrm{d}m) \\ &+ \chi \int_0^\infty [\max\{J(x) - k, B(n)\} - J(x)] \frac{e^{-k/\kappa}}{\kappa} \, dk. \end{aligned} \tag{10}$$

The first line is output plus the return to optimal recruiting, net of recruiting expenditure. The next two lines account for separations into nonemployment and productivity changes. The fourth line is the gain accruing to departing workers when another employer outbids the incumbent; it vanishes at zero worker bargaining power. The final line incorporates both the cost paid upon continuation and the workforce's outside value upon closure.[16]

Equilibrium definition. Given primitives and entry cost k_e^0, a stationary equilibrium with positive entry consists of organizational value J, nonemployment values $\{\bar{U}_s\}$, recruiting policies $\{v_s\}$, a probability distribution μ over firm states, firm mass $\phi > 0$, an entry flow $e > 0$ per unit of firm mass, and contact rates and value distributions $\{\eta_s, \lambda_s^N, \lambda_s^E, F_s, O_s\}$ such that:

1. *Optimality.* Organizational value solves (10), recruiting policies satisfy (6), and nonemployment values solve (7). Hiring and mobility follow the strict value comparison and bargaining rule in Section 4.2; separations and continuation follow Section 4.5.

2. *Matching consistency and worker accounting.* Employment and nonemployment satisfy $E_s = \phi \int n_s(x)\mu(dx)$ and $N_s = \pi_s - E_s \geq 0$. Effective search supply is $S_s = N_s + \iota E_s$,

[16] Incumbent terms are omitted when $n_s = 0$. Appendix D.3 derives the donor-poaching term and states the maintained convention at origins with $c_s(x) < \bar{U}_s$.

aggregate vacancies are $V_s = \phi \int \ell(x) v_s(x) \mu(dx)$, and contact rates satisfy (4), $\lambda_s^N = M_s/S_s$, and $\lambda_s^E = \iota M_s/S_s$. For any measurable set of values D,

$$F_s(D) = \frac{N_s \mathbf{1}\{\bar{U}_s \in D\} + \iota\phi \int n_s(x) \mathbf{1}\{r_s(x) \in D\} \mu(dx)}{S_s},$$
$$O_s(D) = \frac{\phi}{V_s} \int \ell(x) v_s(x) \mathbf{1}\{m_s(x) \in D\} \mu(dx). \tag{11}$$

3. *Stationarity.* Let $\mathcal{L}_0^*$ be the forward operator induced by hiring, poaching, separations, and productivity changes, excluding firm closure. The firm distribution satisfies

$$0 = \mathcal{L}_0^* \mu - h\mu + e\mathcal{B}, \qquad e = \int h(x) \mu(dx), \qquad \int \mu(dx) = 1, \tag{12}$$

where h is given by (8) and $\mathcal{B}$ is the birth distribution of empty firms. Aggregate entry ϕe equals aggregate exit. Employment transitions count each accepted hire or departure in full, regardless of how bargaining divides its surplus.

4. *Free entry.* The expected value of a newborn firm equals its entry cost, $\mathbb{E}_{\mathcal{B}} J(\theta, z, 0, 0) = k_e^0$. Firm mass adjusts so that this condition holds.

Thus values and recruiting policies are optimal given the contact distributions, while those distributions are generated by the resulting stationary allocation. As in Herkenhoff et al. (2024) and Adenbaum et al. (2024), joint values determine real allocations without requiring the distribution of flow wages. Appendix D provides further derivations, and Appendix E describes the solution method.

5 Calibration

We calibrate the model to the 2005–2015 economy. The main targets are the gross hiring rates and college shares of hires across the ten hiring-rate deciles documented above. We supplement these moments with skill-specific worker flows from the Census Job-to-Job Flows (J2J) data and firm size and death rates from the Business Dynamics Statistics (BDS). The three sources cover different populations; their model counterparts use the corresponding sample restrictions rather than a single common sample.

5.1 Parameterization and targets

We set the annual discount rate to $\rho = 0.05$, returns to scale to $\alpha = 0.85$, and the matching elasticity to $\nu = 0.5$. Renegotiation shocks arrive at rate $\psi = 8$ per year, or two opportunities

Table 3: Calibrated parameters

Parameter	Value	Interpretation
$\bar{U}_L$	0.8567	Noncollege outside-value stock
$\bar{U}_H$	1.542	College outside-value stock, $1.8\bar{U}_L$
γ_L	1.550	Noncollege recruiting-cost power
$\gamma_H - \gamma_L$	0.3254	Nonnegative curvature gap
a_H/a_L	1.801	College productivity ratio
C_H	1.068	College matching scale
C_L	2.207	Noncollege matching scale
ϕ	0.06282	Organizations per population worker
δ_H	0.1227	Ordinary college match-break rate
δ_L	0.2040	Ordinary noncollege match-break rate
$q_{\ell h}$	0.06132	Low-to-high productivity transition rate
$q_{h\ell}$	0.6616	High-to-low productivity transition rate
π_H	0.4038	College population share
A_2	1.423	Permanent productivity of type 2
π_2^b	0.009989	Type-2 birth probability
z_h/z_ℓ	1.976	Idiosyncratic productivity ratio
χ	0.1021	Continuation-cost arrival rate
κ	10.98	Mean cost draw, in value units
ι	0.3003	Employed relative search intensity

Rates are per year. Outside values and continuation costs are stocks, not annual flows. $\gamma_H = 1.875$. Permanent-type birth shares need not equal employer or employment shares; the implied high-productivity birth-state probability is approximately 8.48%.

per quarter on average. We impose common bargaining power $\beta = 0.5$ for both types and $\bar{U}_H = 1.8\bar{U}_L$ in the baseline. The latter roughly corresponds to the wage ratio between college and non-college workers during our sample period. The flow payoffs b_s are implied by (7), not independently calibrated.

The remaining parameters are calibrated jointly. We use two idiosyncratic and permanent types, in both cases denoting type 2 as the higher-productivity type. We normalize $a_L = 1$, $z_\ell = 0.1$, and $A_1 = 1$. Table 3 reports the calibrated values, including the derived college outside value. The college population share is estimated, with no separate point target for its level.

We separately target each of the ten decile mean gross hiring rates and the college share of hires in each decile. We construct these moments from simulated annual firm-years using the empirical sample and employment definitions. Deciles and college hiring shares give equal weight to firms. Appendix Table D.1 lists all ten decile comparisons; Appendix D gives the observation rules and their limitations. The remaining empirical targets are mean employer size, employer count shares, and death/stock ratios for firms below 20 and at least 20 employees, together with college and noncollege EE and EN flow/stock ratios. Table

Table 4: Main firm, worker-flow, and composition targets

Moment	Data	Model
Mean employer size, below 20	4.765	3.851
Mean employer size, at least 20	160.0	105.6
Employer count share, below 20	0.8839	0.9062
Employer count share, at least 20	0.1161	0.09377
Annual death/stock ratio, below 20	0.09347	0.09369
Annual death/stock ratio, at least 20	0.01311	0.01244
College EE, annualized	0.08756	0.08153
Noncollege EE, annualized	0.1143	0.1179
College EN, annualized	0.1751	0.1481
Noncollege EN, annualized	0.2407	0.2371
College-share/log-hiring slope	−4.785	−4.532
Provisional annual inaction	0.3840	0.3469

Size moments condition on positive employers. Transition and closure comparisons are annual event/stock ratios, not probabilities of at least one event in a year. BDS and J2J samples are distinct from the hiring-decile sample and from each other. The slope is in percentage points per unit log mean hiring rate across deciles, not the microdata fixed-effect or IV coefficient. Inaction uses the employment-weighted two-worker/two-percent window; its establishment sample makes this a provisional comparison. The ten hiring-rate and college-share targets appear in Appendix Table D.1.

4 reports their levels and the model fit. We also target an employment-weighted annual inaction rate from Elsby, Gottfries, Michaels, and Ratner (2021): the fraction of employment at establishments whose net employment change is within two workers or two percent.

The levels and slope of hiring composition inform relative productivity and recruiting costs. Skill-specific EE and EN flows discipline on-the-job search and match turnover. Firm size and death rates, measured separately among positive employers, inform productivity heterogeneity, firm mass, and continuation costs. These links guide the calibration, but the parameters are chosen jointly rather than identified one at a time.

5.2 Calibrated economy and fit

The calibrated college productivity ratio (a_H/a_L) is 1.80. Recruiting-cost powers (γ_H, γ_L) are 1.875 for college and 1.550 for noncollege labor, implying effort elasticities of 1.14 and 1.82. Thus college labor is more productive but less elastic at the recruiting margin. Ordinary match-break rates (δ_H, δ_L) are 0.123 for college and 0.204 for noncollege workers. Longer college job durations help reconcile a high college share of employment with a lower college share of gross hires.

Table 4 summarizes the firm and worker-flow targets, the composition slope, and the provisional inaction comparison. The model generates a strictly decreasing college share

across all ten hiring-rate deciles, but its slope of -4.532 is flatter than the empirical slope of -4.785. College workers comprise 41.55% of employment, above their hiring share in every decile. Employment-to-population ratios are 0.778 for college and 0.741 for noncollege workers[17].

Figure 4 compares the empirical calibration targets with the simulated decile means, using the two scales in Figure 1. The model reproduces the declining composition gradient, but its hiring-rate distribution is shifted to the left. The fit is less successful for gross hiring at the top of the distribution and for the scale of large firms. Top-decile hiring is 1.734 rather than 3.412, reflecting lower churn in the model. Mean size among employers with at least 20 workers is 105.6 rather than 160.0. Both implied nonemployment flow payoffs are positive, but $b_H/b_L = 10.42$ despite the outside-value ratio of 1.8. The low noncollege flow payoff is an important qualification of the calibration. Recruiting absorbs 10.28% of output, an untargeted implication.

6 Quantitative Results

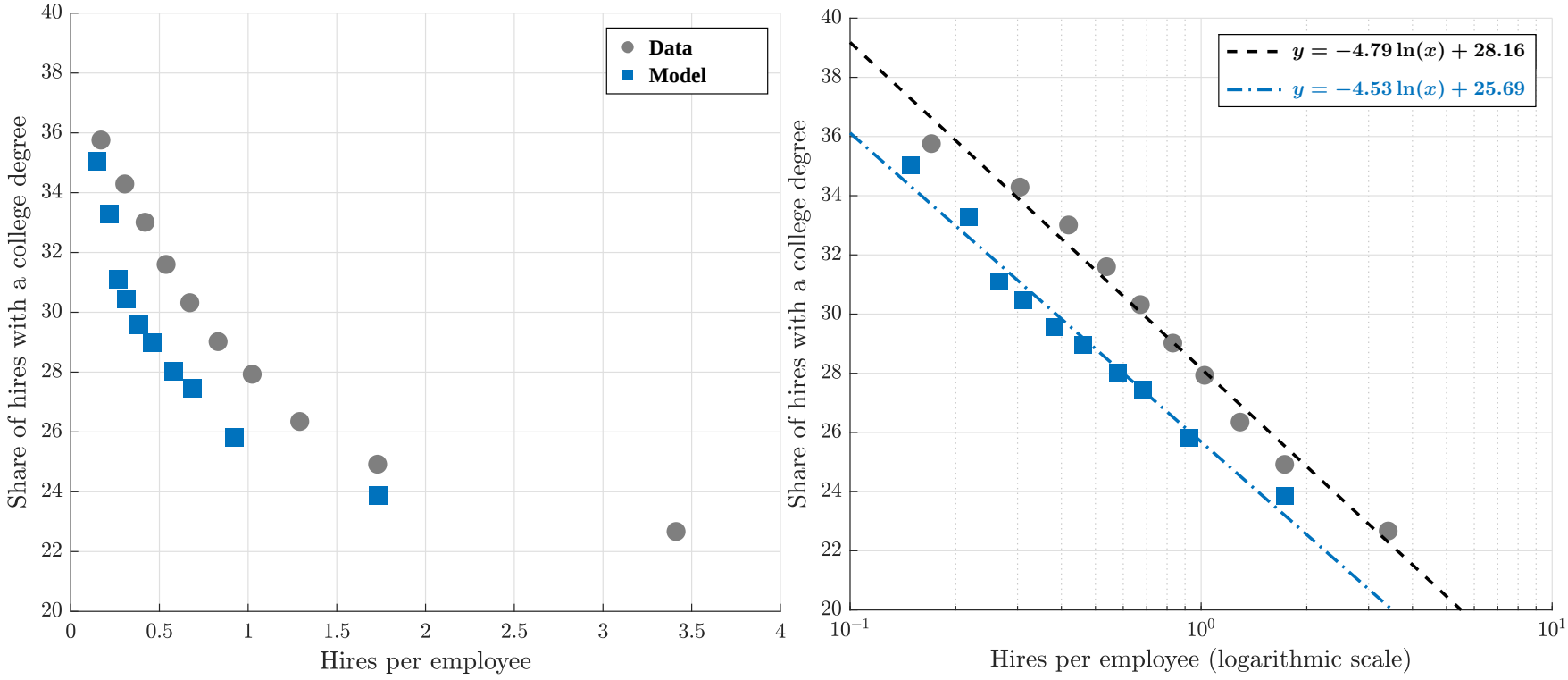
The quantity-skill tradeoff has implications beyond the composition of a given firm's hires. When worker types differ in productivity, turnover, and recruiting technology, changes in their relative supply also change the value of creating a firm and the relative value of an incumbent firm. Established firms that have had time to grow and build out their college-educated workforce could plausibly benefit more from a higher share of college-educated workers than entrants. We use the calibrated economy to study this link between skill composition and business dynamism[18]. First, we construct a 1990s baseline and study how changes in college supply, college productivity, and entry costs since then can explain declining dynamism. We then remove one college–noncollege difference at a time to understand how the different model mechanisms mediate these effects.

6.1 College supply, relative productivity, and business formation

In our first set of exercises, we ask how changes in the relative supply and productivity of college and non-college workers affect business formation. We compare average skill measures in 1990–1999 with those in 2005–2015. Using the CPS Outgoing Rotation Groups, we find that the college share of the population aged 25–64 has risen 27 percent since the 1990s,

[17] This is difficult to target directly with LEHD data, which cannot distinguish workers who leave the labor force altogether from nonemployed job seekers.

[18] In each exercise, unless otherwise stated, we hold fixed structural parameters b_H and b_L along with the entry cost k_e^0, allowing $\bar{U}_H$, $\bar{U}_L$, and ϕ to adjust.



(a) Uniform Scale (b) Logarithmic Scale

Figure 4: College share of hires and hiring rates: data and model

Notes: Each point is a decile mean from eligible annual firm-years. Gray circles are the released empirical decile means underlying Figure 1; blue squares are the model's simulated moments. Each series uses its own hiring-rate deciles and mean hiring rates, not common decile cutoffs. College shares are percentages and firms receive equal weight. The dashed data line and dash-dot model line in panel (b) are separate descriptive least-squares fits of college shares on log mean hiring rates across the ten deciles.

and the college/noncollege wage ratio has risen by about 6 percent. We construct a 1990s baseline with this lower college share and skill premium, and with the higher startup intensity measured in the BDS. We set π_H using the historical college-share ratio, then choose college productivity a_H and entry cost k_e^0 to match the historical skill premium (proxied by the outside-value ratio $\bar{U}_H/\bar{U}_L$) and the change in employer starts per employed worker. We hold a_L, b_H, b_L, and all other structural parameters fixed. As shown in Table 5, the college share rises from 31.84% in the 1990s to 40.38% in 2005–2015, the relative productivity of college workers increased by about 10 percent, and entry costs rose by roughly 6 percent over the same period.

Starting from the 1990s economy, our first exercise raises the college share to its 2005–2015 level in isolation, holding both skill productivities and entry cost fixed. Our second exercise raises college productivity to its later-period level, holding college supply and entry cost fixed. Our third exercise raises entry cost to its later-period level, holding the skill configuration fixed. Table 5, Table 6, and Figure 5 summarize the outcomes of these counterfactual exercises.

Table 5: Historical counterfactual parameters and outcomes in levels

	1990s	2010s	College share	Relative productivity	Entry cost
College population share (%)	31.84	40.38	40.38	31.84	31.84
Productivity ratio a_H/a_L	1.634	1.801	1.634	1.801	1.634
Entry cost k_e	0.2397	0.2539	0.2397	0.2397	0.2539
Firm mass per population worker	0.07663	0.06282	0.07093	0.08140	0.06382
Employer starts per 1,000 employed	8.412	6.606	7.620	8.912	6.894
Gross hires per employed worker	0.3203	0.3029	0.3068	0.3222	0.3142
Mean positive-employer size	10.84	13.39	11.84	10.26	12.96
College employment/population (%)	77.49	77.78	76.89	77.95	77.91
Noncollege employment/population (%)	73.05	74.10	73.84	73.08	73.28
Output per population worker	0.07300	0.07925	0.07573	0.07662	0.07208
Outside-value ratio $\bar{U}_H/\bar{U}_L$	1.697	1.8	1.632	1.861	1.708

All entries are levels. The 2010s reference is calibrated to pooled 2005–2015 data; the 1990s baseline represents 1990–1999. Population is normalized to one; output and firm mass are per population worker. Firm mass includes empty organizations; mean size conditions on positive employment. Employer starts are first hires by empty organizations. Flow intensities are annual. College population shares and employment/population ratios are in percent.

Table 6: Skill composition, productivity, and entry since the 1990s in percent changes

	2010s	College share	Relative productivity	Entry cost
College population share	26.80	26.80	0	0
Productivity ratio a_H/a_L	10.21	0	10.21	0
Entry cost k_e	5.933	0	0	5.933
Firm mass	−18.03	−7.448	6.214	−16.72
Employer starts per employed worker	−21.47	−9.419	5.938	−18.04
Gross hires per employed worker	−5.443	−4.235	0.5668	−1.905
Mean positive-employer size	23.58	9.249	−5.321	19.54
College employment/population	0.3706	−0.7709	0.5876	0.5416
Noncollege employment/population	1.441	1.075	0.04185	0.3132
Output	8.571	3.745	4.966	−1.251
Outside-value ratio $\bar{U}_H/\bar{U}_L$	6.092	−3.830	9.686	0.6566

Entries are percent changes from the 1990–1999 baseline, $100(x/x_{1990s} - 1)$, including the employment/population ratios. The 2010s reference is calibrated to pooled 2005–2015 data. Each counterfactual sets one parameter to its reference value, keeping both nonemployment flow payoffs and all other primitives at their 1990s values. Employer starts are first hires by empty organizations; flow intensities are annual. The 1990s baseline matches historical ratios of college supply, the outside-value-ratio wage proxy, and startup intensity.

Column 2 of Table 6 shows that moving college supply from its lower level in the 1990s to its later-period level would reduce firm mass by 7.5 percent and employer startups per employed worker by 9.4 percent. For context, national BDS data show that employer startups per 1,000 payroll jobs fell from 4.80 in 1990–1999 to 3.77 in 2005–2015, a decline of 21.47 percent. The supply-only response of 9.4 percent is about 44 percent of the observed change. Moving to the later-period college share, employers would be on average larger by 9.3 percent, and gross hiring per employed worker would fall by 4.2 percent. The supply-only exercise therefore links the growth of college attainment to several dimensions of declining dynamism: lower business formation, less gross hiring, and larger employers, even without a change in entry costs.

In isolation, one would expect an increase in relative supply to drive relative wages down. However, the wage premium for college workers increased over the same period, suggesting that skill-biased technological change was also at play. We model this technological change as a change in the productivity of college workers, holding non-college productivity fixed, and study what happens as college productivity rises to its later-period level. We adjust college productivity a_H to target the increase in the skill wage premium from the 1990s to the 2010s, proxied by the ratio of $\bar{U}_H$ and $\bar{U}_L$. We estimate an increase in a_H/a_L from 1.63 to 1.80, 10.2 percent above its 1990s baseline value. Interestingly, we find that skill-biased technological change moves dynamism in the other direction relative to changes in the skill

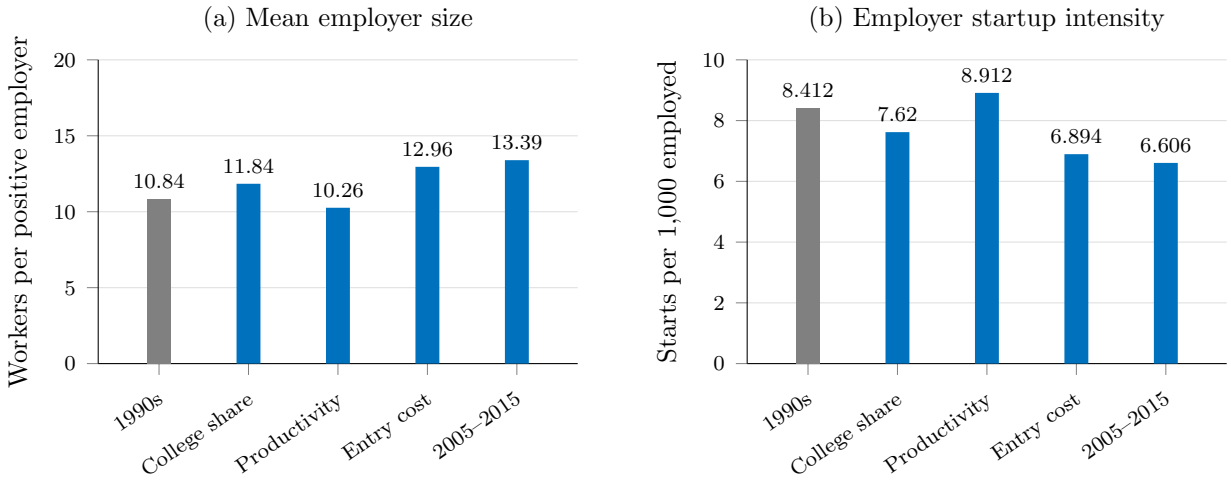


Figure 5: Historical changes, employer size, and startup intensity

Notes: Gray bars denote the 1990s baseline and blue bars the counterfactuals in Table 6 and the 2005–2015 calibration. Each counterfactual moves one parameter to its later-period value. Mean size conditions on positive-employment firms. Employer starts count first hires by previously empty organizations, expressed per 1,000 employed workers per year. All bars start at zero.

share. As shown in Column 3 of Table 6, raising college productivity to its 2010s level would increase firm mass by 6.2 percent and startup intensity by 5.9 percent. The higher productivity of college workers increases the return to creating a firm, hence the equilibrium has more, smaller employers.

Starting from the 1990s economy and raising entry costs by 5.93 percent to the 2010s level would reduce firm mass by 16.7 percent and startup intensity by 18 percent, as shown in Column 4 of Table 6. Employers would be on average larger by 19.5 percent, and gross hiring per employed worker would fall by 1.9 percent. These entry costs act as a residual and encompass all the unaccounted-for changes between the 1990s and 2010s. Note that entry costs are in units of goods, not units of labor. The next subsection explores this assumption.

6.2 Entry costs and labor productivity

Growth models commonly express entry costs in terms of labor, so that the goods cost of starting a business rises with wages as productivity grows (Peters and Walsh, 2026). We assume a goods-only entry technology: entry costs are fixed in output units. Higher labor productivity therefore raises the return to entry holding other margins fixed, because operating returns rise without a corresponding increase in entry costs.

Table 7 compares the entry-cost change with the change in average labor productivity, measured as aggregate output per employed worker, Y/E, where $E = E_H + E_L$. Entry costs rise 5.9 percent in goods units, while average labor productivity rises 7 percent. Expressing

Table 7: Entry costs and average labor productivity

	1990s	2010s	Change (%)
Entry cost, output units	0.2397	0.2539	5.933
Employment / population	0.7446	0.7559	1.507
Output per employed worker (Y/E)	0.09803	0.1049	6.959
Entry cost / (Y/E), worker-years	2.445	2.421	−0.9595

Output and employment are per unit of the fixed worker population. Average labor productivity is gross output divided by employment. Entry cost divided by average labor productivity is measured in output-equivalent worker-years. Changes use unrounded values.

entry costs in labor units using $k_e/(Y/E)$, the ratio falls by 1 percent, from 2.445 to 2.421 output-equivalent worker-years. The inferred increase in entry costs is therefore roughly in line with productivity growth, leaving its output-equivalent labor burden approximately unchanged.

6.3 Which college–noncollege differences matter?

College workers in the baseline are more productive, separate less often, face a different recruiting technology, and have a higher nonemployment flow payoff. To clarify the roles of these differences, we set one college primitive equal to its noncollege counterpart at a time in the 2005–2015 calibration. We set search cost scale and curvature $(C_H, \gamma_H) = (C_L, \gamma_L)$; raise the exogenous separation rate δ_H from 0.123 to $\delta_L = 0.204$; lower relative productivity a_H/a_L from 1.801 to one; or lower flow benefits b_H to b_L. Each exercise retains the original noncollege parameters, entry cost, college population share, and all other primitives. Both flow benefits stay fixed in the first three exercises.[19]

The results in Table 8, summarized in Figure 6, demonstrate that each of the differences between college and non-college workers matters for dynamism. Equalizing recruiting technology has the largest extensive-margin effect on dynamism. Firm mass more than doubles, employer starts rise 139 percent, and mean employer size falls from 13.4 to 6.1 workers. Output rises 12.9 percent. College employment/population increases to 83 percent, but noncollege employment/population falls to 72.7 percent. An easier college recruiting margin therefore changes both business formation and the allocation of jobs across skills.

Equalizing ordinary separation rates raises startup intensity by 28.9 percent and gross hiring per employed worker from 0.303 to 0.346, but lowers college employment/population by more than ten percentage points. Greater turnover creates more hiring activity, but not enough to keep employment shares at their baseline level. Removing the college productivity

[19] Appendix G reproduces Figure 1 for these four counterfactuals.

Table 8: Removing one college–noncollege difference at a time

	Equal recruiting technology	Equal separations	Equal productivity	Equal flow payoffs
Firm mass (% change)	123.0	18.55	−30.74	−10.43
Employer starts (% change)	139.0	21.44	−30.66	−11.60
Starts/employment (% change)	135.0	28.90	−29.31	−12.11
Employment (% change)	1.71	−5.79	−1.91	0.58
Output (% change)	12.91	−5.82	−26.64	−0.14
Mean positive-employer size	6.13	10.71	18.66	15.02
Gross hires per employed worker	0.364	0.346	0.293	0.299
College EPOP (%)	83.05	67.64	74.60	78.52
Noncollege EPOP (%)	72.70	73.62	73.84	74.33
Outside-value ratio $\bar{U}_H/\bar{U}_L$	2.217	1.523	1.044	1.725

Changes are relative to the 2005–2015 calibration. Equal recruiting sets $C_H = C_L$ and $\gamma_H = \gamma_L$; equal separations raises δ_H to δ_L; equal productivity sets $a_H = a_L$; equal flow payoffs sets $b_H = b_L$. EPOP is employment/population. Outside values and firm mass are endogenous. Employer-start and hiring flows have the same definitions as in Table 6.

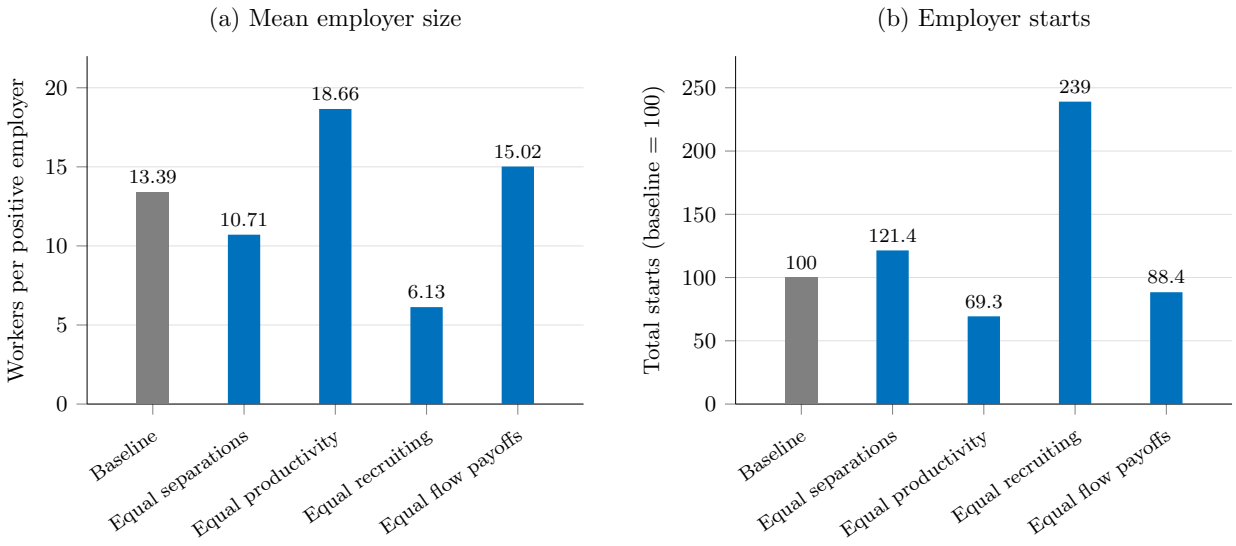


Figure 6: Skill differences, employer size, and employer starts

Notes: Gray bars denote the 2005–2015 baseline; blue bars remove one college–noncollege difference at a time, as in Table 8. Mean size conditions on positive-employment firms. Total employer starts are indexed to baseline = 100, using the table's employer-start changes, not its starts/employment changes. Employer starts are first hires, not organization births. All bars start at zero.

advantage lowers output by 26.6 percent and employer starts by 30.7 percent, decreasing dynamism. This echoes the results in Tables 5 and 6, where the increase in the productivity of college workers (holding other factors constant, crucially including entry costs in goods terms) increases the returns to entry.

The flow-payoff exercise presents a useful contrast. Lowering b_H to b_L increases employment by 0.58 percent, while reducing employer starts by 11.6 percent. It also leaves the outside-value ratio well above one, at 1.73: equal nonemployment flows do not imply equal lifetime values when employment opportunities and productivity differ. The effect on dynamism may seem surprising: lowering the outside option makes college workers more attractive as hires, lowering their productivity makes them less attractive, and yet both affect entry in the same direction. As shown in Appendix F, this is because of contrasting general equilibrium effects.

7 Conclusion

This paper documents a robust quantity-skill tradeoff in U.S. firm-level hiring: a higher gross hiring rate is associated with a lower college share of new hires. While some of this relationship reflects the composition of firms—-hiring intensity and skill composition differ persistently across firms—-our longitudinal analysis reveals a substantial within-firm component. Even after absorbing persistent firm-level heterogeneity through fixed effects, the within-firm semi-elasticity is negative and significant, indicating that individual firms hire a lower college share when they hire more intensively.

We interpret this tradeoff as an optimal response of firms to recruiting constraints. Firms far from their desired scale face a high marginal product of labor that raises the return to expansion. Their recruiting effort responds differently across skill types because college recruiting costs have greater curvature, a stand-in for greater training costs and specialization. Our model demonstrates that these differences can generate the observed quantity-skill tradeoff. They also generate a link between the skill-composition of the workforce and business dynamism. Starting from the 1990s economy, raising the college share to its sample-period level reduces employer startups per employed worker by 9.4 percent, reduces gross hiring, and increases average employer size. This supply-only response is about 44 percent of the observed decline in startup intensity. Greater availability of college workers favors incumbent firms that have had time to scale up their college workforce, at the expense of recruitment-constrained entrants. These results suggest that workforce composition plays an important role in understanding firm dynamics and business dynamism.

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A Data Appendix

A.1 Data Sources and Sample Construction

The primary dataset used in this paper is constructed by linking several components of the Longitudinal Employer-Household Dynamics (LEHD) infrastructure files. We analyze the LEHD snapshot, which allows for the integration of firm-level characteristics with individual-level longitudinal employment histories (U.S. Census Bureau, 2024).

Our sample construction uses the following core components:

1. **Employer Characteristics File (ECF):** The ECF is the primary source for firm-level longitudinal identifiers and attributes. We use this file to obtain industry classifications (NAICS) and to construct our measures of firm age and size.

    - *Firm Identifier and Aggregation:* The ECF provides the Census Bureau's overall "alpha-level" firm identifier (Haltiwanger et al., 2014), which we use as our primary firm identifier to group all establishments belonging to the same entity across states. Because a consistent firm identifier is critical for our longitudinal analysis, we follow the methodology of Cao et al. (2026) and supplement the firm identifier with the Federal Employer Identification Number (EIN) in cases where the primary firm identifier is missing.
    - *Firm Age:* We use the national firm-age measure described by Haltiwanger et al. (2014). When an alpha firm first appears, its age is the age of its oldest establishment; it subsequently ages with calendar time, rather than resetting when an establishment is acquired. Age is expressed in years. Our descriptive groups are 0–1, 2–3, 4–5, 6–10, and 11+ years. This measure need not equal time since the firm's first appearance in the LEHD observation window.
    - *Firm Size:* Our descriptive size groups are 1–19, 20–49, 50–249, 250–499, and 500+ employees. The size-classification variable must be distinguished from the year-edge employment denominator of the annual hiring rate, defined below. In particular, the national firm-size measure in the LEHD firm-age-and-size infrastructure is not generally the four-quarter average of observed employment (Haltiwanger et al., 2014). The separate BDS size moments used in calibration are described in Appendix D.5.
    - *Industry Classification:* We obtain industry information at the establishment level from the ECF. To assign a single industry to a firm that may operate establishments in multiple sectors, we use an employment-weighted modal industry. For

the descriptive heterogeneity analysis in Appendix B, firms are classified into supersectors based on this modal assignment.

2. **Quarterly employment and flow measures:** We construct employment, hires, and separations from the underlying LEHD job records using the quarterly concepts underlying the QWI. State Employer Identification Numbers (SEINs) identify administrative employer units, not the national economic firms used in this paper. Their links to the alpha identifier, with the EIN fallback described above, determine the firm aggregation. Employment and hiring are defined for worker–firm relationships; a move between establishments of the same continuing firm is not by itself a new firm-level hire. The annual hiring-rate denominator is year-edge employment, not the average of four quarterly employment stocks.

3. **Job History File (JHF):** The JHF supplies longitudinal worker–employer links, which are combined with firm identifiers to identify worker–firm relationships. Administrative employer-identifier changes can mimic hiring and separation; successor–predecessor links are a distinct part of the LEHD infrastructure, not an automatic consequence of using the JHF (U.S. Census Bureau, 2024). A change of SEIN alone is therefore not sufficient to identify economic recruitment. Individual identifiers link job histories to the education information in the Individual Characteristics File (ICF).

4. **Individual Characteristics File (ICF):** The ICF provides person-level demographic attributes, most notably educational attainment. These data are sourced from the 2000 Census Long Form and the American Community Survey (ACS). Crucially, our analysis relies exclusively on *observed* educational attainment. While the LEHD infrastructure includes imputed education values for individuals without a direct Census or ACS match to maintain aggregate representativeness, we exclude these imputations from our calculations.[20] As a result, firms in our research sample are required to have at least one hired worker with an observed (non-imputed) education record in a given year.

These files are linked using a common set of protected identification keys (PIKs) for individuals, as well as LEHD employer identifiers (State Employer Identification Numbers, or SEINs). By integrating these records, we can observe the human capital composition of the hiring flow for specific firms at precise points in their growth cycle.

[20] Using reported education avoids dependence on the education imputation procedure, but does not eliminate potential selection associated with survey coverage and linkage.

Our analysis covers 2005–2015. Geographic coverage depends on the particular LEHD file as well as the year: the availability of underlying UI earnings records need not coincide with the QWI/JHF release range (U.S. Census Bureau, 2024). The final sample is an unbalanced panel of firm-years with positive employment in all four quarters and at least one hire with observed education. The four-quarter condition applies within each included year; it does not require a firm to survive throughout 2005–2015. There is no separate exception for midyear entrants.

A.2 Labor Market Measures

We now provide formal definitions of the employment, hire, and separation concepts used throughout this paper. Our definitions follow the framework established in Abowd et al. (2009), adapted to relate quarterly earnings observations to annual hiring intensity.

A.2.1 Employment Concepts

Let w_{ijt} denote the earnings of individual i from employer j in quarter t. An employment relationship, or job, is defined by the presence of positive earnings ($w_{ijt} > 0$). To identify individuals with a stable attachment to an employer, we define beginning- and end-of-quarter employment based on presence in consecutive periods.

An individual is counted as employed at the beginning of quarter t if they had positive earnings at the same employer in the preceding quarter:

$$b_{ijt} = \begin{cases} 1, & \text{if } w_{ijt-1} > 0 \text{ and } w_{ijt} > 0 \\ 0, & \text{otherwise.} \end{cases}$$

Likewise, an individual is counted as employed at the end of quarter t if they have positive earnings at the employer in the subsequent quarter:

$$e_{ijt} = \begin{cases} 1, & \text{if } w_{ijt} > 0 \text{ and } w_{ijt+1} > 0 \\ 0, & \text{otherwise.} \end{cases}$$

A.2.2 Hires and Separations

A hire is identified in quarter t when an individual begins a new earnings stream at employer j. Formally:

$$h_{ijt} = \begin{cases} 1, & \text{if } w_{ijt-1} = 0 \text{ and } w_{ijt} > 0 \\ 0, & \text{otherwise.} \end{cases}$$

Similarly, a separation occurs when the relationship is present in quarter t but absent in quarter $t+1$:

$$s_{ijt} = \begin{cases} 1, & \text{if } w_{ijt+1} = 0 \text{ and } w_{ijt} > 0 \\ 0, & \text{otherwise.} \end{cases}$$

These are relationship-based quarterly events. A worker returning after an absent quarter is counted as a hire, even if the same worker–firm match existed earlier. A separation need not be the worker's last-ever job at that firm. Multiple within-quarter spells do not generate multiple hires when they leave the same quarterly relationship indicator unchanged.

Writing $B_{jt} = \sum_i b_{ijt}$ and $E_{jt} = \sum_i e_{ijt}$, quarterly employment is $(B_{jt} + E_{jt})/2$. The annual sample requires this quantity to be positive in each of the four quarters.

A.2.3 Annual Aggregation and Rates

The annual measures used in Section 3.1 are aggregated from these quarterly indicators. Total annual hires for employer j in year T is the sum of quarterly hires: $H_{jT} = \sum_{t \in T} \sum_i h_{ijt}$.

Following Hyatt et al. (2021), the denominator for our rates is the average of beginning-of-year and end-of-year employment. Let B_{jT} be the employment at the beginning of the first quarter of year T, and E_{jT} be the employment at the end of the fourth quarter of year T. The hiring rate HR_{jT} is defined as:

$$HR_{jT} = \frac{H_{jT}}{(B_{jT} + E_{jT})/2}$$

This denominator averages beginning-of-year and end-of-year employment. It differs from the average of the four quarterly employment measures. Firm-years with zero year-edge employment cannot enter the hiring-rate deciles, even if quarterly employment is positive throughout the year. Unlike the symmetric net growth rate, the gross hiring rate is not bounded above because replacement hiring and churn can generate multiple hires per employee.

Table B.1: Semi-Elasticity of the Share of Hires with a College Degree to the Hiring Rate

Firm Group	Semi-Elasticity	Std. Error	R^2
Overall	-4.79***	(0.22)	0.98
Firm Age			
Age 0 – 1	-4.61***	(0.41)	0.94
Age 2 – 3	-5.30***	(0.35)	0.97
Age 4 – 5	-5.90***	(0.36)	0.97
Age 6 – 10	-6.14***	(0.32)	0.98
Age 11+	-4.75***	(0.40)	0.95
Firm Size			
Size 1 – 19	-3.90***	(0.24)	0.97
Size 20 – 49	-5.42***	(0.28)	0.98
Size 50 – 249	-6.45***	(0.53)	0.95
Size 250 – 499	-9.08***	(1.24)	0.87
Size 500+	-10.58***	(1.41)	0.87
Firm Growth			
Separations more than 20% above hires	-4.65***	(0.15)	0.99
Separations 5% to 20% above hires	-6.51***	(0.45)	0.96
Separations within 5% of hires	-3.99***	(0.31)	0.95
Separations 5% to 20% below hires	-7.06***	(0.45)	0.97
Separations more than 20% below hires	-4.91***	(0.29)	0.97

Notes: Unweighted OLS of the decile mean college share of hires (percentage points) on the log of the decile mean annual hiring rate, using ten deciles within each group. These are descriptive regressions on ten binned points, not the microdata regressions in Table 1. Standard errors are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B The Quantity-Skill Tradeoff, Stratified

This appendix provides additional descriptive evidence on how the quantity-skill tradeoff varies across observable firm characteristics. To quantify these relationships, we use the binned regression approach underlying Figure 1(b). Specifically, we regress the mean college share of hires (in percentage points) on the log of the mean hiring rate across ten deciles within each subgroup.

As a baseline, Table B.1 reports the overall semi-elasticity of -4.79, which implies that a doubling of the hiring rate is associated with an approximately 3.32 percentage point reduction in the share of hires with a college degree ($4.79 \ln 2$). The following subsections explore how this relationship modulates across the dimensions of firm age, size, growth, and

Table B.1: Semi-Elasticity of the Share of Hires
with a College Degree to the Hiring Rate (continued)

Firm Group	Semi-Elasticity	Std. Error	R^2
Industry			
Natural Resources and Mining	-1.20***	(0.29)	0.69
Construction	-2.39***	(0.14)	0.97
Manufacturing	-1.58***	(0.43)	0.63
Trade, Transportation, and Utilities	-2.00***	(0.11)	0.98
Information	-3.65***	(0.36)	0.93
Financial Activities	-4.54***	(0.15)	0.99
Professional and Business Services	-9.67***	(0.58)	0.97
Education and Health Services	-4.31***	(0.56)	0.88
Leisure and Hospitality	-0.74*	(0.38)	0.32
Other Services (Except Public Administration)	-3.60***	(0.45)	0.89
Public Administration	-3.26***	(0.30)	0.94
Time Interval			
2005-2007	-4.63***	(0.26)	0.97
2008-2009	-4.35***	(0.19)	0.99
2010-2012	-4.60***	(0.17)	0.99
2013-2015	-5.25***	(0.28)	0.98

Notes: Unweighted OLS of the decile mean college share of hires (percentage points) on the log of the decile mean annual hiring rate, using ten deciles within each group. These are descriptive regressions on ten binned points, not the microdata regressions in Table 1. Standard errors are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

industry.

B.1 Firm Age

The relationship between quantity and skill is highly consistent across the firm lifecycle. As shown in Table B.1, the estimated semi-elasticities across five distinct age cohorts range narrowly from -4.61 for the youngest firms (Age 0–1) to a peak of -6.14 for mature firms (Age 6–10). Figure B.1 illustrates that the downward-sloping, log-linear relationship holds within each group.

B.2 Firm Size

The magnitude of the quantity-skill tradeoff varies with employer size. Small firms (1–19 employees) exhibit a semi-elasticity of -3.90, compared with -10.58 for firms with 500 or more employees. Figure B.2 illustrates these differences. The comparison concerns hiring

composition within size groups; it does not establish that an individual firm's slope steepens as it grows or directly identify a size-dependent recruiting cost.

B.3 Firm Growth

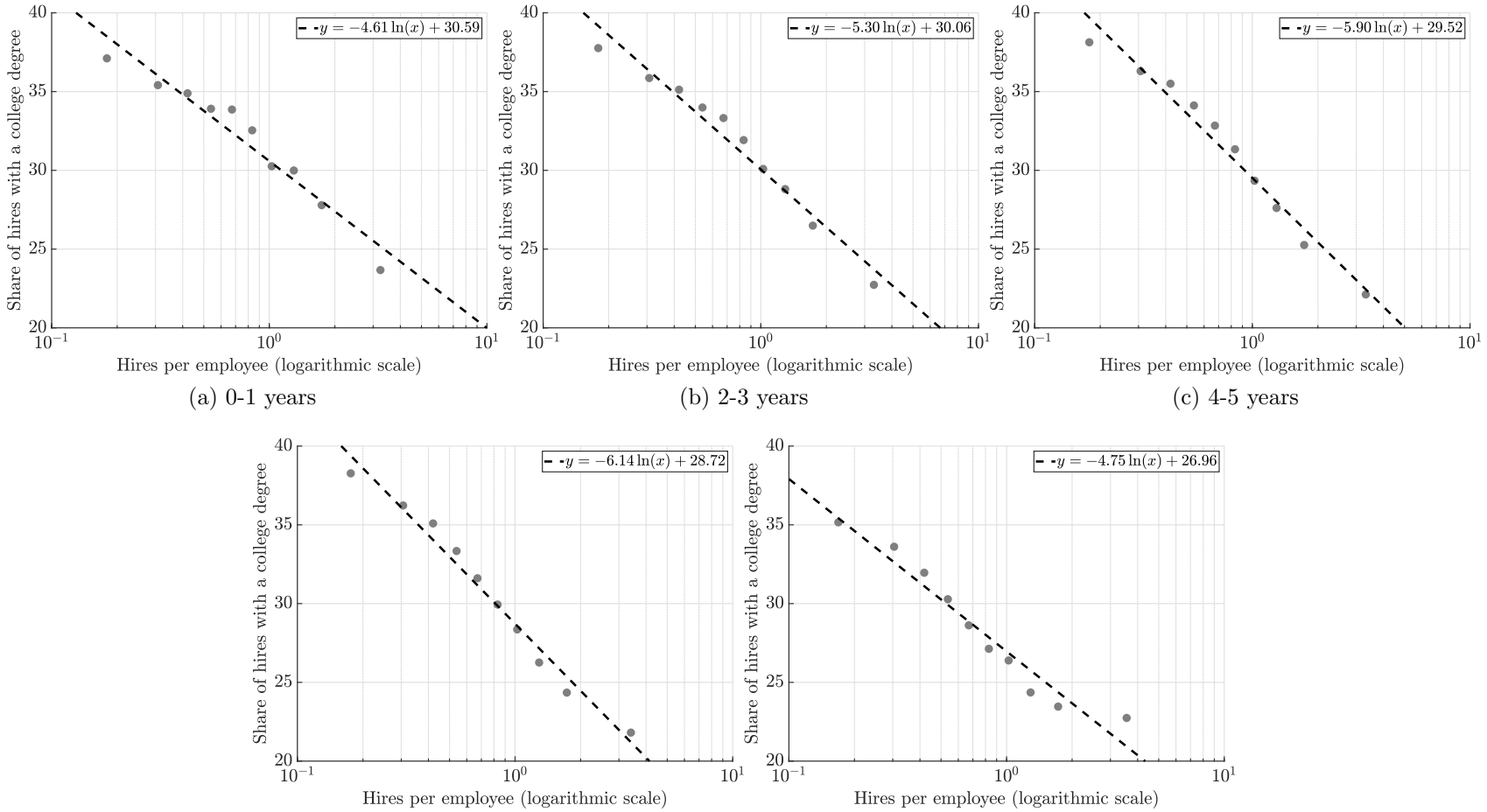
The tradeoff is negative in each group defined by the relationship between separations and hires. The largest magnitude in Table B.1 is −7.06, for separations 5%–20% below hires; the corresponding slope for separations 5%–20% above hires is −6.51. For separations more than 20% below hires, it is −4.91. Figure B.3 presents these conditional relationships. These groups distinguish relative inflows and outflows, not the gross hiring rate itself.

B.4 Industry

We examine variation across industry supersectors. While the quantity-skill tradeoff is negative in every sector, there is significant variation in its magnitude. In knowledge-intensive services, the tradeoff is most pronounced; *Professional and Business Services* exhibits the steepest slope at −9.67, followed by *Financial Activities* (−4.54). In contrast, physical production sectors such as *Manufacturing* (−1.58) and *Natural Resources and Mining* (−1.20) exhibit much shallower tradeoffs, possibly reflecting more standardized skill requirements. *Leisure and Hospitality* shows the smallest semi-elasticity at −0.74, consistent with a sector that maintains lower baseline educational requirements. These supersector-level relationships are visualized in Figure B.4.

B.5 Time Interval

The quantity-skill tradeoff is present in four subperiods: 2005–2007, 2008–2009, 2010–2012, and 2013–2015. The respective slopes in Table B.1 are −4.63, −4.35, −4.60, and −5.25. Figure B.5 shows the corresponding relationships. The slope is flatter during the recession and steepest in the final subperiod, but these descriptive comparisons do not separate changes in firm composition from changes in recruiting behavior or labor-market conditions.

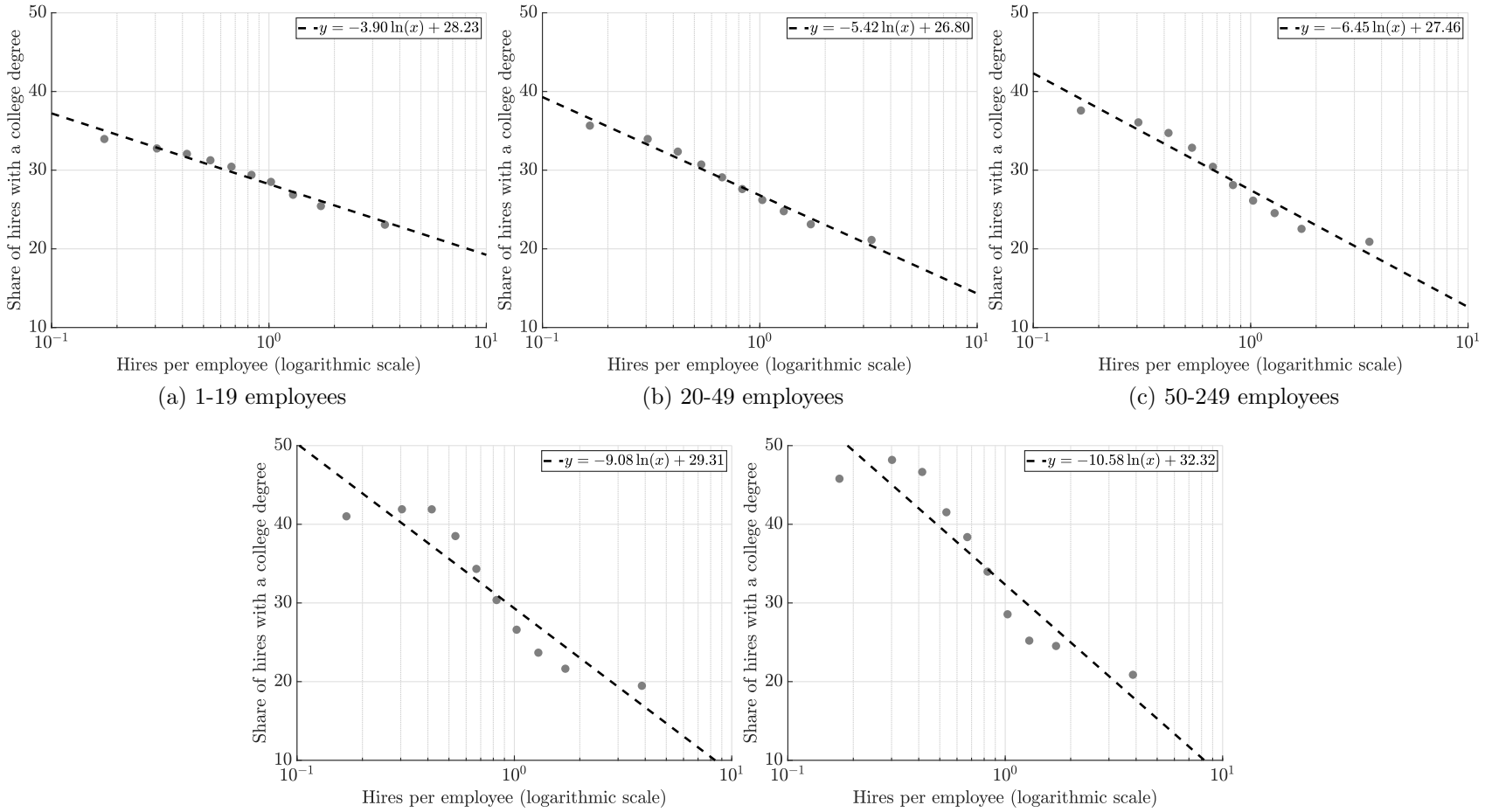


(a) 0-1 years (b) 2-3 years (c) 4-5 years

(d) 6-10 years (e) 11+ years

Figure B.1: Educational attainment by firm age (logarithmic scale).

Notes: Deciles are calculated based on the annual hiring rate. Educational attainment is measured as the share of new hires with at least a four-year college degree. The horizontal axis shows total hires in a calendar year, relative to average annual employment, as obtained from the Longitudinal Employer-Household Dynamics Employer Characteristics File, 2005-2015. College degree attainment is obtained from the Census 2000 long form and the American Community Survey (ACS). Firms must have positive employment in each quarter of the year and at least one hired worker who reported their educational attainment to either the Census 2000 long form or the ACS.

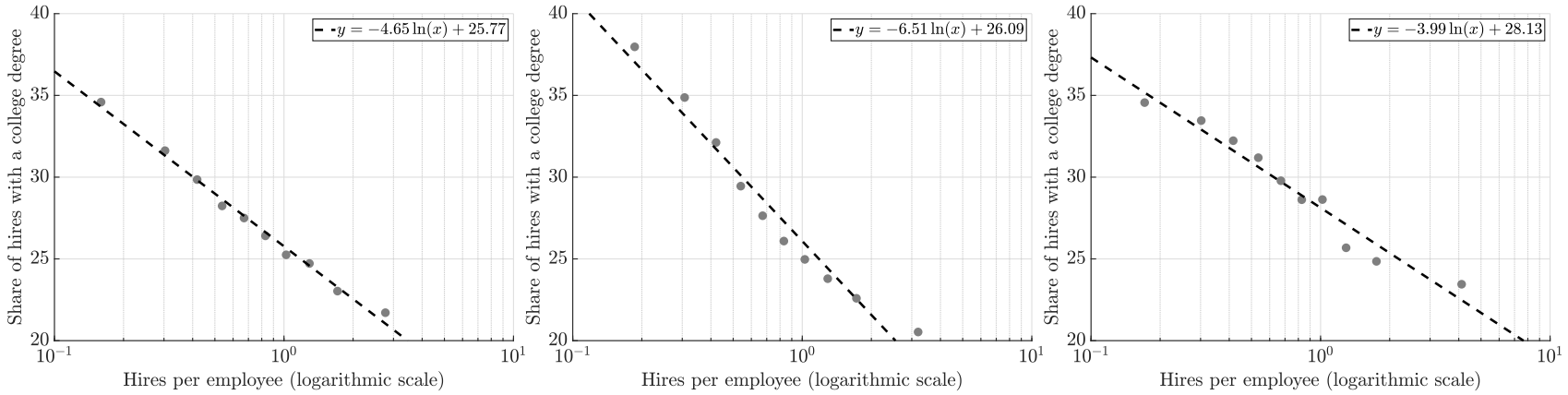


(a) 1-19 employees (b) 20-49 employees (c) 50-249 employees

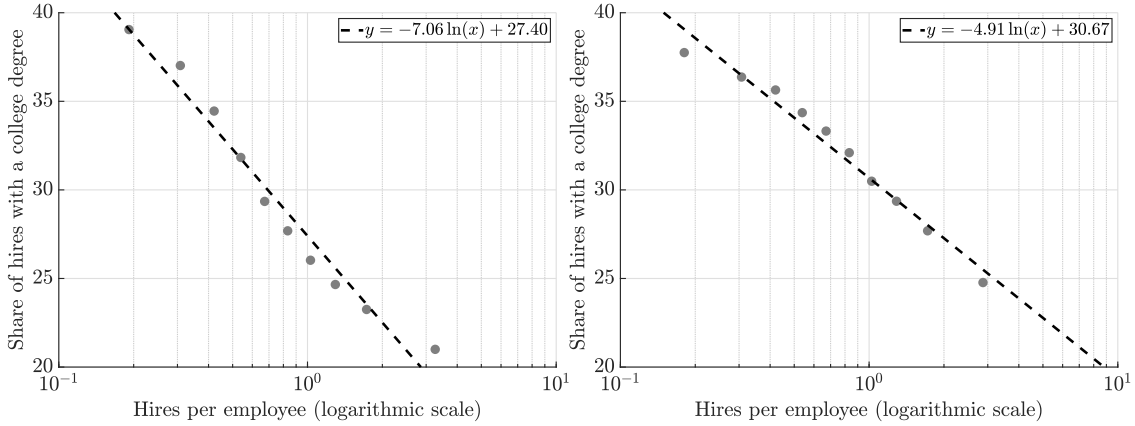
(d) 250-499 employees (e) 500+ employees

Figure B.2: Educational attainment by firm size (logarithmic scale).

Notes: Deciles are calculated based on the annual hiring rate. Educational attainment is measured as the share of new hires with at least a four-year college degree. The horizontal axis shows total hires in a calendar year, relative to average annual employment, as obtained from the Longitudinal Employer-Household Dynamics Employer Characteristics File, 2005-2015. College degree attainment is obtained from the Census 2000 long form and the American Community Survey (ACS). Firms must have positive employment in each quarter of the year and at least one hired worker who reported their educational attainment to either the Census 2000 long form or the ACS.



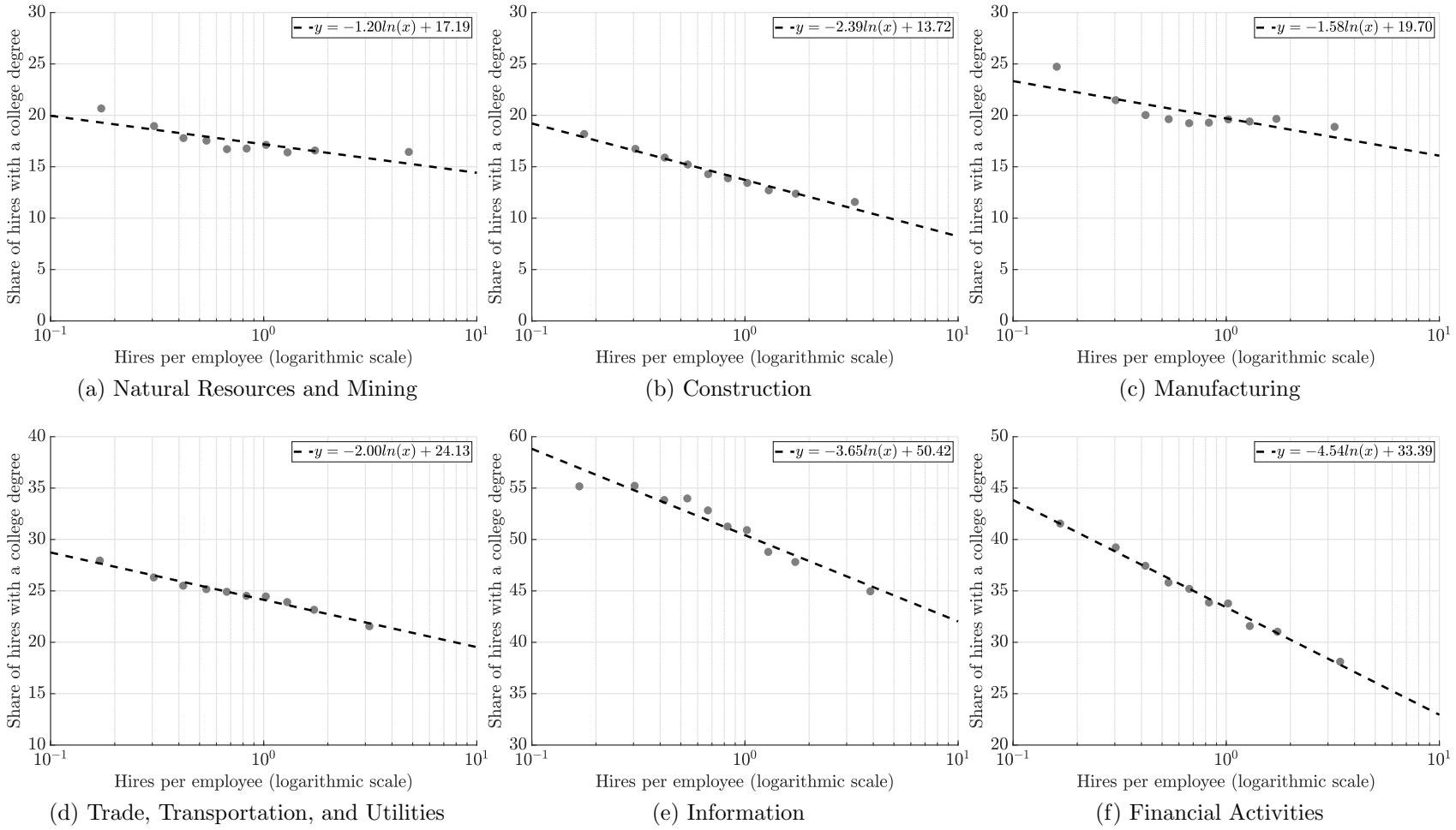
(a) Separations more than 20% above hires (b) Separations 5% to 20% above hires (c) Separations within 5% of hires



(d) Separations 5% to 20% below hires (e) Separations more than 20% below hires

Figure B.3: Educational attainment by firm growth (logarithmic scale).

Notes: Deciles are calculated based on the annual hiring rate. Educational attainment is measured as the share of new hires with at least a four-year college degree. The horizontal axis shows total hires in a calendar year, relative to average annual employment, as obtained from the Longitudinal Employer-Household Dynamics Employer Characteristics File, 2005-2015. College degree attainment is obtained from the Census 2000 long form and the American Community Survey (ACS). Firms must have positive employment in each quarter of the year and at least one hired worker who reported their educational attainment to either the Census 2000 long form or the ACS.

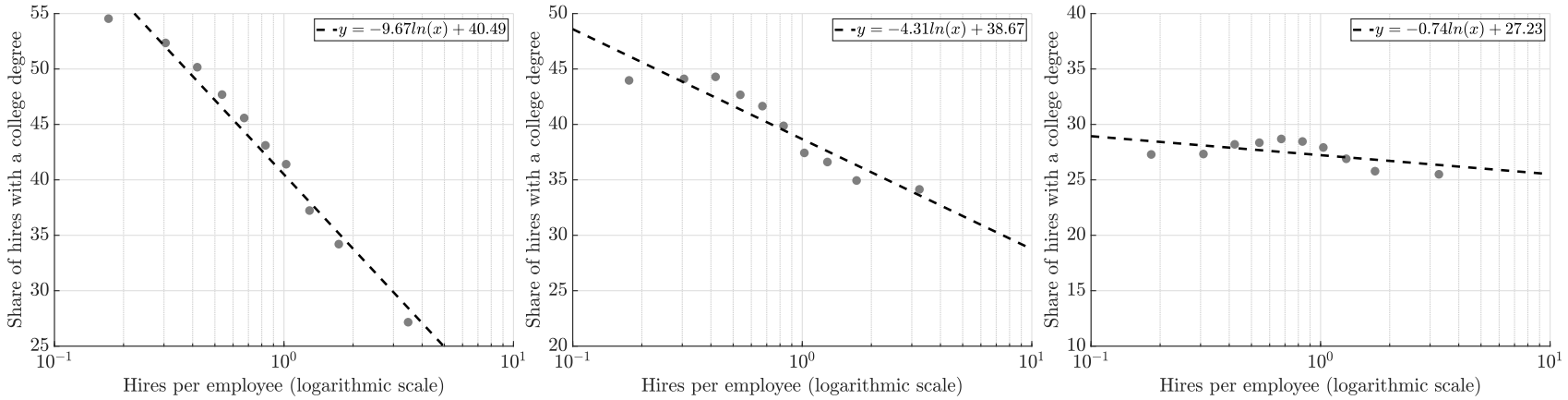


(a) Natural Resources and Mining (b) Construction (c) Manufacturing

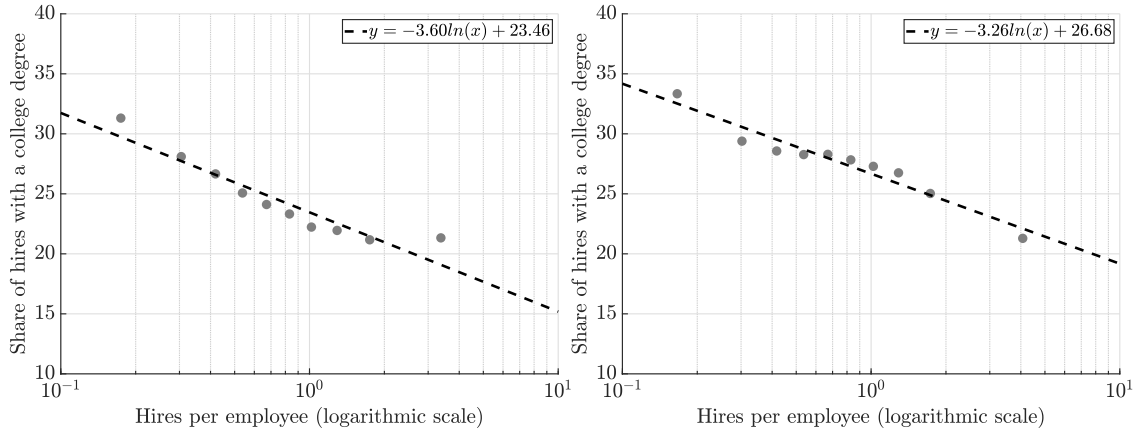
(d) Trade, Transportation, and Utilities (e) Information (f) Financial Activities

Figure B.4: Educational attainment by industry (logarithmic scale).

Notes: Deciles are calculated based on the annual hiring rate. Educational attainment is measured as the share of new hires with at least a four-year college degree. The horizontal axis shows total hires in a calendar year, relative to average annual employment, as obtained from the Longitudinal Employer-Household Dynamics Employer Characteristics File, 2005-2015. College degree attainment is obtained from the Census 2000 long form and the American Community Survey (ACS). Firms must have positive employment in each quarter of the year and at least one hired worker who reported their educational attainment to either the Census 2000 long form or the ACS.



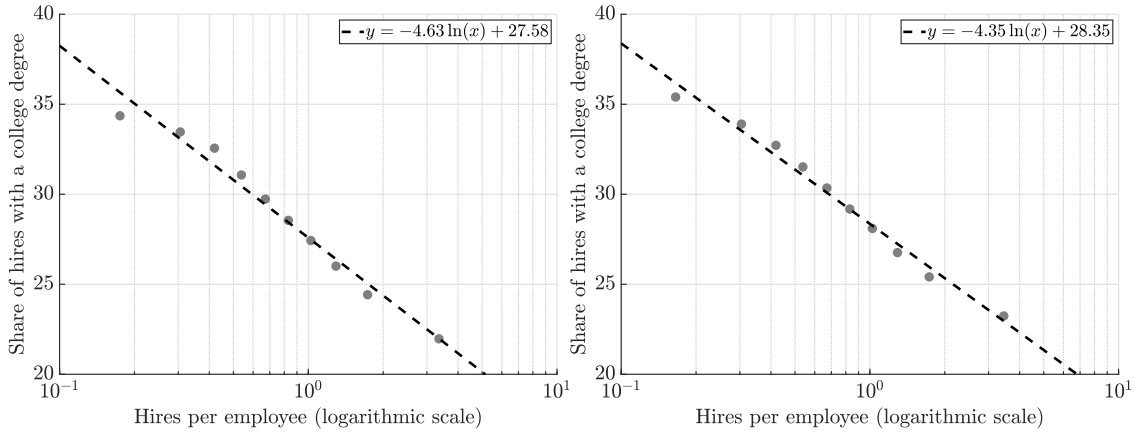
(g) Professional and Business Services (h) Education and Health Services (i) Leisure and Hospitality



(j) Other Services (Except Public Administration) (k) Public Administration

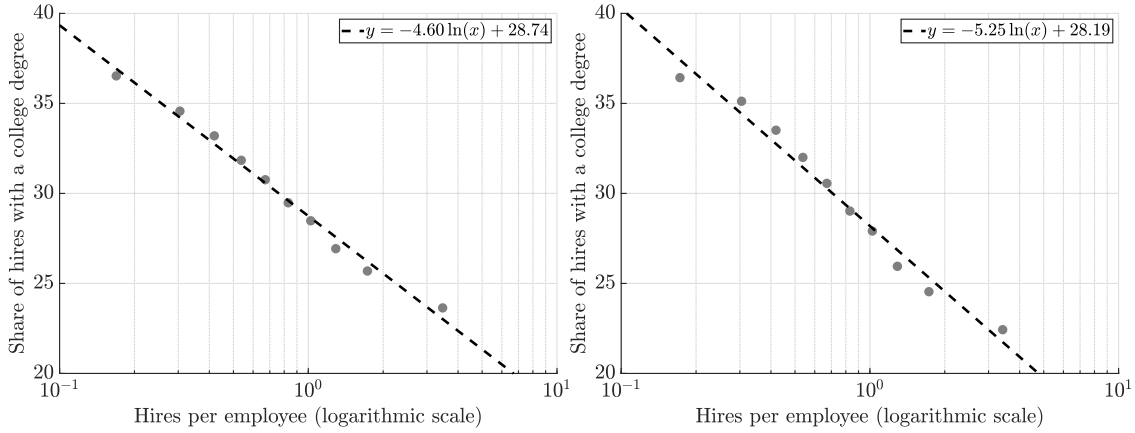
Figure B.4: Educational attainment by industry (logarithmic scale, continued).

Notes: Deciles are calculated based on the annual hiring rate. Educational attainment is measured as the share of new hires with at least a four-year college degree. The horizontal axis shows total hires in a calendar year, relative to average annual employment, as obtained from the Longitudinal Employer-Household Dynamics Employer Characteristics File, 2005-2015. College degree attainment is obtained from the Census 2000 long form and the American Community Survey (ACS). Firms must have positive employment in each quarter of the year and at least one hired worker who reported their educational attainment to either the Census 2000 long form or the ACS.



(a) 2005-2007

(b) 2008-2009



(c) 2010-2012

(d) 2013-2015

Figure B.5: Educational attainment by time interval (logarithmic scale).

Notes: Deciles are calculated based on the annual hiring rate. Educational attainment is measured as the share of new hires with at least a four-year college degree. The horizontal axis shows total hires in a calendar year, relative to average annual employment, as obtained from the Longitudinal Employer-Household Dynamics Employer Characteristics File, 2005-2015. College degree attainment is obtained from the Census 2000 long form and the American Community Survey (ACS). Firms must have positive employment in each quarter of the year and at least one hired worker who reported their educational attainment to either the Census 2000 long form or the ACS.

C Alternative Instrumental Variables Frameworks

C.1 Industry-Level Separation Rate Instrument

This section presents an alternative IV strategy using an industry-level leave-out-mean (LOM) separation rate. For each firm, the instrument uses other firms in the same four-digit NAICS industry, excluding firms whose dominant state matches the focal firm's dominant state. This is a leave-out industry instrument, not a conventional shift-share instrument. The geographic exclusion removes a direct own-state contribution; its validity still requires that the remaining industry variation affect hiring composition only through the instrumented hiring rate, conditional on the controls.

Industry turnover may predict a firm's need to replace departing workers. Poaching is one possible source of this turnover, but common industry demand or technology shocks are also possible. The leave-out construction does not by itself rule out these alternative channels or establish the exclusion restriction.

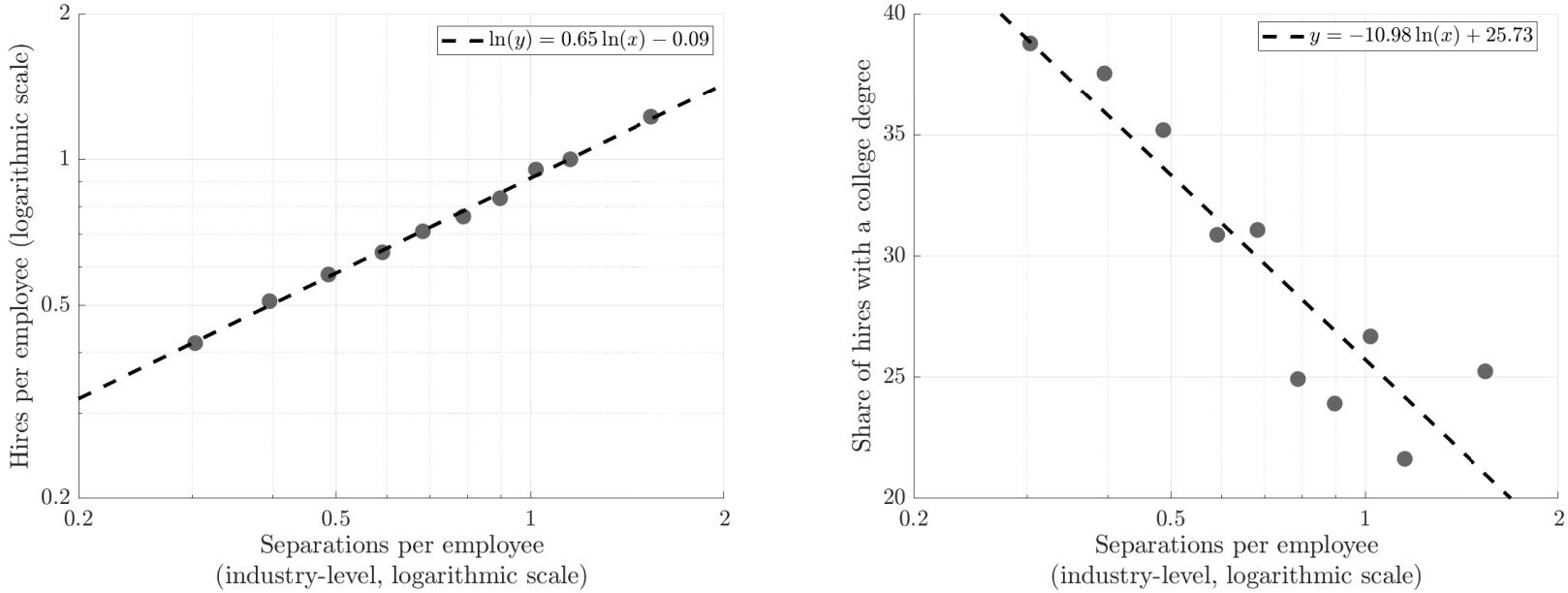
Figure C.1 plots the positive first-stage and negative reduced-form relationships across deciles of the instrument. The fitted lines summarize these binned associations, whereas Table C.1 reports the microdata IV specifications. The plotted relationships are consistent with replacement-hiring pressure but do not by themselves establish its causal interpretation.

Table C.1 reports a strong first stage across all specifications. With firm and year fixed effects (Column 4), the first-stage F-statistic is 2,162 and the second-stage coefficient is -5.416, implying a 3.75-percentage-point decline per doubling of the instrumented hiring rate ($5.416 \ln 2$). Its magnitude exceeds the within-firm OLS estimate. A causal interpretation requires the exclusion restriction discussed above; a strong first stage alone does not establish that restriction.

Table C.1: IV Regression of College Share on Hiring Rates:
Industry-Level Average Separation Rate Instrument

	(1)	(2)	(3)	(4)
Panel A: First Stage				
Dependent Variable:	Log(Hiring Rate)			
Log(LOM Separation Rate)	0.6523***	0.5495***	0.0718***	0.07359***
	(0.0007866)	(0.0007825)	(0.001605)	(0.001583)
Firm Age		−0.01421***		0.02693***
		(3.262×10^{-5})		(0.0004073)
Log(Firm Size)		−0.1098***		−0.1861***
		(0.0003122)		(0.0004959)
R-squared	0.144	0.2265	0.7344	0.7397
Panel B: Two-Stage Least Squares				
Dependent Variable:	College Share (pp)			
Log(Hiring Rate)	−15.62***†	−19.04***†	−5.568***	−5.416***
	(0.05022)	(0.06258)	(1.075)	(1.048)
Firm Age		−0.3905***		0.09007***
		(0.001895)		(0.032)
Log(Firm Size)		−1.325***		−1.154***
		(0.01542)		(0.1962)
First-stage F-stat	687,600†	493,200†	2002	2162
Fixed Effects	No	No	Yes	Yes

Notes: Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Panel A uses log hiring rates; Panel B uses the college share of hires multiplied by 100. The instrument is the four-digit-industry LOM separation rate, excluding firms with the focal firm's dominant state. Columns (3) and (4) include firm and year fixed effects. Firm size is increased by one before taking logarithms. Entries reproduce the released estimates with at most four significant figures; small standard errors are not rounded to zero. †: Large disclosed values were rounded to four significant figures under Census Bureau disclosure requirements.



(a) First Stage (b) Reduced Form

Figure C.1: Hiring rate and share of hires with a college degree for ten deciles of the industry-level separation rate

Notes: Deciles are calculated based on the leave-out-mean (LOM) separation rate, which is calculated at the 4-digit industry level, and excludes all firms in the dominant state in which it operates. Educational attainment is measured as the share of new hires with at least a four-year college degree. The horizontal axis shows industry-level total separations in a calendar year, relative to average annual employment, as obtained from the Longitudinal Employer-Household Dynamics Employer Characteristics File, 2005-2015. Industry is defined at the 4-digit NAICS level. A firm's industry-level separation rate leaves out the dominant state in which firm operates, including that firm. College degree attainment is obtained from the Census 2000 long form and the American Community Survey (ACS). Firms must have positive employment in each quarter of the year and at least one hired worker who reported their educational attainment to either the Census 2000 long form or the ACS.

C.2 Joint Instrumental Variables Estimation

To test whether the two identification strategies capture a common underlying mechanism, we examine a specification that simultaneously incorporates both the demographic replacement instrument and the industry-level separation rate instrument. The results of this joint IV regression are reported in Table C.2.

With the demographic instrument alone (Table 2), the preferred fixed-effects coefficient is -1.843; with the industry instrument alone (Table C.1), it is -5.416. The joint estimate in Table C.2, Column 4, is -2.570, between the two. This numerical ordering does not establish that joint 2SLS is a convex average of distinct causal effects.

The test of overidentifying restrictions has one degree of freedom, with a 5 percent critical value of approximately 3.84. The released fixed-effects statistics are 9.281 and 9.415, with p-values 0.00231 and 0.00215. They reject the joint moment restrictions of the maintained specification. This may reflect failure of an exclusion restriction, functional-form misspecification, or heterogeneous responses to the two instruments. Rejection alone cannot distinguish these explanations or establish that both instruments identify valid local causal effects.

Table C.2: IV Regression of College Share on Hiring Rates:
Age-Predicted Separation Rate Instrument and
Industry-Level Average Separation Rate Instrument

	(1)	(2)	(3)	(4)
Panel A: First Stage				
Dependent Variable:	Log(Hiring Rate)			
Log(LOM Separation Rate)	0.5013***	0.4546***	0.06995***	0.07168***
	(0.0007958)	(0.0007984)	(0.001599)	(0.001577)
Log(Age-Predicted Sep. Rate)	0.7213***	0.547***	0.08259***	0.08535***
	(0.00103)	(0.001013)	(0.0008265)	(0.0008147)
Firm Age		−0.01042***		0.027***
		(3.223×10^{-5})		(0.0004076)
Log(Firm Size)		−0.1027***		−0.1864***
		(0.0002973)		(0.0004949)
R-squared	0.2067	0.2595	0.7346	0.7399
Panel B: Two-Stage Least Squares				
Dependent Variable:	College Share (pp)			
Log(Hiring Rate)	−9.422***	−12.91***†	−2.676***	−2.57***
	(0.0378)	(0.04847)	(0.4901)	(0.475)
Firm Age		−0.2792***		0.01354
		(0.001702)		(0.01969)
Log(Firm Size)		−0.5486***		−0.6243***
		(0.01392)		(0.09079)
First-stage F-stat	715,600†	463,500†	5984	6547
Over-identification J-test	61,940†	50,520†	9.281	9.415
Fixed Effects	No	No	Yes	Yes

Notes: Robust standard errors clustered at the firm level are reported in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Panel A includes both the demographic replacement instrument and the four-digit-industry LOM separation instrument. The latter excludes firms with the focal firm's dominant state. Panel B instruments log hiring rates using both variables. Columns (3) and (4) include firm and year fixed effects. Firm size is increased by one before taking logarithms. The first-stage F-statistic tests joint exclusion of the instruments; the overidentification test has one degree of freedom. Entries reproduce the released estimates with at most four significant figures. †: Large disclosed values were rounded to four significant figures under Census Bureau disclosure requirements.

D Model and Calibration Details

This appendix supplies the value equations, observation rules, and detailed calibration results underlying Sections 4 and 5. Appendix E describes the numerical solution.

D.1 Search pools, offers, and worker mobility

Let μ be the stationary probability distribution over firms, including empty organizations. Employment, nonemployment, and effective search supply of skill s are

$$E_s = \phi \int n_s(x)\mu(dx), \qquad N_s = \pi_s - E_s, \qquad S_s = N_s + \iota E_s. \tag{13}$$

Nonemployed workers search with intensity one; employed workers search with relative intensity ι. For any set D of reservation values, the distribution encountered by a skill-s recruiter is

$$F_s(D) = \frac{N_s \mathbf{1}\{\bar{U}_s \in D\} + \iota\phi \int n_s(x)\mathbf{1}\{r_s(x) \in D\}\mu(dx)}{S_s}. \tag{14}$$

The probability of acceptance and expected gain from trade per contact are

$$p_s(m) = \int \mathbf{1}\{r < m\}F_s(\mathrm{d}r), \qquad G_s(m) = \int (m-r)_+ F_s(\mathrm{d}r). \tag{15}$$

Firms recruit separately by skill but cannot target employment status or reservation values within a skill market. Acceptance follows the strict value comparison $m > r$; ties do not move, and there are no additional match-specific taste shocks.

Aggregate recruiting effort is

$$V_s = \phi \int \ell(x)v_s(x)\mu(dx).$$

Workers' offer opportunities depend on firms' recruiting choices. The distribution of destination bids, weighted by recruiting effort, is

$$O_s(D) = \frac{\phi}{V_s} \int \ell(x)v_s(x)\mathbf{1}\{m_s(x) \in D\}\mu(dx). \tag{16}$$

Offers arrive at rate $\lambda_s^N = M_s/S_s$ in nonemployment and $\lambda_s^E = \iota M_s/S_s$ in employment. A firm's total hiring flow and its hiring flow from nonemployment are, respectively,

$$h_s(x) = \eta_s \ell(x)v_s(x)p_s(m_s(x)), \qquad h_s^N(x) = \eta_s \ell(x)v_s(x)\frac{N_s}{S_s}\mathbf{1}\{m_s(x) > \bar{U}_s\}. \tag{17}$$

The difference is hiring from other employers. Poaching occurs at rate $n_s\lambda_s^E \int \mathbf{1}\{m > r_s(x)\}O_s(\mathrm{d}m)$. Aggregate job-to-job arrivals and departures coincide within each skill: poaching reallocates workers without directly changing aggregate employment.

Ordinary matches break at rate δ_s. Participation or renegotiation opportunities arrive at rate ψ per incumbent, and result in separation if $c_s(x) < \bar{U}_s$. The separation flow into nonemployment, excluding firm closure, is

$$d_s^N(x) = n_s[\delta_s + \psi \mathbf{1}\{c_s(x) < \bar{U}_s\}]. \tag{18}$$

This is a finite-rate participation rule, not an instantaneous dismissal boundary. A match whose incumbent value falls below the outside option can persist until the next opportunity to separate.

Recruiting units and identification. The cost power γ_s in (5) is the exponent of total recruiting cost, not marginal cost. Its implied effort elasticity $1/(\gamma_s - 1)$ need not equal an elasticity estimated from annual realized hires. Contact efficiency, acceptance, and worker turnover also affect realized hires.

The main text expresses recruiting expenditure as $\ell(x)v_s^{\gamma_s}$. The numerical implementation uses different recruiting units, denoted by a superscript code, with cost

$$\mathcal{C}_s^{\text{code}}(u;x) = \ell(x)\frac{\kappa_{\text{rec}}(\gamma_s)}{\gamma_s}u^{\gamma_s}, \qquad \kappa_{\text{rec}}(\gamma) = v_*^{2-\gamma}, \qquad v_* = 0.01. \tag{19}$$

In those units, marginal-cost schedules per unit of firm scale pass through (v_*, v_*): changing curvature rotates the marginal-cost schedule around a common point. This is a choice of recruiting units, not an additional economic friction.

Define $\omega_s = [\kappa_{\text{rec}}(\gamma_s)/\gamma_s]^{1/\gamma_s}$. The exact conversion to the main text's notation is

$$\begin{aligned} v_s &= \omega_s v_s^{\text{code}}, & V_s &= \omega_s V_s^{\text{code}}, \\ C_s &= C_s^{\text{code}}\omega_s^{\nu-1}, & \eta_s &= \eta_s^{\text{code}}/\omega_s. \end{aligned} \tag{20}$$

These transformations preserve recruiting expenditure and each firm's contact intensity: $\eta_s\ell(x)v_s = \eta_s^{\text{code}}\ell(x)v_s^{\text{code}}$. Aggregate meetings, acceptance, worker flows, values, and the stationary allocation are therefore unchanged. The first-order condition in paper units has γ_s in its denominator, as in (6).

Implementation units give $C_H^{\text{code}} = 0.7744811235$ and $C_L^{\text{code}} = 0.9813655421$. Converting the unrounded calibrated vector gives the matching scales reported in Table 3, $C_H = 1.067508$ and $C_L = 2.206645$. The code and its saved parameter vectors retain imple-

mentation units; the paper uses the converted units throughout. An unrestricted recruiting-cost level and matching scale are not separately identified under this change of units.

The conversion uses each counterfactual's own curvature. Holding a code matching scale fixed while changing curvature need not hold the paper matching scale fixed. Equalizing both matching scales and curvatures across skills, however, is the same economic intervention in either notation. Common proportional matching-scale shifts at fixed curvatures are also unchanged. No equilibrium needs to be re-solved for this re-expression of the model.

D.2 A training interpretation of recruiting curvature

The recruiting-cost function in the main text also admits a training interpretation. A worker may have the general skills associated with college or noncollege education while still needing to learn a firm's equipment, software, or production methods. Suppose a firm can initially recruit workers whose experience closely matches its requirements. Expanding recruitment requires reaching workers with less directly relevant experience and larger training needs. The training budget can therefore rise more than proportionally with the scale of recruitment.

A fixed training cost means a one-time resource requirement for a particular prospective worker–firm match. Its amount can differ across matches. In the construction below, these requirements are fixed before the firm chooses how much to recruit. Convex aggregate expenditure arises because expanding recruitment reaches more costly matches.

A training technology with the same cost schedule. Keep v as vacancies per unit of firm scale, $\ell(x)$, as in the main text. Suppose each vacancy must be backed by a funded training place. The firm commits goods and instructor time to these places before learning whether the prospective workers will accept its offers. Rank the marginal training places by worker–firm distance u, from least to most costly. Choose units so that the one-time resource requirement of the marginal place is $\gamma_s u^{\gamma_s - 1}$. The stream of training commitments required to support vacancies v has expenditure

$$\mathcal{C}_s^{\text{train}}(v; x) = \ell(x) \int_0^v \gamma_s u^{\gamma_s - 1}\, du = \ell(x) v^{\gamma_s} = \mathcal{C}_s(v; x). \tag{21}$$

This is exactly the recruiting outlay in (5). The construction interprets that outlay as the cost of funding training for the workers the firm seeks to attract. Actual hires can fall short of the vacancies for which training has been funded.

Hiring decisions and equilibrium. Distance affects training requirements alone. Conditional on skill, reservation values have the same distribution across distance groups. Training

is instantaneous and fully firm-specific; trained workers have the productivity and separation processes specified in the main text. Past training expenditures are sunk and create no additional state. The matching technology is unchanged.

Timing is important. Once the firm meets a worker and observes the reservation value r, its training commitment has already been made. The firm therefore retains the acceptance rule $m_s(x) > r$, and bargaining divides the same gain from trade. The skill-s recruiting choice remains

$$\max_{v \geq 0} \ell(x) \left\{ \eta_s v (1-\beta) G_s(m_s(x)) - v^{\gamma_s} \right\}. \tag{22}$$

Every term in the organizational HJB is consequently unchanged. The two interpretations give the same recruiting policies, worker values, firm entry and survival, and stationary allocation.

For a positive recruiting choice, the first-order condition is

$$\gamma_s v_s(x)^{\gamma_s - 1} = \eta_s (1-\beta) G_s(m_s(x)).$$

At fixed contact efficiency, the elasticity of vacancy posting with respect to its return is $1/(\gamma_s - 1)$. Thus $\gamma_H > \gamma_L$ can represent training requirements that make college recruitment less responsive when the firm wants to expand. College workers can remain more productive after training. Realized hiring additionally depends on contact efficiency and acceptance, as in the baseline model.

Scope of the equivalence. The exact equivalence requires the upfront training commitments just described. A training payment that the firm can avoid after observing a worker's reservation value would enter the acceptance decision and change selectivity. Training that takes time, changes subsequent productivity, or carries over to other employers would also require additional structure. The construction isolates fixed, job-specific training requirements as an interpretation of the existing convex cost schedule; it leaves the model's other primitives unchanged.

D.3 Continuation and organizational value

The aggregate outside value of a firm's employees and its organizational surplus are

$$B(n) = n_H \bar{U}_H + n_L \bar{U}_L, \qquad \mathcal{S}(x) = J(x) - B(n). \tag{23}$$

Organizational value is distinct from the owner's residual value after honoring outstanding wage promises. The continuation rule is a binding commitment made in advance: the owner

pays the full one-time cost $K \sim \text{Exp}(\text{mean } \kappa)$ whenever $K \leq \mathcal{S}(x)$, and closes otherwise. The draw arrives at rate χ, is not scaled by employment or output, and introduces no persistent shock state. Surviving workers' promises are unchanged.[21]

In addition to the closure hazard in (8), cost arrivals contribute the following term to organizational value:

$$\mathcal{A}(\mathcal{S}) = \chi\{\mathbb{E}[(\mathcal{S} - K)_+] - \mathcal{S}\} = \begin{cases} -\chi\kappa(1 - e^{-\mathcal{S}/\kappa}), & \mathcal{S} > 0, \\ -\chi\mathcal{S}, & \mathcal{S} \leq 0. \end{cases} \tag{24}$$

The opportunity to close arises only when a cost is drawn. In particular, negative-surplus firms close at the next arrival, not immediately. Expected continuation-cost expenditure per unit of time is

$$\mathcal{F}(x) = \chi\kappa[1 - (1 + \mathcal{S}/\kappa)e^{-\mathcal{S}/\kappa}] \quad \text{for } \mathcal{S} > 0, \tag{25}$$

and zero otherwise. Thus $\mathcal{A} = -h\mathcal{S} - \mathcal{F}$: continuation shocks affect value through both closure and real resources paid by continuing firms. Because costs are not proportional to size, greater organizational surplus lowers exposure to closure. The resulting survival complementarity appears in $\mathcal{A}''(\mathcal{S}) = h(\mathcal{S})/\kappa > 0$ at positive surplus. Decreasing returns in current production therefore need not imply the same ranking of continuation values or willingness to pay for workers.

For the two-state productivity process, let x^z denote the state following an idiosyncratic productivity change, and q_z its transition rate. Evaluating (10) at optimal recruiting policies and integrating the continuation-cost term gives

$$\begin{aligned} \rho J(x) = y(x) &- \sum_s \mathcal{C}_s(v_s; x) + \sum_s \eta_s \ell(x) v_s (1 - \beta) G_s(m_s(x)) \\ &+ \sum_s d_s^N(x)[\bar{U}_s - c_s(x)] + q_z[J(x^z) - J(x)] \\ &+ \sum_s \beta n_s \lambda_s^E \int (m - r_s(x))_+ O_s(\mathrm{d}m) + \mathcal{A}(J(x) - B(n)). \end{aligned} \tag{26}$$

The first line is output net of recruiting expenditure, plus expected recruiting gains. The second line accounts for separations into nonemployment and productivity changes. The last line captures workers' gains from moving to other employers and continuation-cost shocks. Terms associated with incumbents vanish when the firm employs no worker of that skill.

[21] The commitment requires full recourse against the owner. It is not an unconstrained shareholder default decision based on residual value $J - \sum_i P_i$, where P_i is employee i's outstanding promised value. An owner may be required to pay a cost that exceeds residual value. There is no separate limited-liability default option.

Recruiting maximizes the first line.

The positive donor-poaching term follows from the division of gains from mobility. At an origin with $c \geq \bar{U}_s$, a departing worker receives $c + \beta(m - c)$. The worker's payoff net of the organizational value lost at the origin is $\beta(m - c)$. This is a gain accruing to the worker, not compensation paid to the former employer. It vanishes at zero worker bargaining power. Wage promises to retained workers are transfers within the organization; a departing worker still reduces its employment by one.[22]

The nonemployment equation (7) separates the annual flow payoff b_s from search gains. In the calibration, we select $\bar{U}_L$ and impose $\bar{U}_H = 1.8\bar{U}_L$, then recover $b_s = \rho\bar{U}_s - \beta\lambda_s^N \int (m - \bar{U}_s)_+ O_s(\mathrm{d}m)$. The two flow payoffs are therefore implied primitives, not additional independently estimated parameters. In counterfactuals they remain fixed unless explicitly changed, and both $\bar{U}_s$ adjust endogenously. Thus $\rho\bar{U}_s$ is not itself the underlying benefit flow. The allocation determines promised lifetime values without requiring the distribution of flow wages.

D.4 Stationary equilibrium and entry

Let $\mathcal{L}_0^*$ denote the forward operator for employment and productivity transitions, excluding firm closure. Let $\mathcal{B}$ be the birth distribution of empty entrants. Newborns draw permanent type $\theta \in \{1, 2\}$ from probabilities π_θ^b. Idiosyncratic productivity switches between z_ℓ and z_h at rates $q_{\ell h}$ and $q_{h\ell}$. The high-state birth probability is $q_{\ell h}/(q_{\ell h} + q_{h\ell})$, or one-half if both rates vanish. Endogenous survival allows incumbent type and productivity-state shares to differ from their birth shares. If e is the entry flow per unit of firm mass, stationarity requires

$$0 = \mathcal{L}_0^*\mu - h\mu + e\mathcal{B}, \qquad e = \int h(x)\mu(dx), \qquad \int \mu(dx) = 1. \tag{27}$$

Aggregate entry is ϕe. Replacement describes the stationary cross-section, not an option available to an exiting owner: the owner receives no value from a replacement entrant. Workforce transitions use realized hiring, poaching, and separations, not bargaining-weighted value coefficients. Every accepted move changes the relevant firms' employment by one regardless of the division of gains.

For a given ϕ, equilibrium requires organizational and nonemployment values, recruiting policies, worker stocks, the firm distribution, and contact distributions to satisfy optimal re-

[22] At nonviable origins with $c < \bar{U}_s$, the maintained convention uses $r = \bar{U}_s$ and includes only $\beta(m - \bar{U}_s)_+$ on poaching. A literal joint release would also include $\bar{U}_s - c$ on an accepted departure. That term is omitted to preserve the zero-bargaining convention. The calibrated baseline has zero employed mass in this corner on its solution grid. This convention, rather than globally exact coalition accounting at nonviable origins, defines those states.

cruiting, the bargaining protocol, matching consistency, and stationarity. Both skill-specific marginal values are derived from the same organizational value surface, so mixed skill differences commute. This preserves integrability rather than independently approximating potentially inconsistent marginal-value fields. The calibration estimates ϕ and infers the supporting entry cost from (9); it does not estimate an entry cost independently from a free-entry condition. Organizational and founder values coincide at entry because entrants are empty.

D.5 Observation rules and target sources

Annual hiring and education. The paper's LEHD targets aggregate establishments to national economic firms and link education from the Census 2000 Long Form and ACS (Abowd et al., 2009; U.S. Census Bureau, 2024; Haltiwanger et al., 2014). Let R_{jq} be the set of worker–firm relationships with earnings in quarter q. Beginning employment, ending employment, and hires are

$$B_{jq} = |R_{j,q-1} \cap R_{jq}|, \quad E_{jq} = |R_{jq} \cap R_{j,q+1}|, \quad H_{jq} = |R_{jq} \setminus R_{j,q-1}|. \tag{28}$$

Employment is $(B_{jq} + E_{jq})/2$; hires include recalls after an absent quarter. An eligible firm-year has positive employment in all four quarters. Annual hires and the hiring-rate denominator are

$$H_{jT} = \sum_{q \in T} H_{jq}, \qquad N_{jT} = \frac{B_{j,Q1} + E_{j,Q4}}{2}, \qquad HR_{jT} = H_{jT}/N_{jT}. \tag{29}$$

The denominator is year-edge employment, not time-average employment. The hiring sample requires positive hires and a finite positive rate.

Each eligible firm-year receives equal weight in the deciles, with fractional allocation of ties in the simulation. The reported decile statistics are

$$\overline{HR}_d = \mathbb{E}_d HR_{jT}, \qquad X_d = \log \overline{HR}_d, \qquad Q_d = 100\, \mathbb{E}_d(H^H_{jT}/H_{jT}). \tag{30}$$

The college share thus averages firm-year shares rather than pooling hires, and the horizontal coordinate is the log of the decile mean rate. Table D.1 compares the data and model.[23]

[23] The empirical education sample requires a hire with observed education; all simulated skills are observed. Continuous-time spell overlap proxies positive quarterly earnings. The model has no explicit recall mechanism, multiple jobs, or education-observation selection. Quarterly definitions follow the LEHD public-use schema: https://lehd.ces.census.gov/data/schema/V4.14.0/lehd_public_use_schema.html. Empirical hiring rates and college shares come from the released `09.ALL.educ_hires_rounded.xlsx`, columns C and D, rows 2–11; college shares are multiplied by 100. Log rates are calculated from those released mean

Table D.1: Annual hiring-decile empirical benchmarks and primary fit

	Mean hiring rate		Data log rate	College hires, percent	
Decile	Data	Model		Data	Model
1	0.1705	0.149	−1.769	35.76	35.04
2	0.3049	0.218	−1.188	34.29	33.29
3	0.4192	0.266	−0.8694	33.01	31.11
4	0.5378	0.312	−0.6203	31.60	30.45
5	0.6714	0.382	−0.3984	30.32	29.57
6	0.8308	0.461	−0.1854	29.02	28.97
7	1.023	0.578	0.02274	27.93	28.02
8	1.291	0.684	0.2554	26.35	27.46
9	1.73	0.924	0.5481	24.92	25.83
10	3.412	1.734	1.227	22.67	23.87

Each observation is an eligible annual firm-year. Mean simulated hiring rates determine simulated log rates. Empirical education is observed only for linked survey respondents, whereas all simulated skills are observed.

Worker flows. Public J2J data provide annualized EE and EN event/stock ratios. We pool 2005Q1–2015Q4 counts before dividing, using college cell E4 and noncollege cells E1–E3. With $D_s = \sum_q (\text{MainB}_{sq} + \text{MainE}_{sq})/2$, the targets are

$$EE_s^{\text{data}} = 4\frac{\sum_q \text{EESep}_{sq}}{D_s}, \qquad EN_s^{\text{data}} = 4\frac{\sum_q \text{ENSep}_{sq}}{D_s}. \tag{31}$$

Model EE is poaching outflow divided by employment, and model EN is

$$EN_s^{\text{model}} = \frac{\phi \int [d_s^N(x) + n_s h(x)]\mu(dx)}{E_s}. \tag{32}$$

Ordinary breaks are only one component of EN; setting δ_s equal to the whole target would omit closure and participation separations. These are flow/stock ratios, not annual transition probabilities.[24]

Firm scale and survival. Size and death targets pool employer firms in the 2023 BDS vintage over 2005–2015, without a hiring or four-positive-quarter restriction. Conditional mean size is pooled employment divided by pooled firm counts; death ratios use pooled

hiring rates, as in the MATLAB code generating Figure 1.

[24]We use unadjusted national J2J counts, release R2026Q2, schema 4.14.0, for workers older than 24 in private and state/local government employment. Federal employment is excluded. These are main-job statistics, unlike the all-relationship LEHD sample. Short interruptions, multiple jobs, and quarterly classifications only approximately match the continuous-time one-job model. See https://lehd.ces.census.gov/doc/J2J_quickstart_guide.pdf.

whole-firm deaths and corresponding stocks. The model uses its stationary distribution of positive employers, split at 20 employees, with firm-mass-weighted closure hazards in each bin. Table 4 reports these targets and worker flows. [25]

Counterfactual hiring and employer starts. The full-equilibrium comparisons in Section 6 report continuous-time flow intensities, not the annual relationship-based hiring-decile statistics. With $E = E_H + E_L$, gross hires per employed worker are $\phi \int [h_H(x) + h_L(x)]\mu(dx)/E$. An organization becomes an employer on its first accepted hire before closure. If $p^{\text{emp}}(\theta, z)$ is the probability of this first hire for an empty entrant, annual employer starts per population worker are

$$\mathcal{E}^{\text{start}} = \phi e \, \mathbb{E}_{\mathcal{B}} p^{\text{emp}}(\theta, z). \tag{33}$$

This probability accounts for hiring, productivity transitions, and closure while the entrant is empty. An organization that dies without hiring contributes to organization births ϕe but not employer starts. A previously operating firm that becomes empty and hires again does not create another startup. Startup intensity is $\mathcal{E}^{\text{start}}/E$; changes in total starts and in starts per employed worker therefore need not coincide. Mean positive-employer size is $E/[\phi \, \mu(n_H + n_L > 0)]$, not E/ϕ.

Provisional inaction benchmark. We also compare annual net inaction with a benchmark of 0.384. This employment-weighted benchmark allows changes of two workers or two percent and comes from Elsby et al. (2021). The model counterpart is 0.3469. This comparison is provisional because its JOLTS establishment sample and period differ from the LEHD firm sample.[26]

D.6 Additional calibration considerations and fit

The Figure 1 composition-slope benchmark, −4.785 percentage points per unit log hiring rate, is unweighted OLS across the ten released decile points, not the paper's microdata,

[25] Detailed and coarse Census firm-size tables are https://www2.census.gov/programs-surveys/bds/tables/time-series/2023/bds2023_fz.csv and https://www2.census.gov/programs-surveys/bds/tables/time-series/2023/bds2023_fzc.csv. BDS employment is measured around March 12 and size classes use two-date average employment. Current-state model bins and instantaneous hazards approximate these annual observations. Simulated annual sizes in the LEHD four-positive-quarter sample are not the scored BDS moments.

[26] See Section 5.1 of the October 2021 version: https://eief.it/eief/images/Gottfries.pdf. The simulated statistic weights firm-years by N_{jT}, includes zero-hire years, and counts $|E_{j,Q4} - B_{j,Q1}| \leq \max\{2, 0.02B_{j,Q1}\}$.

fixed-effect, or IV coefficient. It represents about a 3.317-point decline per doubling of hiring. Table D.1 and Figure 4 report the current calibration's fit to the released points underlying Figure 1. The calibration criterion also discourages upward segments in the simulated composition curve; this discipline does not require strict decline. Other economic restrictions discourage very low employment and negative implied nonemployment payoffs. The comparison of reservation annuities $\rho\bar{U}_s$ with employment-weighted mean marginal products is a flow/flow comparison, not a benefit replacement rate, since $\bar{U}_s$ includes the value of search.

The selected calibration gives strictly declining composition curves in two independent simulation samples, with slopes -4.532 and -4.469. College EPOP is 0.7778, compared with 0.7410 for noncollege workers. College workers comprise 41.55% of employment, exceeding their hiring share in every decile. The model captures the central stock–flow ordering without reversing the productivity ranking.

The remaining misses are economically important. Top-decile hiring is 1.734 rather than 3.412. Large-employer mean size is 105.61 rather than 160.02, small-employer mean size is 3.851 rather than 4.765, and college EN is 0.1481 rather than 0.1750. Capturing the declining composition gradient does not imply matching gross flows or the size distribution.

The implied annual nonemployment payoffs are positive, $b_H = 0.0100858$ and $b_L = 0.000967889$, but their ratio is 10.42, not 1.8. Reservation-annuity/MPL ratios are 0.6535 and 0.6243, whereas actual $b_s/\overline{\text{MPL}}_s$ is only 0.0855 and 0.0141. The low implied noncollege flow is a qualification of the calibration. Recruitment absorbs 10.28% of output, an untargeted implication that includes empty recruiters and nonhirers but excludes wages and continuation fees.

The separate LEHD, J2J, and BDS observation rules matter for interpreting the fit. The model approximates a pooled economy spanning aggregate fluctuations, not an individual steady-state year, and does not reproduce the empirical fixed-effect or IV experiments. We do not claim a global optimum. Numerical accuracy is checked separately from fit, as described in Appendix E.

E Numerical Solution

We solve for organizational value levels $J(\theta, z, n_H, n_L)$ and derive both hiring and incumbent marginal values from that surface. The two permanent types and two idiosyncratic productivity states form four blocks on a common two-skill employment grid. The reported calibration uses skill-specific nodes $0, 1, \ldots, 199, 400$: the cap is 400 per skill, not 400 total workers, and the final grid cell is not a full unit lattice. Interpolation at off-grid integer employment counts is therefore a numerical approximation, not an additional economic shock.

At given firm mass and outside values, the policy step updates recruiting, strict acceptance decisions, participation separations, and continuation hazards. The organizational HJB includes the bargaining-dependent recipient and donor terms, while the physical transition generator uses full hiring, poaching, match breaks, and closure rates. These two operators are not interchangeable. Each closed organization is replaced by an empty entrant to construct the stationary cross-section; the closing owner does not receive the entrant's value.

The equilibrium iteration updates the firm distribution, worker employment, and contact efficiencies jointly under aggregate congestion. The ordinary match-break rates are distinct from the endogenous closure hazard. Participation separations occur at finite rate ψ when the incumbent bid falls below the worker's outside value; we do not impose an instantaneous employment-boundary projection. Continuation draws are integrated analytically, including expected paid costs as well as the probability of closure. No normal or exponential worker taste shocks are used.

Numerical certification is separate from the calibration loss or the desired composition slope. We check the Bellman residual, the physical KFE, matching consistency, worker feasibility, generator signs and row sums, and aggregate EE flow balance. The outer tolerance is 10^{-6}, the raw KFE tolerance is 5×10^{-8}, and the inner normalized policy target is 10^{-12}. Small residuals establish accuracy for the maintained grid, not convergence as its cap and resolution change. Boundary mass and inflow are therefore reported and penalized rather than ignored.

For measurement, we simulate integer worker counts and employment spells from the stationary solution and sample worker–firm relationships quarterly. The annual hiring and education statistics use the observation rules in Section 5, rather than instantaneous generator flows. Public J2J and BDS moments have separate simulated counterparts; they do not inherit the hiring-decile sample restriction.

F Value effects and equilibrium recruiting congestion

To separate the value effect of a primitive change from adjustments in market conditions, we re-solve firm values, recruiting policies, and both outside values while holding the original firm distribution, firm mass, and matching efficiencies η_H, η_L fixed. Rival bids and statewise survival still respond to the new value functions. These are deliberately restricted exercises: they do not impose a new invariant distribution or free entry. Their outcome is expected entrant value, not a change in the number of firms.

The restricted exercises recover the natural contrast between productivity and worker

Table F.2: Lower college flow payoff: entrant value under alternative adjustments

Fraction of full benefit equalization	Fixed distribution and matching	Matching adjusts	Distribution and matching adjust
10 percent	0.072	−0.102	−0.313
50 percent	0.356	−0.501	—
100 percent	0.708	−0.985	−2.997

Entries are percentage changes in expected entrant value, holding original firm mass fixed. The interpolation is $b_H(\tau) = (1-\tau)b_H^0 + \tau b_L^0$. The middle column retains the original distribution; the final column also imposes stationarity. All columns re-solve values, outside values, and recruiting. None imposes free entry. The dash denotes an exercise not run. These nested comparisons are not additive contributions of separate channels.

outside options. Setting $a_H = a_L$ lowers entrant value by 28.55 percent before the distribution or matching efficiencies adjust. Setting $b_H = b_L$ instead raises entrant value by 0.71 percent. The latter makes college workers cheaper to attract at the original contact efficiencies. Endogenous search gains partly offset the flow-payoff cut: although b_H falls by 90.4 percent, $\bar{U}_H$ falls by only 2.73 percent in the fixed-distribution, fixed-matching exercise.

We next allow matching efficiencies to clear while retaining the original firm distribution and firm mass. This is already sufficient to reverse the benefit result: the full reduction in b_H now lowers entrant value by 0.99 percent. Allowing the distribution to adjust as well, still at original firm mass, lowers entrant value by 3.00 percent. At the original entry cost, entry is no longer attractive at that firm mass; the full-equilibrium response is a reduction in the number of firms.

Table F.2 shows that the reversal is not confined to an extreme benefit change. At one tenth of the full equalization, entrant value rises 0.072 percent with distribution and matching fixed, but falls 0.102 percent when matching adjusts. Aggregate college recruiting rises by 0.475 percent, reducing contacts per unit of firm effort by 0.237 percent. Nonemployed college workers nevertheless receive contacts 0.237 percent more frequently. The two movements are consistent with the matching technology: at fixed worker search supply, more firm effort raises total meetings but lowers the yield on each unit of recruiting. The average absolute reservation value of encountered college workers falls in this exercise; the reversal does not require them to become more expensive in absolute terms.

The same contrast between fixed and endogenous matching holds at the halfway and full benefit changes. Additional full-equilibrium solutions at 2.5, 25, 50, and 75 percent of both the benefit and productivity equalizations show declining firm mass and employer starts at every tested point. Thus the equalization results are not driven by an observed reversal along the parameter path. These checks establish sampled comparative statics, not global

monotonicity or uniqueness.

Taken together, the exercises identify an equilibrium link between skill composition and business dynamism. Differences in productivity determine the resources firms can create, while differences in turnover and recruiting technology determine how those resources translate into hiring, survival, and entry. The growth of college supply can therefore reduce formation and gross hiring even if entry costs do not rise; skill-biased productivity growth can work in the opposite direction. This mechanism cautions against attributing changes in dynamism entirely to entry barriers or firm-side shocks while treating workforce composition as fixed.

G Hiring composition with equal college–noncollege primitives

In this section, we show how the quantity-skill tradeoff depends on the parameters that distinguish college and non-college workers, building on the exercises in Section 6.3. We display the results in Figures G.2–G.5. We find that equalizing the curvature and scale parameters C, γ of the search technology is the only exercise that substantially changes the slope and curvature of the hiring rate-college share curve. Differences in productivity, separation rates, and flow benefits only shift the level without substantially altering the slope or curvature. A crucial fact that disciplines the model is that the college share of employment is higher than the college population share, which is higher than the college hiring share in any of the deciles of the hiring rate distribution. Differences in surplus between college and non-college workers, whether driven by productivity, separations, or flow benefits, are not sufficient to jointly explain college workers' overrepresentation in employment and their declining share of hires as hiring rates rise: they can explain why the college share of employment is higher than the college share of the population, but not why college hiring shares decline with overall hiring rates. Firms expanding rapidly have strong incentives to hire, making them more likely to win poaching contests and attract nonemployed workers of either type. As acceptance rates approach one, hiring composition increasingly reflects the composition of the workers they meet, rather than differences in acceptance rates across types. To generate a declining college share of hires while college workers remain overrepresented in employment, the model therefore needs noncollege recruiting to respond more strongly to the return to expansion. The greater curvature of college recruiting costs provides this margin. If low college hiring shares instead reflected lower acceptance rates for college workers, these shares would tend to rise as firms' willingness to hire increased.

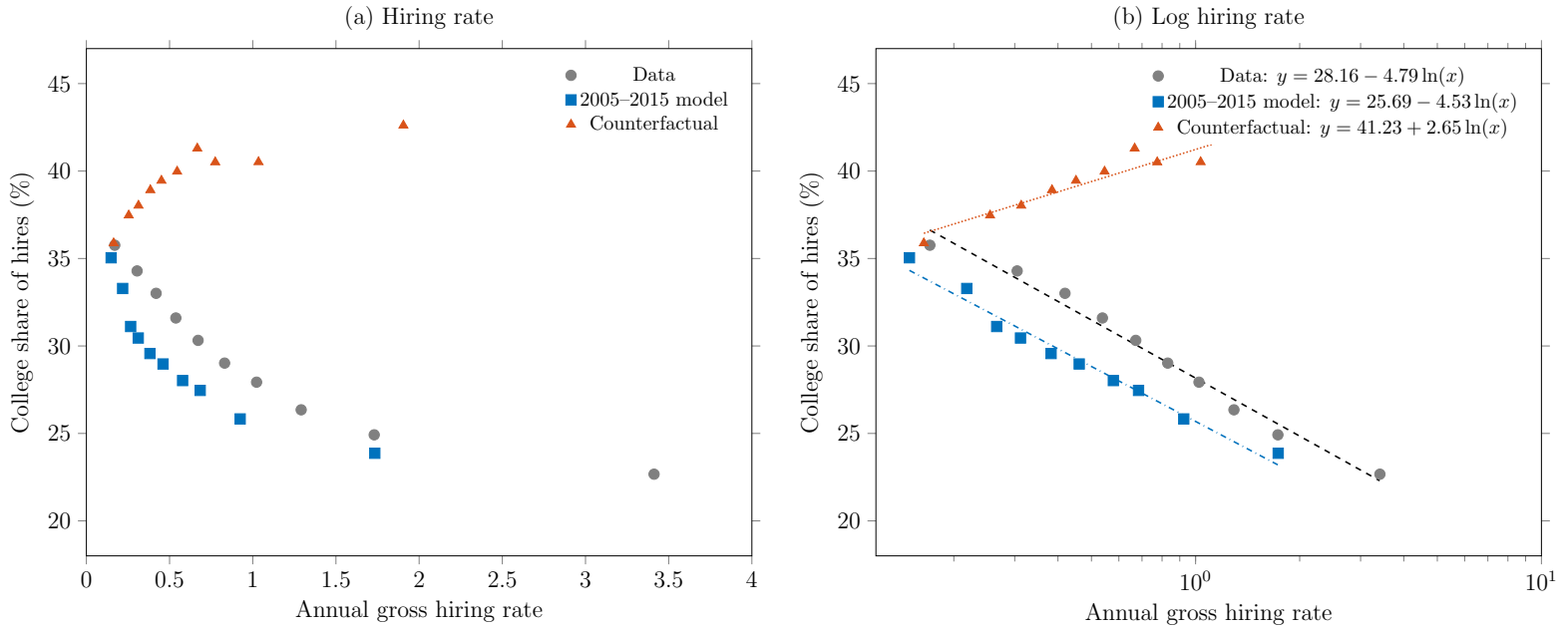


Figure G.2: Hiring composition with equal recruiting parameters

Notes: The counterfactual sets $(C_H, \gamma_H) = (C_L, \gamma_L)$. Gray circles show the data, blue squares the calibrated 2005–2015 economy, and orange triangles the counterfactual. Each series uses its own annual hiring-rate deciles; firms receive equal weight. Panel (b) reports separate log-linear fits. Flow benefits and all other primitives remain at baseline; outside values, matching efficiencies, the firm distribution, and firm mass adjust in general equilibrium.

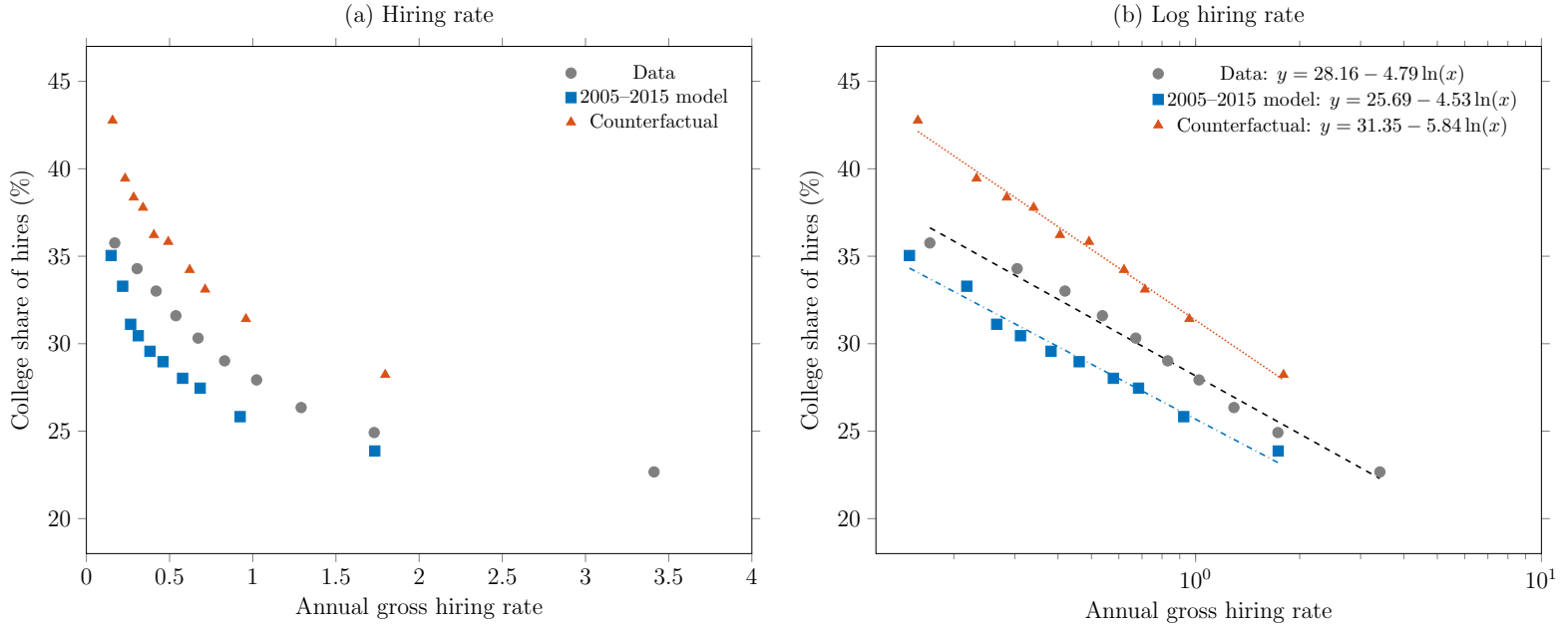


Figure G.3: Hiring composition with equal separation rates

Notes: The counterfactual sets $\delta_H = \delta_L$. Gray circles show the data, blue squares the calibrated 2005–2015 economy, and orange triangles the counterfactual. Each series uses its own annual hiring-rate deciles; firms receive equal weight. Panel (b) reports separate log-linear fits. Flow benefits and all other primitives remain at baseline; outside values, matching efficiencies, the firm distribution, and firm mass adjust in general equilibrium.

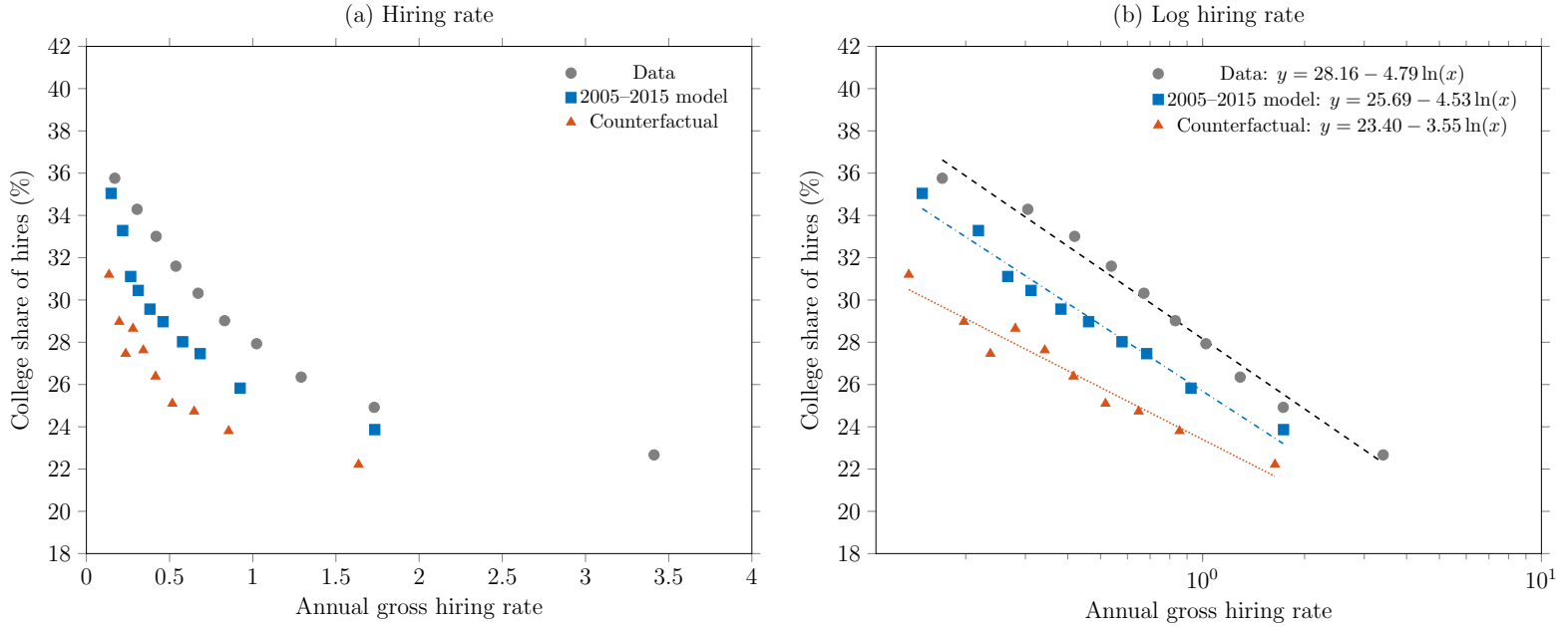


Figure G.4: Hiring composition with equal productivity

Notes: The counterfactual sets $a_H = a_L$. Gray circles show the data, blue squares the calibrated 2005–2015 economy, and orange triangles the counterfactual. Each series uses its own annual hiring-rate deciles; firms receive equal weight. Panel (b) reports separate log-linear fits. Flow benefits and all other primitives remain at baseline; outside values, matching efficiencies, the firm distribution, and firm mass adjust in general equilibrium.

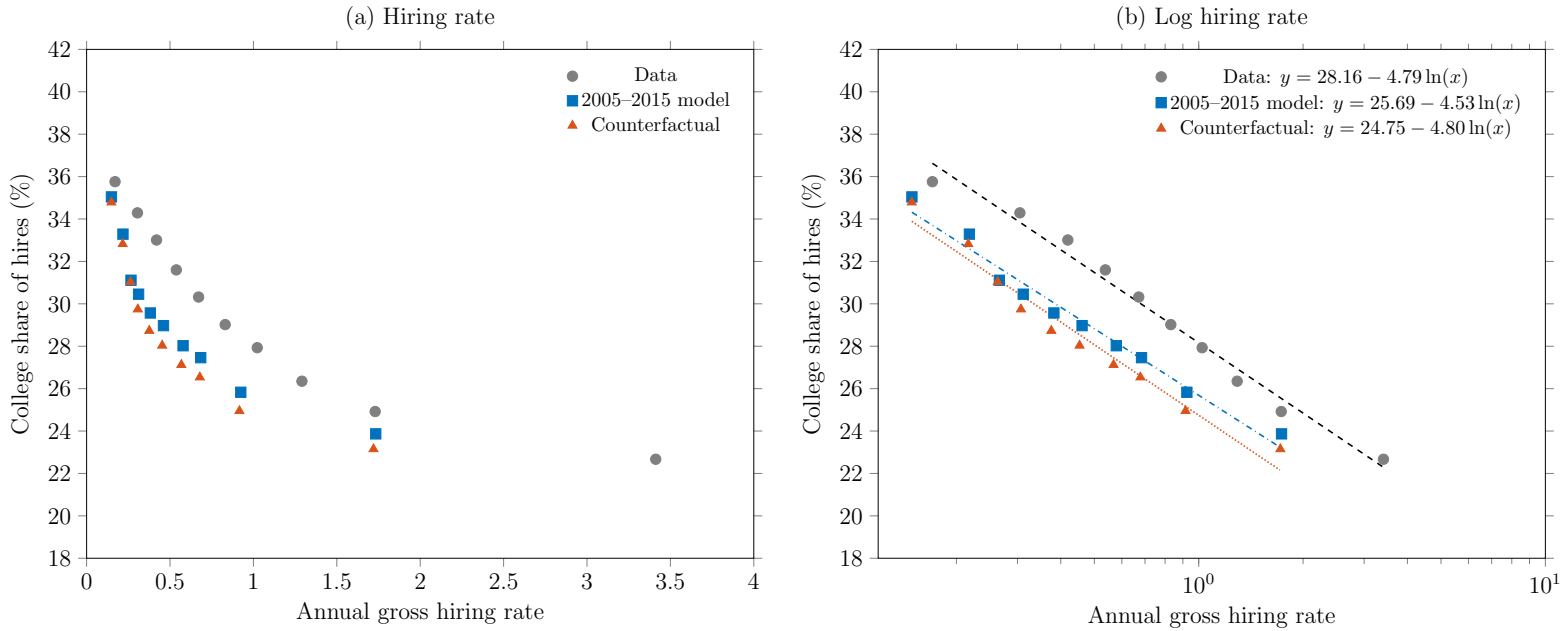


Figure G.5: Hiring composition with equal nonemployment flow values

Notes: The counterfactual sets $b_H = b_L$. Gray circles show the data, blue squares the calibrated 2005–2015 economy, and orange triangles the counterfactual. Each series uses its own annual hiring-rate deciles; firms receive equal weight. Panel (b) reports separate log-linear fits. All other primitives remain at baseline; outside values, matching efficiencies, the firm distribution, and firm mass adjust in general equilibrium.