Beyond the Jack-of-All-Trades Hypothesis: The Importance of Business and Specialized Skills for Self-Employment Entry and Success

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Abstract

Lazear's (2004) jack-of-all-trades hypothesis holds that balanced skills promote both entry into and success in entrepreneurship. A number of empirical analysts have tested this idea using occupation counts or employer counts as a proxy for skill balance, while also defining entrepreneurship as any form of self-employment. I introduce three extensions to this literature. First, I argue that what matters is not "skill balance" per se, but two particular kinds of skill: business skills and the specialized expertise a given business requires. Second, I argue that it is important to distinguish between basic (unincorporated, low-capital) and advanced (incorporated, capital-intensive) self-employment because the latter is more likely to approximate Lazear's concept of entrepreneurship. Third, I argue that tests of Lazear's hypothesis should measure skill balance more directly. Using nearly forty years of NLSY79 work histories linked to O*NET, I construct time-in-occupation-weighted measures of business skills, specialized skills, and skill balance, and use them as key regressors in models of the decision to transition into either basic or advanced self-employment, as well as models of "success" (measured by earnings, revenue, and how spells end) of self-employment spells. I find support for all three extensions. Business and specialized skills matter; balanced skills do not. Moreover, the roles of business and specialized skills depend on the type of self-employment. Business skills are particularly important for advanced self-employment entry and success. Specialized skills discourage entry but, once in self-employment, predict success. Measured directly, skill balance predicts neither entry nor success. The conventional occupation count, by contrast, does predict entry into basic self-employment, but partly because it reflects involuntary job losses rather than accumulated skills. These findings imply that preparation for business ownership comes from accumulating business and specialized skills, not from balance across unrelated domains.

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1 Introduction

What kind of work experience prepares someone to start a business? The most well-known answer comes from Lazear's jack-of-all-trades (JOAT) hypothesis (Lazear, 2004, 2005), which posits that entrepreneurs need a balanced set of skills to handle the many sides of running a business. An active literature finds evidence in support of this hypothesis (e.g., Wagner, 2003, 2006; Stuetzer, Goethner and Cantner, 2012; Stuetzer, Obschonka and Schmitt-Rodermund, 2013; Bublitz and Noseleit, 2014; Aldén, Hammarstedt and Neuman, 2017), typically by finding some measure of skill balance to be an important predictor of entry into business ownership. While this literature has been influential, it has three important limitations. First, it treats balance as what matters regardless of content, so that any mix of skills counts equally, although balance across an arbitrary set of skills need not prepare a worker for the specific demands of running a business. Second, it pools incorporated, capital-intensive firms with unincorporated freelance work, even though the hypothesis applies most directly to the former, whose owners must combine a broader range of functions. Third, it measures balance only indirectly, usually by counting the occupations or employers a worker has held, a proxy that can reflect job mobility rather than skill accumulation.

In this study, I address these limitations of the JOAT literature by introducing three extensions. First, I argue that workers do not need to be jacks of *all* trades to start a business. Instead, they need business skills, meaning core business knowledge, managerial competence, and people skills, together with specialized skills relevant to their business. Second, I argue that the importance of business and specialized skills is likely to vary with the type of business. Businesses that are incorporated and capital intensive (which I term *advanced* self-employment) should rely heavily on business skills because owners must manage legal, financial, and personnel responsibilities. Unincorporated, low-capital work such as cleaning or childcare (*basic* self-employment) may require little beyond occupation-specific expertise. Third, I argue that overall skill balance can be measured more directly than by counting the number of occupations or employers a worker has held to date, which allows Lazear's JOAT hypothesis to be tested on its own terms. What appears to be skill balance in occupation counts may instead reflect job churning that eventually leads workers into self-employment.

I test these ideas using near-complete work histories from the 1979 National Longitudinal Survey of Youth (NLSY79), which follows a large sample of workers over roughly four decades. I combine these histories with occupation-level ratings of the skill and knowledge requirements of each job to construct time-in-occupation-weighted measures of business skills and specialized skills, together with a direct measure of overall skill balance. I classify self-employment into basic and advanced using incorporation status and financial investment, and examine entry into each type from non-self-employment, as well as success after entry, measured by weekly earnings, business revenue, and exit, distinguishing exits to wage employment, to another business, and to nonemployment.[1] I estimate competing-risks models for entry and exit, an individual fixed-effects model for earnings, and a Tobit model for business revenue.

I construct the skill measures by weighting the skill content of each occupation, taken from the Occupational Information Network (O*NET), by the number of years a worker spent in it. The business skill measure captures accumulated experience in occupations requiring business, managerial, and social skills. Consider a worker who spent fifteen years in an occupation that O*NET rates high on supervising employees, managing budgets, and coordinating business operations. Compare that worker with one who spent the same fifteen years moving through five unrelated occupations, none of which carried managerial responsibility. Ranked by occupation count, the second worker is the more balanced of the two and, on the JOAT logic, the better prepared to start a business. Ranked by the business content of their careers, the order is reversed. I construct specialized skills using a similar approach, capturing accumulated experience within a worker's own area of expertise. Finally, I build a direct measure of skill balance from the same work histories to reexamine the original JOAT

[1]Throughout the paper, I use *business ownership* and *self-employment* interchangeably. While these concepts can differ conceptually, this is largely due to the fact that my primary data source, the NLSY79, does not make a distinction between the two: it records self-employment at the job level, identifies self-owned businesses separately, and links the two wherever possible. I discuss the data in Section 3.1.

hypothesis on its own terms. It uses the same inputs as the other two measures—years spent in each occupation and the skill and knowledge requirements of that occupation—but summarizes them by how evenly a worker's accumulated skills are spread across skill domains rather than by the amount accumulated in any one of them. The result can be read as the effective number of distinct skills a worker has accumulated.

Because these measures are built from the occupations workers actually chose, they may capture more than skill. Workers drawn to self-employment—by a preference for autonomy or latent entrepreneurial ambition—may also sort into business-intensive occupations and accumulate more experience in them. The same traits may independently shape how much these workers earn, how much revenue they generate, and how their businesses end. My estimates therefore rely on selection on observables. The NLSY79's unusually rich controls for cognitive ability, personality traits, risk tolerance, and family background (including whether any family member owned a business) absorb many of these characteristics. The business- and specialized-skill estimates retain their sign and significance as these controls are added progressively, and they persist when I add prior self-employment and entrepreneurial identity as direct proxies for these traits. In the earnings analysis, individual fixed effects further absorb any time-invariant individual trait, whether or not I observe it.

Business skills are a strong positive predictor of entry into advanced self-employment and a negative predictor of entry into basic self-employment: a half-standard-deviation increase is associated with a 24 percent higher probability of advanced entry and a 19 percent lower probability of basic entry. Business skills are directly useful in advanced self-employment, which is incorporated and capital intensive, while workers who hold them have better alternatives than basic self-employment offers. The same contrast between the two types appears after entry. In advanced self-employment, a half-standard-deviation increase in business skills is associated with about 26 percent higher revenue, fewer exits to nonemployment, and more transitions into another business. In basic self-employment, business skills predict neither revenue nor earnings.

Specialized skills discourage entry into both types of self-employment but pay off for those who enter. A half-standard-deviation increase lowers entry by about 9 percent for basic and 12 percent for advanced self-employment, because greater specialization raises the opportunity cost of leaving wage employment. Among those who do enter, specialized skills are the strongest predictor of success, with roughly 36 percent higher revenue and earnings in basic self-employment and 22 percent higher revenue and 27 percent higher earnings in advanced self-employment. Specialized skills also lower exits to wage employment in both types.

My direct measure of skill balance predicts neither entry nor success. Once business and specialized skills are accounted for, it is unrelated to entry into either type of self-employment, to revenue, and to exit destination. The conventional occupation count, by contrast, does predict entry into basic self-employment, but part of that relationship is explained by involuntary job loss. Earlier studies used the number of occupations a worker has held as a proxy for balanced skills. My results suggest that this count may partly reflect career instability that eventually leads some workers into low-capital self-employment.

These findings also have implications for policies that promote business ownership. Programs such as the Small Business Administration's management and technical assistance are designed to help prospective business owners develop business-related skills before starting a business. The evidence here is consistent with this approach. Rather than emphasizing balanced skills, policies may be more effective when they help prospective business owners build the managerial, financial, and interpersonal skills needed to operate more complex businesses.

2 Related Literature

Lazear's JOAT hypothesis (Lazear, 2004, 2005) formalizes the argument that entrepreneurs must be generalists. He argues that because business owners often oversee marketing, operations, finance, and personnel decisions, individuals with balanced skills are more likely to pursue entrepreneurship than are those with deep but narrow expertise. Using data on Stanford MBA graduates, Lazear (2005) finds that individuals who have worked in more roles and studied more fields are indeed more likely to become entrepreneurs.

Researchers have tested this hypothesis primarily on entry into self-employment. The studies differ mainly in how they measure skill balance. The most common approach counts the occupations, employers, or fields of training a worker has accumulated over a career (Wagner, 2003, 2006; Silva, 2007; Åstebro and Thompson, 2011; Lechmann and Schnabel, 2014; Sorgner and Fritsch, 2018; Laffineur et al., 2020). A second approach uses pre-market measures of balanced ability, such as cognitive and noncognitive skill profiles in the NLSY79 (Hartog, Van Praag and Van Der Sluis, 2010) or aptitude test batteries from military enlistment records (Aldén, Hammarstedt and Neuman, 2017). A third and less common approach measures balance more directly, from survey responses on how evenly workers' experience is distributed across business functions (Stuetzer, Obschonka and Schmitt-Rodermund, 2013) or by inference from detailed career histories (Chen and Thompson, 2016). Despite these differences in measurement, the evidence is broadly consistent: workers who score higher on these measures are generally more likely to enter self-employment.

However, there are several notable exceptions. Silva (2007) finds that the relationship disappears after controlling for individual fixed effects. Lechmann and Schnabel (2014) report that occupation counts predict entry into solo self-employment but not employer entrepreneurship, whereas Lazear's theory suggests that balanced skills should matter most for entrepreneurs who manage employees. Focusing on women college graduates, Tegtmeier, Kurczewska and Halberstadt (2016) find little evidence supporting the hypothesis. Syme and Mueller (2022) question a key premise of the theory by showing limited evidence that self-employed workers actually perform a broader range of tasks than wage workers. Finally, Åstebro and Thompson (2011) argue that the observed relationship may reflect a preference for variety rather than the productivity benefits of balanced skills.

A smaller and more recent set of studies extends the hypothesis beyond entry. On earnings, Hartog, Van Praag and Van Der Sluis (2010) find that balanced cognitive and social ability raises the returns to entrepreneurship more than the returns to wage employment, while Åstebro and Thompson (2011) find that workers who have held more occupations earn less. Bublitz and Noseleit (2014) find that broad expertise pays off in some settings but not others, and Lechmann and Schnabel (2014) test the income implications of Lazear's model directly and find only partial support. Other outcomes examined include progress through the venture creation process (Stuetzer, Goethner and Cantner, 2012), survival and success in self-employment (Koster and Andersson, 2018), and start-up performance (Kurczewska and Mackiewicz, 2020; Wu et al., 2022). The evidence here is thinner and less consistent than for entry, with several studies reporting null or negative relationships. Two outcomes have not been examined, and I study both: business revenue, and the ways self-employment ends—exit to wage employment, to another business, or to nonemployment—which carry different implications for success. Most of these studies also inherit the count-based measures used in the entry literature.

Taken together, these studies share three features that limit what their evidence can establish. First, balance is treated as what matters regardless of content, so that any mix of skills counts equally. However, the activities Lazear describes—marketing, operations, finance, and personnel management—are specific forms of human capital, and balance across an arbitrary set of skills need not prepare a worker for them. Stuetzer, Obschonka and Schmitt-Rodermund (2013) come closest by measuring experience across business-related domains, although with broad categories and simple counts.[2] Second, most studies treat self-employment as a single outcome, pooling subsistence activities such as cleaning and childcare with complex businesses whose owners must coordinate finance, operations, and personnel decisions. Because the hypothesis applies most directly to the latter, pooling may obscure where balanced or business-related skills matter most. Lechmann and Schnabel

[2]A separate question is whether prior experience is related to the venture (Ohyama, 2015; Koster and Andersson, 2018; Wu et al., 2022), a matter of fit rather than of business content.

(2014) and Bublitz and Noseleit (2014) are the exceptions, separating solo from employer self-employment and examining differences by firm size.[3]

Third, most studies measure skill balance only indirectly, and the most common proxy captures a different concept. Lazear's hypothesis is fundamentally about comparative rather than absolute advantage. Entrepreneurship rewards workers whose skills are relatively balanced across tasks, whereas wage employment rewards workers whose skills are concentrated in a particular area. What matters is therefore balance in a worker's skill profile, not simply the number of distinct domains in which the worker has experience. By contrast, the commonly used count of occupations, employers, or fields measures variety. A worker can accumulate experience across many domains while remaining highly specialized if most skills are concentrated in one area. Moreover, occupational counts may partly reflect job mobility rather than the accumulation of balanced skills. The pre-market measures described above come closer to Lazear's concept, but they capture only individuals' initial endowments rather than the skills accumulated through work experience.

I address this gap by separately identifying business skills, specialized skills, and overall skill balance from workers' accumulated experience and by distinguishing between basic and advanced self-employment. This framework allows the core predictions of the JOAT hypothesis to be evaluated more directly than existing approaches do. The results indicate that business skills—not balanced skills per se—predict entry into advanced self-employment, whereas occupation counts primarily predict entry into basic self-employment because they partly reflect job mobility associated with involuntary job loss. Business skills also predict higher revenue and fewer exits to nonemployment in advanced self-employment. Overall, these findings suggest that much of the mixed evidence in the JOAT literature reflects differences in what studies measure and which forms of self-employment they examine.

[3]While the JOAT literature has largely treated self-employment as a single category, the broader entrepreneurship literature distinguishes innovation-driven and traditional businesses from subsistence enterprises (Botelho, Fehder and Hochberg, 2021) and separates self-employment by incorporation status (Levine and Rubinstein, 2017).

3 Data and Measurements

3.1 Data Sources

The primary data source for this study is the 1979 National Longitudinal Survey of Youth (NLSY79). This survey began in 1979 with a nationally representative sample of 12,686 individuals born between 1957 and 1964 and residing in the United States. The respondents were surveyed annually from 1979 to 1994 and biennially thereafter. I use survey waves from 1979 through 2020.

The NLSY79 are well-suited for my study because it follows respondents over a long horizon. They were 14 to 22 at the 1979 baseline interview and 55 to 63 by their 2020 interview, which gives a near-complete work history of roughly four decades. That coverage matters for self-employment, which is often entered mid or late career, and few other datasets pair it with the detailed job-level records that also identify individual businesses.

For every job held, defined as a unique employer, respondents report start and stop dates (year and month), class of worker (e.g., wage-employed, self-employed), occupation, industry, hours worked, hourly wage, and reason for job separation. Self-employed respondents additionally report the incorporation status of the business, which I use to classify different types of self-employment.

Starting in 2010, the NLSY79 introduced a business ownership module that identifies all businesses owned by respondents since age 18. At first encounter with the module, each respondent retrospectively reported every business owned to date, including start and stop dates and company names. Survey staff used this information to link each business to previously reported employers, and these links were verified in the 2012 interview. In each subsequent wave, respondents report any new businesses started since the previous interview, and survey staff continue to link these to contemporaneously reported jobs. This linkage allows me to identify self-employment and business ownership. I therefore observe business ownership from the start of each respondent's career through 2020, linked to the job-level record of self-employment. The module also collects detailed information on each business, including the year and month of acquisition, the year the business ended, the amount of financial investment, and typical annual sales or revenue. In addition, beginning in 2010, all respondents—regardless of business ownership—were asked about family business ownership, patent-seeking activity, and whether they consider themselves entrepreneurs.

I also utilize the O*NET database, version 18.1, administered by the U.S. Department of Labor. O*NET has collected information on U.S. occupations since 1998, combining surveys of randomly sampled workers with input from occupational experts. For each occupation, it provides standardized measures of skill and knowledge requirements, along with job zone (a five-level classification of the preparation required for the occupation). I use these measures to construct the skill variables described in Section 3.4, which are the main independent variables in the analysis.

I merge the NLSY79 and O*NET datasets using a crosswalk between their occupational classification systems. The NLSY79 uses the 1970 Census occupation codes through 2000 and the 2000 Census codes thereafter, while O*NET uses the 2010 Standard Occupational Classification (SOC). To link both NLSY79 coding schemes to the 2010 SOC, I use the crosswalks developed by Lise and Postel-Vinay (2020).

3.2 Sample Construction

I construct four analysis samples, one for each outcome studied in the paper: (1) entry into self-employment, (2) weekly earnings, (3) business revenue, and (4) exit from self-employment. The latter three are used to assess self-employment success. I use separate samples because the four outcomes require different data structures. The entry and exit decisions are modeled as year-by-year transitions constructed from job start and stop dates. Earnings and business revenue, in contrast, are reported at the interview date. Revenue is reported in two separate modules—the business ownership module and, from 2010 onward, the employer supplement—which raises additional sample selection issues that I discuss below. All four samples share the same set of individual-level selection criteria, described in the Entry Sample and applied to the other three.

Entry Sample The entry sample is used to estimate the sequential multinomial logit model described in Section 4.1, which models the year-by-year decision to remain outside self-employment or transition into different types of self-employment. The sample begins with all NLSY79 respondents and constructs an individual-level career sample. Respondents enter the sample at their career start date, defined as the beginning of the first nonenrollment spell lasting at least twelve months.

Starting from the 12,686 NLSY79 respondents, I first exclude 392 individuals who leave the survey before their career start date or before holding at least one job after the start date. Second, I remove 936 individuals with incomplete job start or stop dates, which prevents the construction of a person-year panel. Third, I drop 4,037 individuals who exit the survey before 2010, when the business ownership module was introduced. Fourth, I exclude 25 individuals who are already self-employed within the first twelve months of their careers and remain self-employed throughout the sample period. Finally, I remove 180 individuals whose career histories exceed 45 years. These individuals entered the labor market at unusually young ages, and information on their employment prior to the 1979 survey is limited. These restrictions leave a sample of 7,116 individuals.

The sample is expanded into a person-year panel in which each individual contributes one observation per twelve-month period from career start until entering self-employment or reaching their final interview. The entry sample focuses on periods before self-employment entry. Thus, the non-self-employed state includes both wage employment and nonemployment, and individuals are classified based on whether they transition from this state into self-employment. Individuals who return to non-self-employment after a self-employment spell reenter the sample and contribute additional observations. The final sample contains 251,214 person-year observations from 7,116 individuals.

Earnings Sample The earnings sample is used to estimate the wage models described in Section 4.2, which compare earnings across wage employment and self-employment among individuals who enter self-employment. I restrict the entry sample to the 2,503 individuals who enter self-employment at least once during the observation period.

The unit of observation is a person-interview-job, and the sample includes wage observations from both non-self-employment and self-employment periods. For non-self-employed periods, I restrict attention to wage employment because earnings are only observed for individuals working in wage jobs. During self-employment spells, I include observations when self-employment earnings are reported for the relevant self-employment job. Each individual contributes one observation for each job and interview period in which earnings are available. Because earnings are reported at the interview date, variables are measured at the interview level rather than over a twelve-month window. The final sample contains 69,586 observations for individuals who enter basic self-employment and 32,096 observations for individuals who enter advanced self-employment.

Business Revenue Sample The business revenue sample is used to estimate the relationship between skills and business performance among self-employed individuals. I restrict the sample to self-employment jobs observed in the entry sample, with the self-employment job-year as the unit of observation.

Revenue information comes from two sources. The business ownership module reports typical annual sales or revenue for each business, while the employer supplement reports revenue repeatedly from 2010 onward. When both sources are available for the same job-year, I use the employer supplement and otherwise rely on the business ownership module. The sample includes only self-employment job-years with valid revenue information and contains 2,430 and 2,465 observations in the basic and advanced samples, respectively.

Exit Sample The exit sample is used to estimate the duration model described in Section 4.1, which examines the year-by-year decision to remain in or leave self-employment. I restrict the exit sample to individuals who enter self-employment at least once and construct a panel of self-employment spells.

Each individual contributes one observation per twelve-month period while a self-employment spell is ongoing, beginning at the start of the spell and continuing until exit or the final interview. Thus, unlike the entry sample, the exit sample includes only periods in self-employment. Individuals who leave self-employment and later reenter contribute observations for subsequent self-employment spells. The sample contains 10,383 person-year observations for basic self-employment and 5,938 person-year observations for advanced self-employment.

3.3 Outcome Variables

As discussed above, I study the decision to enter self-employment and, conditional on entering, how successful the business is. I measure success along three dimensions—earnings, business revenue, and exit destination.

Transition into Different Types of Self-Employment Because I estimate the probability of entry using a multinomial logit model (Section 4.1), the dependent variable records transitions over the next 12 months among three categories: entry into basic self-employment, entry into advanced self-employment, and remaining in non-self-employment. Non-self-employment includes wage employment, unemployment, and being out of the labor force. Changes between jobs within the same category are not counted as transitions.

I define self-employment using information from the NLSY79 employer history and business ownership modules. To account for cases in which respondents report working for their own business as an employee, I combine information from both sources and classify respondent-owned businesses as self-employment. Businesses that are not linked to an employer history job are excluded because the analysis samples are constructed from the job panel.[4]

Self-employment is often treated as a single category, but recent research emphasizes substantial heterogeneity across self-employed workers. A common approach distinguishes businesses by incorporation status (Levine and Rubinstein, 2017). However, incorporation status alone may not capture differences in business scale because businesses with the same legal structure can vary substantially in the resources invested at entry (Figure 1). I therefore classify self-employment using incorporation status and initial financial investment.

A self-employment spell is classified as "basic" if it is unincorporated and the initial investment is less than 20,000 USD in 2010 dollars. It is classified as "advanced" if it is incorporated or if the initial investment is 20,000 USD or more. The 20,000 USD cutoff is approximately the median investment among spells with positive investment.[5]

Earnings I measure earnings as log weekly earnings. Weekly earnings are taken directly when respondents report being paid on a weekly basis. For other payment frequencies, I convert reported hourly wages into weekly earnings by multiplying the hourly wage by the number of hours worked per week. I use weekly earnings rather than hourly wages because self-employment provides greater flexibility in hours worked than wage employment, allowing workers to increase earnings through both higher hourly returns and greater labor input. Earnings are adjusted to 2010 USD using the annual consumer price index for the four United States regions (Northeast, Midwest, South, and West).

Business Revenue I measure business revenue as annual sales or revenue generated by the business. Revenue is adjusted to 2010 dollars using the annual consumer price index. I study revenue alongside earnings because they capture different dimensions of business

[4]The business ownership module identifies businesses that were never reported as jobs in the NLSY79 employer history. These unlinked businesses are excluded because the analysis samples are constructed from the job panel.

[5]I do not use two other common classifiers, firm size and industry entry barriers. Employee counts were not collected from 1981 to 1985, which would bias measurement early in a career, and industry entry barriers are measured at the industry level rather than for the specific business. Incorporation and investment are both reported for the business itself.

performance: revenue reflects the scale of the business, while earnings capture the income received by the owner.

Transition Out of Self-Employment The exit variable is categorical. It records where a worker is twelve months later: in wage employment, in another self-employment spell, in nonemployment, or still in the current spell. A worker is coded as nonemployed if she has no job within two months of the spell ending. Section 4.1 describes how the variable enters the model.

3.4 Independent Variables

The analysis of entry decisions and business success relies on the same set of key independent variables. To capture skill content, I include measures of business and specialized skills. To reevaluate the JOAT hypothesis, I construct an additional measure of skill balance that captures how evenly an individual's skills are distributed across domains. I compare this measure to the conventional proxy for skill balance, the number of occupations held.

3.4.1 Business skills

I construct business skills from the Skills and Knowledge sections of O*NET, which rate each occupation on 35 skill elements and 33 knowledge elements, for 68 elements in total. Each element receives a level score from 0 to 7, measuring the degree to which the occupation requires the skill, and an importance score from 1 to 5, measuring how central the skill is to the occupation. I multiply the two scores for each element and refer to the product as the element score. The element score is the building block for all three skill measures used in the paper.

From these 68 elements, I select the 15 most relevant for running a business. I identify these elements as those that rank highest for chief executives, based on the reasoning that the CEO occupation captures the main activities of a business owner: making financial and strategic decisions, managing staff and resources, and interacting with customers. I group the 15 elements into three categories. Core business skills include economics and accounting, sales and marketing, and judgment and decision making. Managerial skills include administration and management, as well as the management of time, financial, material, and personnel resources. Social skills include customer and personal service, social perceptiveness, coordination, persuasion, and negotiation. Table A1 lists all 68 elements and identifies the 15 used in the analysis.

I then measure how much business skill a worker has built through her occupational history. For worker i at time t,

$$BX_{it} = \sum_{o \in O_i} \omega_o^{BX} \cdot OccTenure_{iot}, \tag{1}$$

where O_i is the set of occupations she has ever held and $OccTenure_{iot}$ is the years she has spent in occupation o by time t. The weight ω_o^{BX} is the business content of occupation o, normalized so that the most business-intensive occupation is at 1 and every other occupation is placed at a fraction of it,

$$\omega_o^{BX} = \frac{(B_o n_B + M_o n_M + S_o n_S)/(n_B + n_M + n_S)}{\max_{o'}\{\cdot\}}, \tag{2}$$

where B_o, M_o, and S_o are the average element scores of the core, managerial, and social elements in occupation o, and n_B, n_M, and n_S are the number of elements in each group. The most business-intensive occupation is the chief executive, with a raw score of 4.76, so a worker's business skills are measured against time spent in that role.

To illustrate, ten years of uninterrupted employment as a chief executive yield a BX of 10, because CEO is the benchmark. Ten years as an agricultural product grader or sorter, one of the lowest business-intensive occupations with a raw score of 1.10, gives a BX of $(1.1/4.76) \times 10 = 2.3$.

A natural concern is that this measure just picks up high-skill occupations in general, since occupations with more business content also tend to require more preparation, meaning more education, training, and prior experience. To check this, I re-estimate the entry models with controls for O*NET job zone, a five-level ranking of the preparation an occupation requires, from zone 1 for little or none to zone 5 for extensive. Table A4 reports the estimated marginal effects with and without the job-zone controls. The business-skills estimates are similar across the two, which indicates that the measure captures content specific to running a business rather than the general skill level of the occupation.

3.4.2 Specialized skills

Specialized skills measure how much a worker has invested in the particular expertise her business draws on. If she opens a tech firm, what matters is her accumulated experience in programming, not business skill in general. The relevant skill area is therefore specific to each worker.

I identify each worker's area of specialization from a target occupation. For workers who enter self-employment, the target is the occupation held at the start of the self-employment spell. For workers who never enter, it is the occupation held eighteen years into the career, which is the average point of entry in the sample. For each target occupation, I rank all 68 elements by their element score (defined, as discussed in Section 3.4.1, as the product of their importance score and level score) and select the top one to three elements as the worker's specialization elements. I place the cutoff at a natural break in the ranking, where the scores drop sharply and the remaining elements no longer stand out. I drop any element that also ranks near the top in most occupations, since a generic requirement does not mark a specialization.[6]

The measure is then built like business skills, as a tenure-weighted sum of occupation

[6]This procedure is similar in spirit to TF-IDF (term frequency–inverse document frequency) weighting in information retrieval: the importance $\times$ level score plays the role of term frequency, and dropping elements that rank near the top across most occupations plays the role of inverse document frequency.

weights, except that the weight is specific to the worker,

$$SX_{it} = \sum_{o \in O_i} \omega_{io}^{SX} \cdot OccTenure_{iot}, \tag{3}$$

where ω_{io}^{SX} is the average element score of worker i's specialization elements in occupation o, scaled by the maximum across occupations so that the occupation with the highest score in her specialization area is at 1. For example, consider two workers whose target occupation is software developer, which requires specialized skills such as programming and software design. The worker who spends ten years in software development accumulates a high SX, whereas the worker who spends ten years in an unrelated occupation accumulates little because that occupation scores low on the programming-related skill elements. The measure therefore rewards experience that builds the specific expertise required for the target business rather than work experience in general.

3.4.3 Skill Balance

I also construct a direct measure of skill balance using O*NET so that I can reexamine the JOAT hypothesis on its own terms. I measure how evenly the skills accumulated from a person's work experience are spread across elements to capture the true balance of one's skill portfolio.

For each individual i at time t, I begin with the 68 O*NET skill and knowledge elements and retain those for which she has accumulated at least six months of experience, weighting each element by both the amount of experience and its score. Across the kept elements, p_{its} is the share of her experience that falls in element s. I summarize this distribution with the Shannon index,

$$H_{it} = -\sum_{s} p_{its} \log p_{its}, \tag{4}$$

which takes a high value when experience is spread evenly across many elements and a low value when it is concentrated in a few. To ease interpretation, I exponentiate to obtain the effective number of skills, $\exp(H_{it})$: the number of equally abundant skills that would produce the same overall distribution of experience as the one observed. For example, $\exp(H_{it}) = 10$ means the portfolio is as evenly spread as if the individual had spent equal time on exactly ten skills; a value of 1 means all her time has been concentrated in a single skill. I use $\exp(H_{it})$ as my measure of skill balance.

This measure improves on conventional proxies for skill balance, such as the number of distinct occupations or employers an individual has worked in. These counts capture job mobility, but changing jobs does not necessarily mean acquiring new skills. By constructing skill balance from the skill content of each occupation, the Shannon-based measure captures what an individual has actually learned rather than how often she has changed jobs. To reconcile my findings with the existing literature, I also report results using a conventional count-based measure, the cumulative number of distinct 2-digit occupations an individual has held.

3.4.4 Baseline regressors

In each model, I include a set of rich control variables. The choice of controls follows a large literature on the determinants of business ownership, including family background (Hout and Rosen, 2000; Hvide and Oyer, 2025), risk tolerance (Ahn, 2010; Hsieh, Parker and van Praag, 2017), and access to credit and household wealth (Hurst and Lusardi, 2004; Fairlie and Krashinsky, 2012). I control for past work experience (potential experience, and actual experience in wage employment and self-employment); demographics (gender, race/ethnicity, marital status, and whether the youngest child in the household is age six or younger[7]); education (four categories from less than high school to college and above); and AFQT percentile as a proxy for cognitive ability.

I also include risk tolerance, total net family wealth, and net family income. Risk tol-

[7]Having a young child can motivate entry into self-employment as a means to balance work and family, especially for women. See Lim (2019); Lim and Michelmore (2018).

erance is a four-category measure built from the income-gamble question in the 1993 and 2002–2014 NLSY79 waves, with missing values linearly interpolated. Net family wealth is available from 1985, and I use predicted values from a linear model on age, age squared, gender, race/ethnicity, marital status, and educational attainment.

I add measures of family background: whether any family member owned a business, whether the respondent's father had at least some college education, and the father's one-digit occupation in 1979.

I also control for personality traits: sociability at age 6 (four categories from extremely shy to extremely outgoing), Rotter's locus of control score (from 4 to 16), and three self-rated items on a 1-7 scale capturing how extraverted/enthusiastic, open to new experiences/complex, and conventional/uncreative the respondent describes herself.

These covariates are included in the self-employment entry models. In the success analysis, I continue to control for demographics, human capital, work experience, but omit the family background and personality measures because they are primarily included to account for selection into self-employment.

3.5 Data Patterns

Table 1 reports means and standard deviations by employment type. The statistics are calculated from the earnings sample before restricting it to individuals who ever enter self-employment, so the wage employment group includes respondents who are never self-employed. Panel A shows that basic and advanced self-employment differ sharply. Workers earn roughly twice as much per week in advanced self-employment spells as in basic spells (966 vs. 503 in 2010 USD). Advanced spells also generate five times the business revenue (253,000 vs. 52,000 in 2010 USD), last almost twice as long on average (6.8 vs. 3.5 years, with 43 percent lasting five years or more compared to 19 percent of basic spells), and concentrate in management, business, science, and arts occupations (44 percent vs. 24 percent). These gaps justify treating basic and advanced self-employment as qualitatively different types rather than collapsing them into a single category.

Panel B turns to work experience and the O*NET-based skill measures. Advanced self-employment entrants have accumulated roughly twice the business skills (8.0 vs. 4.1 years of BX) and twice the specialized skills (8.2 vs. 4.5 years of SX) of basic entrants, and their skill balance is higher as well (40.5 vs. 34.7 effective skills). Wage workers lie below both groups on all three measures. Part of these gaps reflects more total work experience among advanced entrants (17.2 vs. 11.3 actual years), and the regressions in Section 4.1 control for experience explicitly. Advanced entrants also show less job churn: scaled by years of actual experience, they hold fewer distinct 2-digit occupations (0.72 per year, compared to 1.44 for basic entrants and 1.85 for wage workers) and report fewer involuntary job losses (0.22 vs. 0.52 and 0.71). This combination—more accumulated business and specialized skills alongside less churn—foreshadows the finding in Section 5 that conventional count-based proxies capture instability rather than skill accumulation.

Panel C summarizes individual characteristics. Basic and advanced self-employment entrants are distinct populations on many dimensions: advanced entrants are more likely to be male, married, and college-educated, to score higher on AFQT, to come from wealthier families with a family business background, and to self-identify as entrepreneurs. Personality measures—sociability at age 6, Rotter locus of control, and the three self-rated traits—differ more modestly. The regressions in Section 4.1 control for all of these characteristics.

Table 2 reports the distribution of individuals by the number of self-employment spells they hold. Most individuals never enter self-employment (59.5 percent), and among those who do, roughly four in five hold only one or two spells.

Table 3 reports partial correlations among the skill measures and the conventional count-based measures, measured at the start of a job spell and controlling for actual work experience, separately by employment type. The correlations help assess whether the proposed measures capture distinct dimensions of human capital or simply reflect the same underlying skill accumulation. The table reveals three patterns. First, business and specialized skills are positively correlated across all employment types, with the correlation rising from 0.45 among wage spells to 0.68 among advanced self-employment spells. Individuals who accumulate more business skills also tend to accumulate more specialized skills, indicating that the two dimensions are related rather than independent. Second, skill balance is only weakly and negatively correlated with business and specialized skills (correlations between -0.08 and -0.26). This suggests that skill balance captures how skills are distributed across domains rather than how much human capital an individual has accumulated. Third, the conventional count-based measures, the number of 2-digit occupations held and the number of involuntary job losses, are negatively correlated with business and specialized skills but positively correlated with skill balance. This pattern supports the earlier argument that count-based measures primarily capture job instability rather than genuine skill investment.

4 Empirical Strategy

I estimate four models. A discrete-time competing risks multinomial logit for entry into self-employment addresses who becomes self-employed. Three further models address success once a spell is under way: a second competing risks multinomial logit for exit, which captures how a spell ends, an individual fixed-effects model for weekly earnings, and a Tobit model for business revenue. The two transition models share an estimator, but they answer different questions. Before turning to each model, I describe how the skill measures are scaled and how their effects are reported, which is the same throughout. Business skills, specialized skills, and skill balance are placed on a common standardized scale, so that every effect I report corresponds to the same half standard deviation increase in a skill. Each skill measure enters the entry, exit, and revenue models quadratically, so no single coefficient summarizes its role. I therefore report average marginal effects rather than coefficients. For the transition models, I express these as percentage changes relative to the unconditional transition probability, which keeps effects on basic and advanced entry comparable despite their different base rates. For earnings and revenue the dependent variable is in logs, so the marginal effects are percentage changes in the outcome itself. I describe each calculation in table notes.

4.1 Entry into and Exit from Self-Employment

I model entry into self-employment as a discrete-time competing risks problem. In each year, a worker who is not currently self-employed faces three options. She can move into basic self-employment, move into advanced self-employment, or stay out of self-employment. I estimate this as a multinomial logit. The latent value of option j for worker i in year t is

$$V_{ijt} = \alpha_{0j} + \alpha_{1j} BX_{it} + \alpha_{2j} BX_{it}^2 + \alpha_{3j} SX_{it} + \alpha_{4j} SX_{it}^2 + \alpha_{5j} BSC_{it} + \alpha_{6j} BSC_{it}^2 + X_{it}\alpha_{Xj} + \varepsilon_{ijt}, \tag{5}$$

where BX_{it} is business skills, SX_{it} is specialized skills, and $BSC_{it} \equiv \exp(H_{it})$ is skill balance, all three defined in Section 3.4, and X_{it} is the set of baseline covariates from Section 3.4.4. The coefficients carry a j subscript because each skill measure and each covariate can affect entry into basic and advanced self-employment differently. I also allow for a nonlinear relationship between each skill measure and entry by including a quadratic term. Equation (5) is the full specification; I also report versions that enter business and specialized skills without skill balance, and skill balance on its own, so that the contribution of each can be seen separately. The errors are clustered at the individual level to account for correlation over time for a given individual.

I model exit from self-employment the same way, but for a different purpose. Where the entry model asks who becomes self-employed, the exit model is one of my measures of success: where a spell ends up—in wage employment, in another business, or in nonemployment—is informative about whether the business worked out. I estimate a discrete-time competing risks multinomial logit on the sample of self-employment spells, with person-year observations and four possible outcomes at each year of tenure: remaining in self-employment, exiting to wage employment, exiting to another self-employment spell, and exiting to nonemployment. An exit is classified as nonemployment if the worker has no job within two months of the spell ending. Distinguishing among these destinations helps separate transitions that reflect alternative labor market opportunities from those that reflect unsuccessful self-employment spells. The independent variables are the same as in equation (5), with the addition of a quadratic term in spell tenure. I estimate the model separately for basic self-employment, advanced self-employment, and the pooled sample.

4.2 Earnings

I examine weekly earnings using an individual fixed-effects specification that lets the returns to each skill vary over the self-employment spell:

$$\ln w_{it} = \alpha_i + \sum_{k=0}^{3} \left(\delta_k + \gamma_k BX_{it} + \theta_k SX_{it} + \pi_k BSC_{it}\right) D_{it}^{(k)} + X_{it}'\beta + \epsilon_{it}, \tag{6}$$

where $D_{it}^{(0)} = SE_{it}$, $D_{it}^{(1)} = \text{1stYearSE}_{it}$, $D_{it}^{(2)} = SE_{it}\tau_{it}$, and $D_{it}^{(3)} = SE_{it}\tau_{it}^2$, and BX_{it}, SX_{it}, and BSC_{it} are as defined above.

The dependent variable $\ln w_{it}$ is log weekly earnings in 2010 USD, and the individual fixed effect α_i absorbs all time-invariant individual characteristics. SE_{it} equals one when the worker is in the self-employment type of interest and zero in wage employment. 1stYearSE_{it} is an indicator for the first year in self-employment. τ_{it} is tenure in the current self-employment job, set to zero in the first year of self-employment and outside self-employment. Together, these four terms trace the earnings path over a spell: δ_0 and δ_1 give the gap relative to wage employment at entry, and δ_2 and δ_3 the subsequent growth with tenure. Interacting each of them with business skills, specialized skills, and skill balance allows each skill to shift both the initial gap and the growth profile. The control vector X_{it} includes quadratics in actual and potential experience, cohabitation and marital status, whether the age of the youngest child is 6 or younger, and region and industry fixed effects, together with actual experience at self-employment entry interacted with 1stYearSE_{it} to control for the timing of the transition. I estimate the specification separately for workers who ever enter basic and advanced self-employment. Standard errors are clustered at the individual level. To address survivorship bias, I weight observations by the inverse of the number of observations within each job spell, so that each spell receives equal weight regardless of length. Appendix B reports the simpler version of equation (6) that omits the skill interactions, which establishes the baseline trajectory against which the skill measures shift earnings.

To illustrate how skills shape earnings over the self-employment spell, I generate predicted earnings paths for wage employment, self-employment, and the counterfactual wage employment path. Most covariates are held at their observed values. For the experience measures, I assume workers enter self-employment after 10 years of actual experience and remain continuously employed, so potential and actual experience are equal throughout the spell. I then vary each skill measure from its mean to one standard deviation above the mean. Figures 2 and 3 plot predicted log weekly earnings against actual experience for basic and advanced self-employment, separately by business skills, specialized skills, and skill balance.

4.3 Business Revenue

One limitation of earnings as a measure of self-employment success is that owners choose how much income to withdraw from the business. They may retain profits within the firm, pay themselves a relatively small salary, or reinvest earnings to support future growth. As a result, personal earnings may not fully reflect business performance. I therefore also examine annual business revenue, which captures the performance of the business itself rather than the owner's compensation.

I estimate the relationship between skills and annual business revenue using self-employment spells with valid revenue information from the NLSY79 business ownership module and, beginning in 2010, the employer supplement. Revenue is observed only for respondents who report operating a business. Workers who classify a self-employment job as work but not as a business, such as many short-term freelance or gig arrangements, are not asked about revenue and are therefore excluded from the analysis.

Because revenue is top-coded in the NLSY79, I use a Tobit estimator:

$$\log R_{ist} = \gamma_0 + \gamma_1 BX_{it} + \gamma_2 BX_{it}^2 + \gamma_3 SX_{it} + \gamma_4 SX_{it}^2 + \gamma_5 BSC_{it} + \gamma_6 BSC_{it}^2 + X_{it}\gamma_X + \epsilon_{ist}, \tag{7}$$

where $\log R_{ist}$ is log annual business revenue for individual i in self-employment spell s and survey year t. Controls X_{it} include female, race/ethnicity, AFQT percentile, whether any family member ever owned a business, marital status, whether the age of the youngest child is 6 or younger, the number of past self-employment spells, and region and industry fixed effects. Standard errors are clustered at the individual level.

Because revenue is observed only for a selected subset of self-employment spells, I re-estimate the earnings specification on this same sample using OLS with log weekly earnings. Comparing revenue and earnings on an identical sample helps isolate whether differences across outcomes reflect what is being measured rather than differences in sample composition. Revenue captures business performance, whereas earnings capture what the owner withdraws from the business. The estimates therefore need not coincide, and comparing them provides a more complete picture of the returns to different skills.

4.4 Selection on Observables

The estimates from equation (5) can be interpreted as the effect of accumulated skills if, conditional on the baseline covariates, the remaining unobserved determinants of self-employment entry are unrelated to the skill measures. The main concern is that workers who have a stronger preference for business ownership may deliberately sort into occupations that build business or specialized skills. In that case, part of the estimated skill effect would reflect preferences for business ownership or autonomy rather than the skills themselves. The same concern applies to the outcomes I examine after entry. In the earnings specification, the individual fixed effect α_i absorbs any time-invariant trait of this kind, whether or not I observe it; for revenue and exit, I rely on the same conditioning set as for entry.

I assess the plausibility of the selection-on-observables assumption by testing whether the estimated effects of the skill measures remain stable as progressively richer sets of controls are added. Table 4 reports these estimates. The baseline specification controls for potential and actual work experience. The seven columns then sequentially add demographic characteristics, personality traits including risk tolerance, resources (net family wealth, net family income, and father's education and occupation in 1979), and education and cognitive ability. Because preferences for business ownership or autonomy are unobserved, I also include several observable proxies that may capture these preferences, including past self-employment experience, family business ownership, and whether the respondent considers oneself an entrepreneur. These proxies are imperfect, but they absorb observable variation related to the underlying preferences that might otherwise remain in the error term. If the estimated effects of business skills remain largely unchanged after these controls are added, it suggests that the results are unlikely to be driven primarily by selection on these observable dimensions.

Table 4 shows that the estimated effect of business skills is fairly stable as demographic characteristics, personality, family background, and past self-employment are added. The largest reductions occur after controlling for resources and education, indicating that part of the association reflects differences in financial and human capital rather than business skills alone. Adding entrepreneurial identity further attenuates the estimates for advanced self-employment, suggesting that preferences for business ownership or autonomy account for some of the remaining association. However, entrepreneurial identity may itself be influenced by prior self-employment experiences, so this specification likely overcontrols for factors that are jointly determined with business skills and business ownership. Even under this demanding specification, business skills remain economically meaningful and highly statistically significant, indicating that the relationship cannot be explained entirely by observable characteristics or the available proxies for business ownership preferences.

I also estimated specifications with individual fixed effects and an instrumental variables strategy based on the occupational composition of the worker's county when she entered the labor market. Both approaches rely on stronger assumptions and proved less informative in practice. Within-person variation in different types of skills is limited once experience is held fixed, and the instrument is too weak to precisely identify the effect of specific skills. I therefore explain the approaches attempted in Appendix C.

5 Findings

I take business skills, specialized skills, and skill balance in turn, following each through entry, earnings, revenue, and exit destination, so that the role of each skill in entering self-employment and in succeeding at it can be assessed together.

5.1 Business Skills

Business skills predict entry into advanced self-employment and discourage entry into basic self-employment. Table 5 reports estimated marginal effects on entry, with business skills alone in column (1), specialized skills alone in column (2), and both together in column (3). In the joint specification, a half standard deviation increase in business skills is associated with a 24 percent higher probability of entering advanced self-employment and a 19 percent lower probability of entering basic self-employment.

Business skills are directly useful in advanced self-employment, which is incorporated and capital intensive. The negative association with basic entry suggests that business skills are more valuable in wage employment than in basic self-employment. Workers with strong business skills have better outside options than the freelance or gig arrangements that characterize much of basic self-employment.

The same contrast between the two types appears in earnings after entry. Figures 2 and 3 plot predicted earnings before and after entry into self-employment, alongside the wage path those workers would have followed had they not entered. Appendix B gives the average pattern, a drop at entry followed by faster growth with tenure. The figures show whether that drop and that growth differ with business skills. In basic self-employment, workers with higher business skills experience a larger earnings decline at entry but recover somewhat faster. Their earnings remain above those of workers with lower business skills but never catch up to the wage path. In advanced self-employment, higher business skills are associated with a much larger and steadily growing earnings premium. Earnings eventually catch up to and exceed the counterfactual wage path, and the gap continues to widen with tenure. One interpretation is that the returns to business skills accumulate as the business develops.

5.2 Specialized Skills

Specialized skills discourage entry into both types of self-employment. A half standard deviation increase in specialized skills is associated with a 9 percent lower probability of entering basic self-employment and a 12 percent lower probability of entering advanced self-employment. This pattern is consistent with the JOAT hypothesis. Greater specialization raises the opportunity cost of leaving wage employment.

However, specialized skills pay off among those who ultimately enter self-employment. The returns are largest in basic self-employment, where workers with higher specialized skills earn substantially more throughout the spell. In advanced self-employment, specialized skills mainly reduce the initial earnings loss at entry, and the gap between workers with high and low specialized skills narrows over time as the two paths converge. It is possible that specialized skills are productive from entry, rather than becoming more valuable as the business develops.

5.3 Skill Balance and the Conventional Proxies

To examine the JOAT hypothesis more directly, column (4) of Table 5 includes my direct measure of skill balance on its own. Skill balance is positively associated with entry into advanced self-employment, although the estimated effect is modest at about 7 percent per half standard deviation, and it is unrelated to entry into basic self-employment. Column (5) adds skill balance to the specification that already includes business and specialized skills. Once the content of skills is taken into account, skill balance is no longer significantly associated with either type of entry. The direct measures of business and specialized skills capture the variation that skill balance reflects when considered on its own.

After entry, skill balance shows little relationship to success. It is not significantly associated with revenue or with weekly earnings on the revenue sample, in either type of self-employment, and it does not predict any exit destination. The earnings paths are the one exception, where workers with more balanced skills earn less in both types and the gap widens with tenure. The revenue sample shows no such association, and the two estimates come from different samples and specifications, so I do not read the negative result as robust.

The conventional occupation count that the JOAT literature uses to proxy skill balance behaves differently. Column (6) includes it on its own. Consistent with that literature, workers who have held more occupations are more likely to enter both types of self-employment, and the association is substantially stronger for basic self-employment, where a half standard deviation increase is associated with a 15 percent higher probability of entry, than for advanced self-employment, where the corresponding estimate is about 5 percent. Column (7) adds the occupation count to the specification with the direct skill measures. It is no longer associated with entry into advanced self-employment, while the estimated effects of business and specialized skills remain essentially unchanged. For basic self-employment, however, it continues to predict entry.

A high occupation count may reflect job churn rather than accumulated skill. To test this, column (8) adds the cumulative number of involuntary job losses. Involuntary job loss strongly predicts entry into basic self-employment, with a half standard deviation increase associated with roughly a 13 percent higher probability of entry, and the estimated effect of the occupation count falls by about one-third once it is included. The occupation count may therefore partly reflect career instability that eventually leads some workers into low-capital self-employment, rather than the accumulation of a broader set of skills.

6 Conclusion

I study what kind of work experience prepares someone to start a business. I extend the JOAT literature in three ways. I ask which skills a worker has accumulated rather than how balanced they are, I separate incorporated, capital-intensive businesses from unincorporated low-capital work, and I measure skill balance directly rather than by counting occupations. Using NLSY79 work histories linked to O*NET, I construct time-in-occupation-weighted measures of business skills, specialized skills, and skill balance, and use them to predict entry into each type of self-employment and success after entry, measured by earnings, revenue, and how spells end.

Which skills a worker has accumulated matters, and their payoffs dependd on the type of business. Business skills predict entry into advanced self-employment, where owners must manage legal, financial, and personnel demands, but discourage entry into basic self-employment, where workers who hold them have better options in wage employment. Among those who are in self-employment, business skills are predicted to raise revenue and keep owners attached to business ownership in advanced self-employment. Their returns also accumulate as the business develops, since the earnings advantage of workers with stronger business skills widens with tenure rather than appearing at entry.

Specialized skills work differently. They discourage entry into both types, because specialization raises the cost of leaving wage employment, which is consistent with the prediction of the JOAT hypothesis. However, among those who do enter, specialized skills are the strongest predictor of earnings and revenue. They also translate into earnings immediately rather than building over the spell. Once workers are self-employed, specialized skills reduce exits back to wage employment in both types, which suggests that expertise raises the value of the business, not only of the wage job.

Measuring skill balance directly allows the JOAT hypothesis to be tested on its own terms. On that test, the direct measure of skill balance, which captures how evenly a worker's skills are distributed, predicts neither entry into self-employment nor success after entry, once business and specialized skills are accounted for. However, the conventional proxy of skill balance, occupation count, predicts entry into basic self-employment only. Moreover, about a third of that relationship can be explained by involuntary job losses. Empirical support for the JOAT hypothesis in the existing literature may therefore rest in part on job churning rather than on productive skill accumulation. Pooling advanced forms of self-employment with basic ones masks this pattern, because it lets basic self-employment—the form the hypothesis fits least—drive the result.

This analysis points to several directions for further work. The first is about interpretation. My estimates rely on selection on observables, and they change little as the NLSY79's rich controls for cognitive ability, personality, risk tolerance, and family background are added. Still, workers whose ambitions shift over time may move into business-intensive occupations and into business ownership together. I explore individual fixed effects and an instrument based on local occupational composition in Appendix C, both of which rest on stronger assumptions. Variation in skill accumulation that is independent of preferences for business ownership would allow these associations to be given a causal interpretation. A second is about whose skills matter. Owners can obtain skills they lack by building a team, which the NLSY79 does not record. Data on founding teams would show whether the skills that prepare a successful business must be held by the owner or can be supplied by another member of the team. A third is about measurement, since my measures are built from occupation averages and task-level data would separate workers who have held the same occupations but did different things in them. A fourth is about whether these skills can be built. Testing whether business skills developed through training carry the same returns as those accumulated on the job would show how far preparation for business ownership can be acquired deliberately rather than over the course of a career.

My results also have implications for policies that prepare people for business ownership. Programs such as the U.S. Small Business Administration's 7(j) Management and Technical Assistance and Emerging Leaders programs help prospective owners build managerial and business skills. The evidence here is consistent with this approach rather than with encouraging workers to build balanced skills. Which skills to emphasize depends on the goal. Programs that aim to increase the number of advanced businesses should focus on business skills, which predict both entry into advanced self-employment and higher revenue. Programs that aim to improve the performance of existing businesses should focus on specialized skills, which are the strongest predictor of earnings and revenue among owners. Basic self-employment is a different case. Many workers enter it after losing a job, so policies for these owners may be closer to displacement assistance than to business training.

Lazear's hypothesis directs attention to skill balance. My findings direct it instead to skill content. Preparation for business ownership comes from accumulating business and specialized skills, not from balance across unrelated domains.

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Tables

Table 1: Mean and Standard Deviations by Employment Type

	Wage	Self-Employed			Diff.
	Employed	Any	Basic	Advanced	(4)-(3)
	(1)	(2)	(3)	(4)	(5)
Panel A: Job Characteristics					
Weekly earnings ($)	536.15	548.79	439.55	855.71	416.16***
	(550.28)	(898.36)	(714.58)	(1,230.05)	
Hours worked per week	37.75	34.17	31.84	40.71	8.87***
	(13.25)	(20.38)	(19.71)	(20.82)	
1 if business revenue is top coded	.	0.05	0.01	0.09	0.09***
	(.)	(0.21)	(0.09)	(0.29)	
Business revenue (excluding top-coded) (thousands of $s)	.	125.24	55.01	226.93	171.92***
	(.)	(341.29)	(225.81)	(440.48)	
Job duration (years)	3.25	4.79	3.87	7.39	3.53***
	(5.59)	(6.26)	(5.43)	(7.56)	
1 if job lasted less than 1 year	0.45	0.26	0.31	0.14	-0.17***
	(0.50)	(0.44)	(0.46)	(0.35)	
1 if job lasted 5 years or more	0.17	0.30	0.23	0.48	0.25***
	(0.38)	(0.46)	(0.42)	(0.50)	
1 if job is ongoing (right-censored)	0.07	0.17	0.12	0.32	0.20***
	(0.25)	(0.38)	(0.33)	(0.47)	
Occupation					
Management, business, science, and arts	0.21	0.30	0.25	0.43	0.18***
Service	0.22	0.28	0.34	0.11	-0.23***
Sales and office	0.26	0.16	0.14	0.21	0.07***
Natural resources, construction, and maintenance	0.12	0.18	0.19	0.15	-0.05***
Production, transportation, and material moving	0.19	0.09	0.08	0.11	0.03***
Industry					
Mining and construction	0.08	0.15	0.15	0.15	0.00
Manufacturing	0.14	0.04	0.04	0.06	0.02***
Transportation, communications, public utilities	0.06	0.05	0.04	0.09	0.05***
Wholesale and retail	0.24	0.12	0.10	0.19	0.09***
Services	0.20	0.39	0.42	0.29	-0.12***
Professional services	0.20	0.17	0.17	0.15	-0.02*
Other	0.07	0.08	0.09	0.06	-0.02***
Panel B: Work Experience					

Continued on next page

Table 1 (continued)

	Wage	Self-Employed			Diff.
	Employed	Any	Basic	Advanced	(4)-(3)
	(1)	(2)	(3)	(4)	(5)
Potential experience (years)	12.36	16.79	15.99	19.04	3.05***
	(10.53)	(10.46)	(10.49)	(10.05)	
Actual experience (years)	8.54	12.55	11.27	16.14	4.87***
	(9.08)	(9.82)	(9.44)	(9.96)	
O*NET Business skills (years)	2.91	4.87	4.07	7.12	3.05***
	(3.92)	(5.18)	(4.58)	(6.02)	
O*NET Specialized skills (years)	2.65	4.38	3.72	6.22	2.50***
	(4.07)	(5.05)	(4.55)	(5.85)	
O*NET Skill balance	28.40	28.65	28.57	28.86	0.29***
	(0.86)	(0.76)	(0.78)	(0.65)	
Number of 2-digit occupations per year of actual experience	1.83	1.11	1.28	0.63	-0.65***
	(6.29)	(3.95)	(4.44)	(1.94)	
Number of involuntary job losses to date per year of actual experience	0.81	0.39	0.46	0.17	-0.29***
	(6.17)	(2.68)	(3.00)	(1.42)	
Number of past self-employment spells per year of actual experience	0.09	0.10	0.10	0.09	-0.01
	(1.55)	(0.32)	(0.31)	(0.37)	
Panel C: Individual Characteristics					
1 if female	0.50	0.43	0.48	0.30	-0.18***
	(0.50)	(0.50)	(0.50)	(0.46)	
Race/Ethnicity					
White	0.50	0.59	0.58	0.62	0.04***
Hispanic	0.19	0.17	0.17	0.18	0.01
Black	0.32	0.24	0.25	0.20	-0.06***
AFQT percentile	38.87	44.05	42.54	48.31	5.77***
	(28.41)	(29.74)	(29.69)	(29.45)	
1 if any family member owned business	0.28	0.35	0.33	0.42	0.09***
	(0.45)	(0.48)	(0.47)	(0.49)	
1 if considers oneself an entrepreneur	0.20	0.41	0.35	0.57	0.21***
	(0.40)	(0.49)	(0.48)	(0.50)	
Marital status					
Never married	0.36	0.22	0.24	0.15	-0.08***
Cohabit	0.05	0.03	0.03	0.03	-0.01
Married	0.40	0.55	0.52	0.64	0.13***
Separated/Divorced/Widowed	0.20	0.20	0.21	0.17	-0.04***
1 if child in household aged 6 or under	0.21	0.25	0.27	0.21	-0.06***
	(0.41)	(0.44)	(0.44)	(0.41)	
Education					
Less than high school	0.15	0.12	0.13	0.07	-0.07***

Continued on next page

Table 1 (continued)

	Wage	Self-Employed			Diff.
	Employed	Any	Basic	Advanced	(4)-(3)
	(1)	(2)	(3)	(4)	(5)
High school graduate	0.47	0.42	0.44	0.37	-0.07***
Some college	0.23	0.22	0.22	0.24	0.02
College+	0.16	0.24	0.21	0.32	0.11***
Net family wealth (thousands of $s)	86.42	213.97	163.82	354.90	191.08***
	(285.93)	(539.04)	(420.06)	(764.60)	
Net family income (thousands of $s)	53.30	80.94	68.60	115.60	46.99***
	(70.84)	(134.43)	(115.73)	(172.06)	
Risk tolerance					
Least risk tolerant	0.46	0.44	0.45	0.43	-0.02
Less risk tolerant	0.12	0.14	0.14	0.13	-0.01
More risk tolerant	0.15	0.15	0.15	0.15	0.00
Most risk tolerant	0.25	0.25	0.24	0.28	0.03***
Unknown risk tolerance	0.02	0.02	0.02	0.01	-0.01***
Sociability personality trait at age 6					
Extremely shy	0.15	0.13	0.14	0.11	-0.03***
Somewhat shy	0.52	0.50	0.51	0.47	-0.04***
Somewhat outgoing	0.22	0.24	0.23	0.28	0.05***
Extremely outgoing	0.11	0.12	0.12	0.14	0.02**
Rotter Locus of Control (4-16)	7.49	7.29	7.36	7.10	-0.26***
	(2.10)	(2.10)	(2.09)	(2.12)	
Extraverted, enthusiastic (1-7)	5.13	5.18	5.15	5.27	0.12***
	(1.46)	(1.45)	(1.43)	(1.49)	
Open to new experiences, complex (1-7)	5.30	5.35	5.33	5.40	0.08*
	(1.34)	(1.33)	(1.32)	(1.36)	
Conventional, uncreative (1-7)	3.17	3.04	3.05	3.02	-0.03
	(1.64)	(1.64)	(1.62)	(1.68)	
N. spells	62,194	5,509	4,063	1,446	

Note: This table reports means at the start of each job spell, with standard deviations in parentheses for continuous variables. Rows for categorical variables report the share of spells in each category. "Basic" self-employment is unincorporated and low-capital; "Advanced" is incorporated or has start-up capital of at least 20,000 USD. Earnings and revenue are in 2010 USD, adjusted with the regional CPI; revenue is available only for spells linked to the NLSY79 business ownership module. Column 5 reports the Advanced minus Basic difference, with significance from two-sample t-tests allowing unequal variances; for categorical variables the test is applied to an indicator for each category. *p < .10; **p < .05; ***p < .01.

Table 2: Distribution of Individuals by Number of Self-Employment Spells

N. self-employment spells	N. individuals	Share (%)
0	4,237	59.5
1	1,505	21.1
2	753	10.6
3	302	4.2
4	171	2.4
5	72	1.0
6	40	0.6
7	19	0.3
8–20	17	0.2
Total	7,116	100.0

Note: This table reports the number and share of individuals by the total number of self-employment spells they are observed to hold. The unit of observation is the individual, and shares are calculated over all individuals in the earnings sample. Shares may not sum to 100 because of rounding.

Table 3: Partial Correlation Coefficients of Experience Variables by Employment Type

	(1)	(2)	(3)	(4)	(5)
Panel A: Wage Job Spells					
(1) O*NET Business skills	1.000				
(2) O*NET Specialized skills	0.451***	1.000			
(3) O*NET Skill balance	0.107***	-0.044***	1.000		
(4) Number of 2-digit occupations	-0.163***	-0.218***	0.292***	1.000	
(5) Number of involuntary job losses to date	-0.098***	-0.065***	0.069***	0.196***	1.000
N = 62,194					
Panel B: Any Self-Employment Job Spells					
(1) O*NET Business skills	1.000				
(2) O*NET Specialized skills	0.494***	1.000			
(3) O*NET Skill balance	0.136***	-0.016	1.000		
(4) Number of 2-digit occupations	-0.186***	-0.228***	0.246***	1.000	
(5) Number of involuntary job losses to date	-0.038***	-0.057***	0.058***	0.181***	1.000
N = 5,509					
Panel C: Basic Self-Employment Job Spells					
(1) O*NET Business skills	1.000				
(2) O*NET Specialized skills	0.430***	1.000			
(3) O*NET Skill balance	0.144***	-0.026*	1.000		
(4) Number of 2-digit occupations	-0.132***	-0.191***	0.266***	1.000	
(5) Number of involuntary job losses to date	-0.008	-0.048***	0.070***	0.165***	1.000
N = 4,063					
Panel D: Advanced Self-Employment Job Spells					
(1) O*NET Business skills	1.000				
(2) O*NET Specialized skills	0.566***	1.000			
(3) O*NET Skill balance	0.097***	-0.019	1.000		
(4) Number of 2-digit occupations	-0.242***	-0.282***	0.233***	1.000	
(5) Number of involuntary job losses to date	-0.064**	-0.058**	0.038	0.205***	1.000
N = 1,446					

Note: This table reports partial correlation coefficients of experience measures at the start of each job spell, controlling for actual work experience, separately by employment type. Business and specialized skills are time-in-occupation-weighted measures (in years). Skill balance is the effective number of skills (exponentiated Shannon index). Occupation count uses 2-digit codes. *p < .10; **p < .05; ***p < .01.

Table 4: Testing Selection on Observables: Estimated Average Marginal Effects on Self-Employment Entry (Based on MNL Estimates Shown in Table A2)

	Dep. Var.: Type of Self-Employment Entry							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Basic SE (Unconditional Prob. = 0.011)								
Std. O*NET Business skills	-0.151***	-0.168***	-0.191***	-0.226***	-0.187***	-0.192***	-0.207***	-0.236***
	(0.047)	(0.047)	(0.048)	(0.049)	(0.051)	(0.051)	(0.050)	(0.050)
Std. O*NET Specialized skills	-0.084***	-0.078***	-0.077***	-0.079***	-0.077***	-0.075***	-0.075***	-0.065**
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
Std. O*NET Skill balance	0.047***	0.027	0.026	0.024	0.026	0.024	0.018	0.011
	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)
Panel B: Advanced SE (Unconditional Prob. = 0.007)								
Std. O*NET Business skills	0.337***	0.405***	0.347***	0.271***	0.230***	0.225***	0.226***	0.137**
	(0.051)	(0.051)	(0.051)	(0.052)	(0.054)	(0.055)	(0.054)	(0.053)
Std. O*NET Specialized skills	-0.124***	-0.090***	-0.097***	-0.099***	-0.100***	-0.099***	-0.117***	-0.101***
	(0.025)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
Std. O*NET Skill balance	0.117***	0.039*	0.038*	0.039*	0.035*	0.031	0.019	0.005
	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Potential & actual experience	✓	✓	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓	✓	✓
Personality			✓	✓	✓	✓	✓	✓
Resources				✓	✓	✓	✓	✓
Education & cognitive skills					✓	✓	✓	✓
Family business background						✓	✓	✓
N. past SE spells							✓	✓
Entrepreneur identity								✓
N. individuals	7,116	7,116	7,116	7,116	7,116	7,116	7,116	7,116
N. individual-year obs.	251,214	251,214	251,214	251,214	251,214	251,214	251,214	251,214

Note: This table reports estimated average marginal effects of standardized business, specialized, and balanced skills on annual transitions into basic (Panel A) and advanced (Panel B) self-employment, across specifications that progressively add controls. Marginal effects are computed for a 0.5 standard deviation increase in each skill, holding other variables at observed values. All specifications control for potential and actual experience and their squares; columns 2–7 progressively add the control groups indicated at the bottom of the table. Standard errors clustered at the individual level are in parentheses. *p < .10; **p < .05; ***p < .01.

Table 5: Estimated Average Marginal Effects of Business, Specialized, and Balanced Skills on Self-Employment Entry Probabilities (Based on MNL Estimates Shown in Table A3)

	Dep. Var.: Type of Self-Employment Entry							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Basic SE (Unconditional Prob. = 0.011)								
Std. O*NET Business skills	-0.234***		-0.198***		-0.207***		-0.184***	-0.129**
	(0.046)		(0.047)		(0.050)		(0.052)	(0.053)
Std. O*NET Specialized skills		-0.113***	-0.084***		-0.075***		-0.044	-0.053*
		(0.024)	(0.026)		(0.026)		(0.028)	(0.027)
Std. O*NET Skill balance				0.006	0.018		-0.011	-0.012
				(0.015)	(0.016)		(0.016)	(0.016)
Std. N. occupation count						0.155***	0.140***	0.088***
						(0.015)	(0.016)	(0.019)
Std. N. involuntary job losses to date								0.133***
								(0.022)
Panel B: Advanced SE (Unconditional Prob. = 0.007)								
Std. O*NET Business skills	0.201***		0.239***		0.226***		0.229***	0.257***
	(0.051)		(0.052)		(0.054)		(0.055)	(0.056)
Std. O*NET Specialized skills		-0.081***	-0.117***		-0.117***		-0.115***	-0.117***
		(0.026)	(0.026)		(0.026)		(0.026)	(0.026)
Std. O*NET Skill balance				0.071***	0.019		0.016	0.013
				(0.020)	(0.021)		(0.022)	(0.022)
Std. N. occupation count						0.050***	0.015	-0.006
						(0.019)	(0.021)	(0.023)
Std. N. involuntary job losses to date								0.055**
								(0.026)
N. individuals	7,116	7,116	7,116	7,116	7,116	7,116	7,116	7,116
N. individual-year obs.	251,214	251,214	251,214	251,214	251,214	251,214	251,214	251,214

Note: This table reports estimated average marginal effects from a multinomial logit on annual transitions into basic and advanced self-employment, on person-year observations for individuals not currently self-employed. The dependent variable takes three values: entry into basic SE, entry into advanced SE, or remaining in non-SE (reference). Marginal effects are computed for a 0.5 standard deviation increase in each skill, holding other variables at observed values, and expressed as a percentage change relative to the unconditional transition probability. All skill measures are standardized to mean zero and SD 0.5. Controls follow Section 3.4.4. Standard errors clustered at the individual level are in parentheses. *p < .10; **p < .05; ***p < .01.

Table 6: Estimated Average Marginal Effects of Business, Specialized, and Balanced Skills on Self-Employment Revenue and Weekly Earnings (Based on Estimates Shown in Table A5)

	Log Annual Revenue (Tobit)			Log Weekly Earnings (OLS)		
	Any (1)	Basic (2)	Advanced (3)	Any (4)	Basic (5)	Advanced (6)
Std. O*NET Business skills	0.439***	0.247**	0.365***	0.209***	0.120	0.158**
	(0.077)	(0.110)	(0.097)	(0.065)	(0.108)	(0.080)
Std. O*NET Specialized skills	0.326***	0.253***	0.198***	0.277***	0.197***	0.252***
	(0.043)	(0.059)	(0.062)	(0.041)	(0.061)	(0.057)
Std. O*NET Skill balance	-0.022	0.043	-0.050	-0.038	-0.016	-0.031
	(0.041)	(0.044)	(0.069)	(0.036)	(0.046)	(0.052)
N. obs.	4,895	2,430	2,465	4,895	2,430	2,465
Mean revenue or earnings	132,738	56,859	215,578	749	412	1,081

Note: This table reports estimated average marginal effects on log annual revenue (Tobit, columns 1–3) and log weekly earnings (OLS, columns 4–6) on the same sample of self-employment spells with reported revenue. Marginal effects are computed for a 0.5 standard deviation increase in each standardized skill, holding other variables at observed values; since the dependent variables are in logs, the estimates are interpretable as percentage changes. "Any" pools all spells; "Basic" and "Advanced" are defined as in Table 1. Controls follow Section 3.4.4. Observations are weighted by the inverse of spell-report frequencies to address survivorship bias. Standard errors clustered at the individual level are in parentheses. *p < .10; **p < .05; ***p < .01.

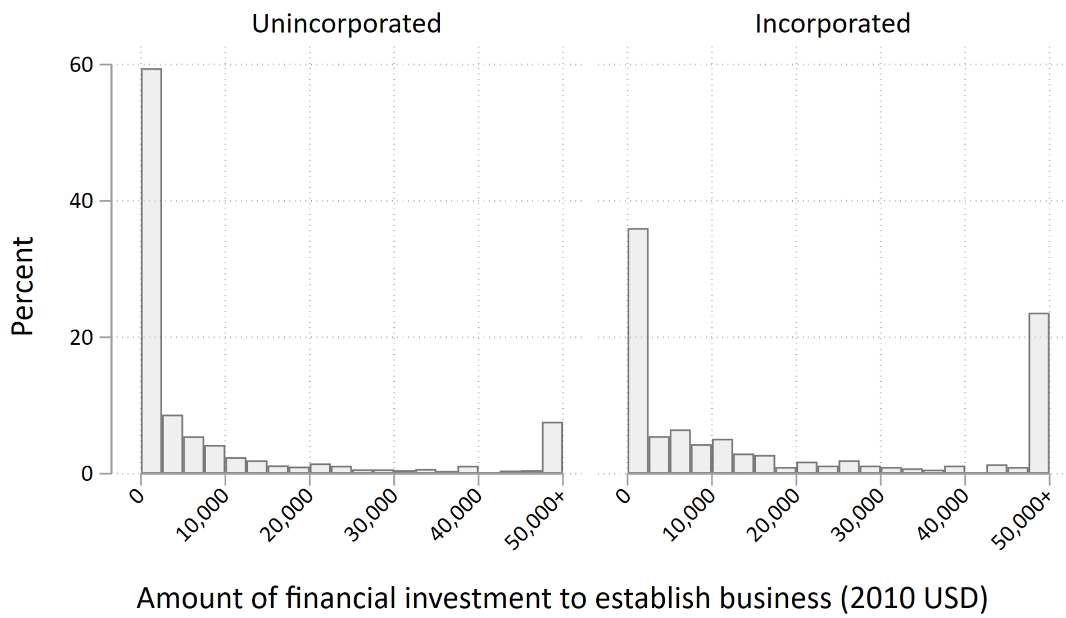
Table 7: Estimated Average Marginal Effects on Self-Employment Exit Destination Probabilities (Based on MNL Estimates Shown in Table A6)

	From Type of Self-Employment		
	Any	Basic	Advanced
	(1)	(2)	(3)
Panel A: Exit to Wage Employment			
Std. ONET Business Skills	-0.074	0.018	-0.115
	(0.055)	(0.067)	(0.085)
Std. ONET Specialized Skills	-0.106***	-0.079**	-0.132**
	(0.033)	(0.039)	(0.056)
Std. ONET Skill Balance	-0.004	0.017	-0.063
	(0.033)	(0.034)	(0.071)
Unconditional Prob.	0.054	0.070	0.031
Panel B: Exit to Another SE			
Std. ONET Business Skills	0.200**	0.137	0.388***
	(0.083)	(0.105)	(0.122)
Std. ONET Specialized Skills	0.035	0.147**	-0.063
	(0.055)	(0.070)	(0.081)
Std. ONET Skill Balance	0.010	0.020	0.042
	(0.063)	(0.069)	(0.121)
Unconditional Prob.	0.017	0.021	0.012
Panel C: Exit to Non-Employment			
Std. ONET Business Skills	-0.203**	-0.155	-0.288***
	(0.079)	(0.113)	(0.106)
Std. ONET Specialized Skills	0.034	0.005	0.095
	(0.043)	(0.054)	(0.066)
Std. ONET Skill Balance	0.025	0.039	-0.039
	(0.041)	(0.044)	(0.093)
Unconditional Prob.	0.022	0.029	0.011
N. individuals	2,879	2,370	1,103
N. individual-year obs.	16,321	10,383	5,938

Note: This table reports estimated average marginal effects from a multinomial logit on annual transitions out of self-employment, on person-year observations within self-employment spells. The dependent variable takes four values: remain in the current spell (reference), exit to wage employment (Panel A), exit to another self-employment spell (Panel B), or exit to non-employment (Panel C). Marginal effects are computed for a 0.5 standard deviation increase in each standardized skill, holding other variables at observed values. "Any" pools all spells; "Basic" and "Advanced" are defined as in Table 1. Controls follow Section 3.4.4. Standard errors clustered at the individual level are in parentheses. *p < .10; **p < .05; ***p < .01.

Figures

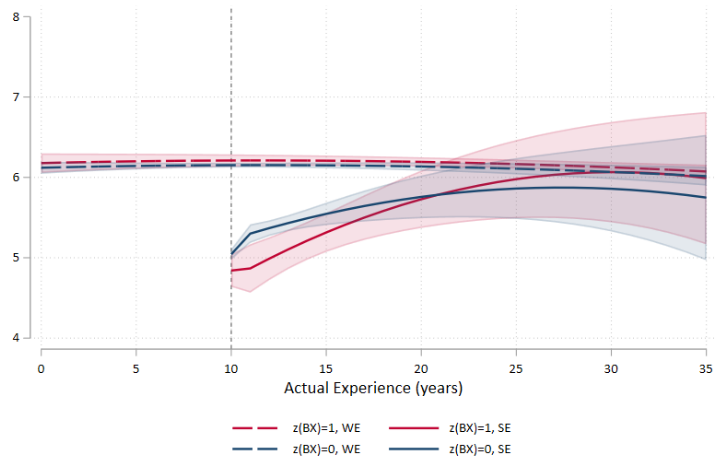
Figure 1: Distribution of the Amount of Start-Up Capital by Incorporation Status



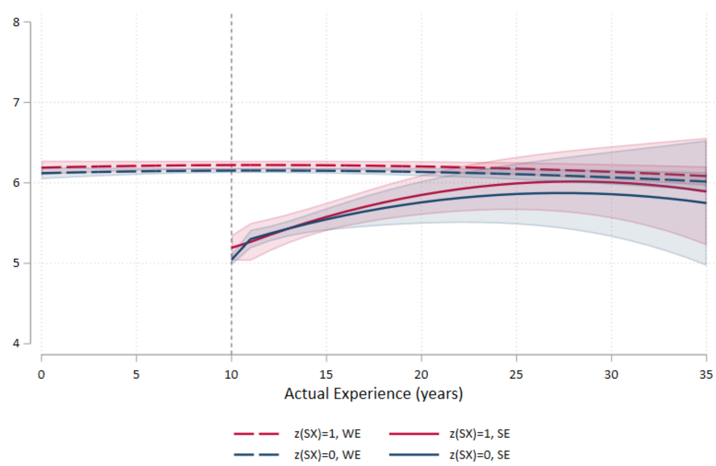
Note: This figure plots the distribution of the amount of financial investment at the start of each self-employment spell, separately for incorporated and unincorporated spells.

Figure 2: Predicted Log Weekly Earnings for Basic Self-Employment

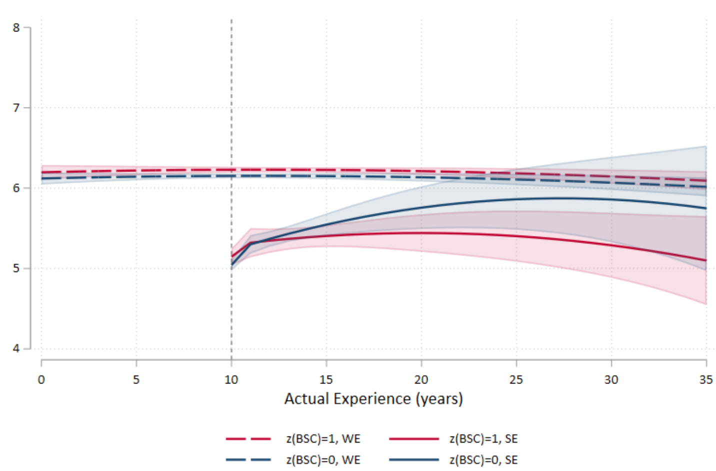
(a) by Business Skills (BX)



(b) by Specialized Skills (SX)



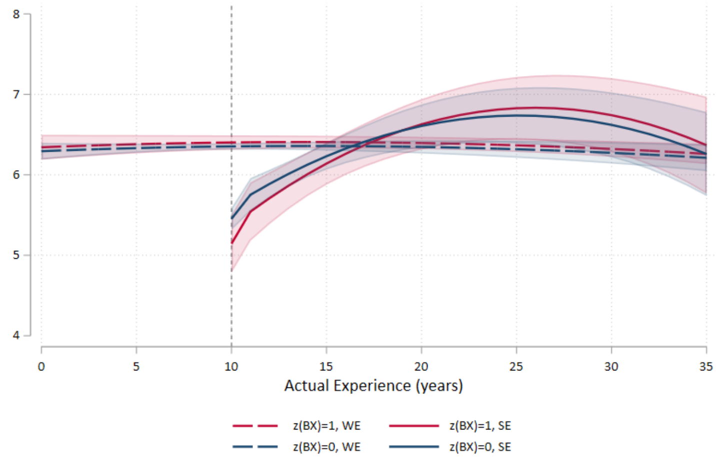
(c) by Skill Balance (BSC)



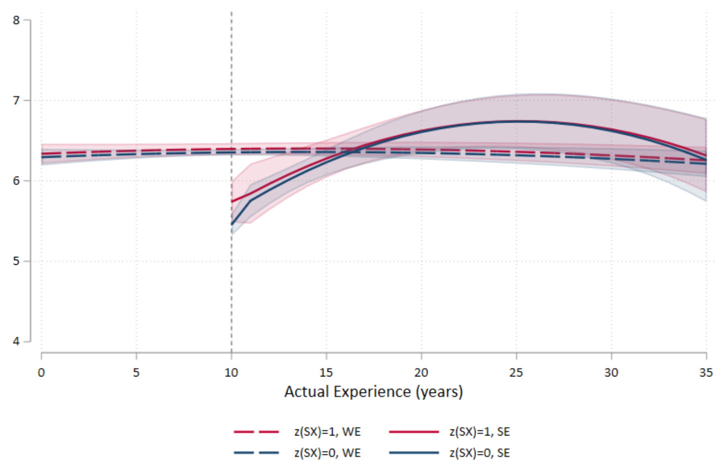
Note: This figure plots predicted log weekly earnings as a function of actual experience for workers who ever enter basic self-employment, separately for wage employment (dashed) and self-employment (solid), and for the indicated skill measure at the mean (z=0, blue) and one standard deviation above the mean (z=1, red). Predictions come from the individual fixed-effects specification in equation (6). Self-employment entry occurs at 10 years of actual experience (vertical dashed line); other covariates are held at observed values. Shaded bands are 95 percent confidence intervals.

Figure 3: Predicted Log Weekly Earnings for Advanced Self-Employment

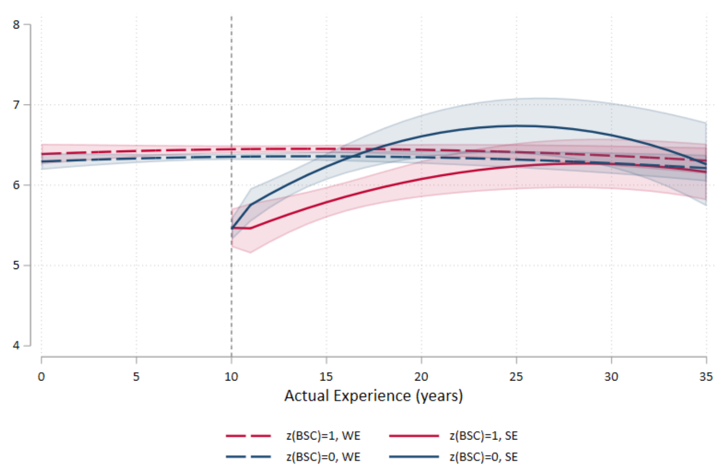
(a) by Business Skills (BX)



(b) by Specialized Skills (SX)



(c) by Skill Balance (BSC)



Note: This figure plots predicted log weekly earnings as a function of actual experience for workers who ever enter advanced self-employment, separately for wage employment (dashed) and self-employment (solid), and for the indicated skill measure at the mean (z=0, blue) and one standard deviation above the mean (z=1, red). Predictions come from the individual fixed-effects specification in equation (6). Self-employment entry occurs at 10 years of actual experience (vertical dashed line); other covariates are held at observed values. Shaded bands are 95 percent confidence intervals.

Appendix

A Additional Tables

Table A1: Classification of Skill and Knowledge Elements in O*NET Data by Skill Type

Skill Type	Skill Elements	Knowledge Elements
Business	Service Orientation	Economics and Accounting
		Sales and Marketing
		Production and Processing
		Customer and Personal Service
Managerial	Management of Financial Resources	Administration and Management
	Management of Material Resources	Personnel and Human Resources
	Management of Personnel Resources	
Social	Social Perceptiveness	
	Coordination	
	Persuasion	
	Negotiation	
	Instructing	
Other	Judgment and Decision Making	Clerical
	Systems Analysis	Transportation
	Systems Evaluation	Food Production
	Monitoring	Computers and Electronics
	Time Management	Engineering and Technology
	Reading Comprehension	Design
	Active Listening	Building and Construction
	Writing	Mechanical
	Speaking	Mathematics
	Mathematics	Physics
	Science	Chemistry
	Critical Thinking	Biology
	Active Learning	Psychology
	Learning Strategies	Sociology and Anthropology
	Complex Problem Solving	Geography
	Operations Analysis	Medicine and Dentistry
	Technology Design	Therapy and Counseling
	Equipment Selection	Education and Training
	Installation	English Language
	Programming	Foreign Language
	Operation Monitoring	Fine Arts
	Operation and Control	History and Archeology
	Equipment Maintenance	Philosophy and Theology
	Troubleshooting	Public Safety and Security
	Repairing	Law and Government
	Quality Control Analysis	Telecommunications
		Communications and Media

Note: This table lists the O*NET skill and knowledge elements assigned to each skill type used in constructing the business-skills measure.

Table A2: Testing Selection on Observables: MNL Coefficient Estimates for Self-Employment Entry

	Dep. Var.: Type of Self-Employment Entry							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Basic SE (Unconditional Prob. = 0.011)								
Std. O*NET Business skills	-0.153***	-0.170***	-0.193***	-0.229***	-0.190***	-0.195***	-0.210***	-0.240***
	(0.048)	(0.048)	(0.049)	(0.049)	(0.052)	(0.052)	(0.051)	(0.051)
Std. O*NET Business skills^2	0.032***	0.034***	0.035***	0.038***	0.034***	0.035***	0.032***	0.033***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Std. O*NET Specialized skills	-0.085***	-0.079***	-0.078***	-0.080***	-0.077***	-0.076***	-0.076***	-0.066**
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)
Std. O*NET Specialized skills^2	-0.013	-0.014	-0.014	-0.015*	-0.014	-0.015*	-0.007	-0.008
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Std. O*NET Skill balance	0.048***	0.028*	0.027	0.025	0.027	0.024	0.019	0.012
	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)
Std. O*NET Skill balance^2	-0.003	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.006
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Panel B: Advanced SE (Unconditional Prob. = 0.007)								
Std. O*NET Business skills	0.338***	0.406***	0.347***	0.270***	0.229***	0.224***	0.225***	0.134**
	(0.051)	(0.052)	(0.052)	(0.053)	(0.055)	(0.055)	(0.055)	(0.054)
Std. O*NET Business skills^2	-0.010	-0.018**	-0.013	-0.008	-0.005	-0.003	-0.005	-0.002
	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)
Std. O*NET Specialized skills	-0.124***	-0.089***	-0.097***	-0.098***	-0.099***	-0.099***	-0.117***	-0.101***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)	(0.028)
Std. O*NET Specialized skills^2	-0.041***	-0.047***	-0.046***	-0.048***	-0.049***	-0.049***	-0.038***	-0.036***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)
Std. O*NET Skill balance	0.118***	0.040*	0.039*	0.039*	0.036*	0.031	0.020	0.005
	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)
Std. O*NET Skill balance^2	0.009**	0.001	0.001	0.001	0.001	0.001	0.000	-0.001
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Potential & actual experience	✓	✓	✓	✓	✓	✓	✓	✓
Demographics		✓	✓	✓	✓	✓	✓	✓
Personality			✓	✓	✓	✓	✓	✓
Resources				✓	✓	✓	✓	✓
Education & cognitive skills					✓	✓	✓	✓
Family business background						✓	✓	✓
N. past SE spells							✓	✓
Entrepreneur identity								✓
N. individuals	7,116	7,116	7,116	7,116	7,116	7,116	7,116	7,116
N. individual-year obs.	251,214	251,214	251,214	251,214	251,214	251,214	251,214	251,214

Note: This table reports MNL coefficient estimates underlying the selection-on-observables analysis in Table 4. Sample, dependent variable, and progressive controls follow Table 4. All skill measures are standardized to mean zero and SD 0.5. Standard errors clustered at the individual level are in parentheses. *p < .10; **p < .05; ***p < .01.

Table A3: MNL Coefficient Estimates for Self-Employment Entry

	Dep. Var.: Type of Self-Employment Entry							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Basic SE (Unconditional Prob. = 0.011)								
Std. O*NET Business skills	-0.238***		-0.201***		-0.210***		-0.186***	-0.130**
	(0.047)		(0.048)		(0.051)		(0.053)	(0.054)
Std. O*NET Business skills^2	0.028***		0.032***		0.032***		0.029***	0.024***
	(0.006)		(0.007)		(0.007)		(0.007)	(0.007)
Std. O*NET Specialized skills		-0.115***	-0.086***		-0.076***		-0.045	-0.054*
		(0.025)	(0.026)		(0.027)		(0.028)	(0.028)
Std. O*NET Specialized skills^2		0.002	-0.007		-0.007		-0.008	-0.008
		(0.007)	(0.009)		(0.008)		(0.008)	(0.008)
Std. O*NET Skill balance				0.007	0.019		-0.011	-0.012
				(0.015)	(0.016)		(0.016)	(0.016)
Std. O*NET Skill balance^2				-0.007**	-0.005		-0.005	-0.005
				(0.004)	(0.003)		(0.003)	(0.003)
Std. N. occupation count						0.158***	0.143***	0.090***
						(0.015)	(0.017)	(0.019)
Std. N. occupation count^2						-0.013***	-0.011**	-0.009*
						(0.004)	(0.004)	(0.005)
Std. N. involuntary job losses to date								0.135***
								(0.022)
Std. N. involuntary job losses to date^2								-0.012***
								(0.004)
Panel B: Advanced SE (Unconditional Prob. = 0.007)								
Std. O*NET Business skills	0.199***		0.238***		0.225***		0.228***	0.257***
	(0.051)		(0.053)		(0.055)		(0.055)	(0.057)
Std. O*NET Business skills^2	-0.020***		-0.006		-0.005		-0.005	-0.008
	(0.008)		(0.009)		(0.009)		(0.009)	(0.009)
Std. O*NET Specialized skills		-0.082***	-0.118***		-0.117***		-0.115***	-0.117***
		(0.026)	(0.027)		(0.027)		(0.027)	(0.027)
Std. O*NET Specialized skills^2		-0.033***	-0.039***		-0.038***		-0.038***	-0.039***
		(0.008)	(0.009)		(0.009)		(0.009)	(0.009)
Std. O*NET Skill balance				0.071***	0.020		0.016	0.013
				(0.020)	(0.021)		(0.022)	(0.022)
Std. O*NET Skill balance^2				0.006	0.000		0.000	-0.000
				(0.004)	(0.005)		(0.005)	(0.005)
Std. N. occupation count						0.053***	0.017	-0.005
						(0.019)	(0.022)	(0.024)
Std. N. occupation count^2						-0.003	-0.001	-0.002
						(0.005)	(0.006)	(0.006)
Std. N. involuntary job losses to date								0.057**
								(0.027)
Std. N. involuntary job losses to date^2								-0.003
								(0.005)
N. individuals	7,116	7,116	7,116	7,116	7,116	7,116	7,116	7,116
N. individual-year obs.	251,214	251,214	251,214	251,214	251,214	251,214	251,214	251,214

Note: This table reports MNL coefficient estimates for the entry models reported in Table 5. Sample, dependent variable, and controls follow Table 5. All skill measures are standardized to mean zero and SD 0.5. Standard errors clustered at the individual level are in parentheses. *p < .10; **p < .05; ***p < .01.

Table A4: Are Business Skills Reflecting Experience in High-Skill Occupations?

	Dep. Var.: Type of Self-Employment Entry					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Basic SE (Unconditional Prob. = 0.011)						
Std. Actual exp. in Job Zone 4+ occupations	-0.085***	-0.025	-0.070**	-0.028	-0.087***	-0.031
	(0.030)	(0.033)	(0.031)	(0.033)	(0.030)	(0.033)
Std. O*NET Business skills		-0.219***		-0.184***		-0.193***
		(0.051)		(0.052)		(0.054)
Std. O*NET Specialized skills			-0.103***	-0.082***		-0.072***
			(0.025)	(0.026)		(0.027)
Std. O*NET Skill balance					0.014	0.019
					(0.015)	(0.016)
Panel B: Advanced SE (Unconditional Prob. = 0.007)						
Std. Actual exp. in Job Zone 4+ occupations	0.036	-0.013	0.042	-0.026	0.011	-0.030
	(0.029)	(0.031)	(0.029)	(0.032)	(0.030)	(0.032)
Std. O*NET Business skills		0.208***		0.258***		0.247***
		(0.055)		(0.057)		(0.058)
Std. O*NET Specialized skills			-0.083***	-0.112***		-0.111***
			(0.026)	(0.026)		(0.027)
Std. O*NET Skill balance					0.069***	0.021
					(0.021)	(0.021)
N. individuals	7,116	7,116	7,116	7,116	7,116	7,116
N. individual-year obs.	251,214	251,214	251,214	251,214	251,214	251,214

Note: This table tests whether the estimated effects of business skills in Table 5 reflect business-specific skill content rather than a general high-skill occupation effect, by adding controls for O*NET job zone (a five-level classification of the preparation required for an occupation). Sample, dependent variable, and other controls follow Table 5. All skill measures are standardized to mean zero and SD 0.5. Standard errors clustered at the individual level are in parentheses. *p < .10; **p < .05; ***p < .01.

Table A5: Tobit and OLS Coefficient Estimates for Self-Employment Revenue and Weekly Earnings

	Log Annual Revenue (Tobit)			Log Weekly Earnings (OLS)		
	Any (1)	Basic (2)	Advanced (3)	Any (4)	Basic (5)	Advanced (6)
Std. O*NET Business skills	0.439***	0.208**	0.398***	0.209***	0.076	0.200**
	(0.077)	(0.097)	(0.108)	(0.065)	(0.093)	(0.089)
Std. O*NET Business skills^2	-0.042***	-0.040*	-0.034*	-0.045***	-0.044*	-0.043***
	(0.014)	(0.024)	(0.019)	(0.012)	(0.023)	(0.016)
Std. O*NET Specialized skills	0.326***	0.271***	0.215***	0.277***	0.230***	0.254***
	(0.043)	(0.051)	(0.068)	(0.041)	(0.053)	(0.062)
Std. O*NET Specialized skills^2	-0.018	0.020	-0.019	0.007	0.037**	-0.002
	(0.013)	(0.020)	(0.017)	(0.012)	(0.018)	(0.016)
Std. O*NET Skill balance	-0.022	0.048	-0.052	-0.038	-0.017	-0.032
	(0.041)	(0.046)	(0.065)	(0.036)	(0.049)	(0.049)
Std. O*NET Skill balance^2	0.003	0.008	0.004	-0.001	-0.001	0.003
	(0.005)	(0.006)	(0.009)	(0.005)	(0.006)	(0.007)
N. obs.	4,895	2,430	2,465	4,895	2,430	2,465
Adjusted R^2	0.057	0.037	0.044	0.123	0.101	0.082
Mean revenue or earnings.	132,738	56,859	215,578	749	412	1,081

Note: This table reports Tobit (columns 1–3) and OLS (columns 4–6) coefficient estimates underlying the marginal effects in Table 6. Sample, dependent variables, weighting, and controls follow Table 6. All skill measures are standardized to mean zero and SD 0.5. Standard errors clustered at the individual level are in parentheses. *p < .10; **p < .05; ***p < .01.

Table A6: MNL Coefficient Estimates for Self-Employment Exit Destinations

	From Type of Self-Employment		
	Any	Basic	Advanced
	(1)	(2)	(3)
Panel A: Exit to Wage Employment			
Std. ONET Business Skills	-0.094	0.015	-0.188*
	(0.065)	(0.075)	(0.108)
Std. ONET Business Skills^2	0.011	0.002	0.029*
	(0.011)	(0.015)	(0.015)
Std. ONET Specialized Skills	-0.116***	-0.084*	-0.101
	(0.039)	(0.044)	(0.071)
Std. ONET Specialized Skills^2	0.004	0.007	-0.015
	(0.009)	(0.009)	(0.013)
Std. ONET Skill Balance	-0.007	0.017	-0.066
	(0.031)	(0.034)	(0.061)
Std. ONET Skill Balance^2	0.003	0.005	-0.000
	(0.005)	(0.006)	(0.010)
Unconditional Prob.	0.054	0.070	0.031
Panel B: Exit to Another SE			
Std. ONET Business Skills	0.195**	0.132	0.478***
	(0.094)	(0.111)	(0.154)
Std. ONET Business Skills^2	-0.003	0.024	-0.040**
	(0.014)	(0.020)	(0.019)
Std. ONET Specialized Skills	0.046	0.149**	-0.047
	(0.063)	(0.074)	(0.099)
Std. ONET Specialized Skills^2	-0.016	-0.030*	-0.008
	(0.012)	(0.017)	(0.017)
Std. ONET Skill Balance	-0.001	0.016	0.013
	(0.057)	(0.067)	(0.101)
Std. ONET Skill Balance^2	0.012	0.014	0.017
	(0.009)	(0.011)	(0.019)
Unconditional Prob.	0.017	0.021	0.012
Panel C: Exit to Non-Employment			
Std. ONET Business Skills	-0.227**	-0.161	-0.323**
	(0.090)	(0.120)	(0.144)
Std. ONET Business Skills^2	0.016	0.030**	0.013
	(0.012)	(0.015)	(0.021)
Std. ONET Specialized Skills	0.026	0.001	0.134
	(0.049)	(0.058)	(0.082)
Std. ONET Specialized Skills^2	0.002	0.003	-0.018
	(0.008)	(0.010)	(0.014)
Std. ONET Skill Balance	0.021	0.039	-0.044
	(0.038)	(0.043)	(0.078)
Std. ONET Skill Balance^2	0.004	0.005	0.002
	(0.007)	(0.007)	(0.014)
Unconditional Prob.	0.022	0.029	0.011
N. individuals	2,879	2,370	1,103
N. individual-year obs.	16,321	10,383	5,938

Note: This table reports MNL coefficient estimates underlying the marginal effects in Table 7. Sample, dependent variable, and controls follow Table 7. All skill measures are standardized to mean zero and SD 0.5. Standard errors clustered at the individual level are in parentheses. *p < .10; **p < .05; ***p < .01.

B Baseline Earnings Trajectories

Before introducing the skill interactions, I estimate a simpler version of equation (6) in which the four self-employment terms enter on their own, setting $\gamma_k = \theta_k = \pi_k = 0$ for all k:

$$\ln w_{it} = \alpha_i + \sum_{k=0}^{3} \delta_k D_{it}^{(k)} + X_{it}'\beta + \epsilon_{it}. \tag{B1}$$

All terms are defined as in Section 4.2, and the specification is estimated on the same sample of workers who have ever entered self-employment.

I estimate equation (B1) separately for workers who ever enter basic and advanced self-employment. Table B1 reports the estimates. δ_0 captures the earnings gap between self-employment and wage employment after the first year of self-employment (when $\tau_{it} = 0$ and $\text{1stYearSE}_{it} = 0$), and δ_1 captures the additional adjustment in the first year; the total gap at entry is $\delta_0 + \delta_1$, and a negative value is consistent with an initial earnings drop. δ_2 and δ_3 trace the subsequent earnings growth over self-employment tenure.

The estimates show two patterns. First, entering self-employment is accompanied by an immediate earnings drop relative to wage employment, which is more pronounced for basic self-employment. In basic self-employment, the first-year earnings gap is about 43 log points ($\delta_0 + \delta_1 = -0.227 - 0.199$). In advanced self-employment, the first-year earnings gap is about 31 log points ($\delta_0 + \delta_1 = -0.430 + 0.116$, with δ_1 not statistically significant). Second, earnings grow faster in self-employment than in the counterfactual wage path. The tenure return δ_2 implies annual earnings growth of about 6 log points in basic self-employment and 11 log points in advanced self-employment, on top of the potential and actual experience profile. Combined with the initial drop, this produces a U-shaped trajectory in which earnings dip at entry and then recover with tenure, more sharply in advanced self-employment. Section 5 reads the skill-specific earnings paths against this baseline.

Table B1: Baseline Coefficient Estimates for Log Earnings with Individual Fixed Effects (Without Skill Interactions)

	Dep. Var.: Log(Weekly Earnings + 1)			
	Basic SE		Advanced SE	
	(1)	(2)	(3)	(4)
Actual experience	0.063***	0.050***	0.069***	0.060***
	(0.005)	(0.005)	(0.010)	(0.010)
Actual experience^2	-0.001***	-0.000***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Potential experience	-0.027***	-0.019***	-0.029***	-0.026***
	(0.005)	(0.005)	(0.010)	(0.009)
Potential experience^2	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
1 if basic self-employment	-0.482***	-0.432***		
	(0.071)	(0.070)		
1 if advanced self-employment			-0.421***	-0.412***
			(0.099)	(0.109)
1 if first year in self-employment	0.111	0.055	0.275**	0.141
	(0.071)	(0.075)	(0.117)	(0.146)
Tenure in self-employment job - 1	0.032**	0.047***	0.069***	0.095***
	(0.013)	(0.016)	(0.012)	(0.016)
(Tenure in self-employment job - 1)^2	-0.001	-0.001	-0.002***	-0.002***
	(0.000)	(0.001)	(0.000)	(0.000)
Weighted by inverse of spell-report frequency		✓		✓
Mean dep. var.	5.998	5.998	6.299	6.299
N. obs.	69,586	69,586	32,096	32,096
Adjusted R^2	0.376	0.354	0.290	0.298

Note: This table reports coefficient estimates for the baseline earnings specification in equation (B1), estimated separately for workers who ever enter basic (columns 1–2) and advanced (columns 3–4) self-employment. Columns 1 and 3 are unweighted; columns 2 and 4 weight observations by the inverse of the number of observations within each job spell to address survivorship bias. The dependent variable is log weekly earnings in 2010 USD. Standard errors clustered at the individual level are in parentheses. *p < .10; **p < .05; ***p < .01.

C Approaches to Address Endogeneity Concerns: Individual Fixed Effects and Instrumental Variables

The identification in Section 4.4 relies on selection on observables. In this appendix section, I describe two approaches that rely on stronger assumptions: individual fixed effects and an instrumental variables strategy. Both approaches address important sources of endogeneity, but neither provides sufficiently informative evidence to replace the baseline specification. I therefore discuss them as complementary approaches rather than as the primary identification strategy.

The error term ϵ_{ijt} in equation (5) captures factors that shift the utility of option j but are not included in the observed regressors. Because BX_{it} and SX_{it} are constructed from workers' occupational histories, they reflect not only the skills associated with the occupations workers hold but also the choices that determine which occupations they enter and remain in. The baseline specification already controls for potential and actual experience, demographic characteristics, cognitive ability, risk tolerance, personality traits, and family background, leaving occupational sorting—how workers allocate their years across occupations—as the primary remaining concern.

To illustrate how occupational sorting may affect the estimates, decompose ϵ_{ijt} as $\epsilon_{ijt} = u_{ij} + v_{ijt}$, where u_{ij} is time-invariant and v_{ijt} varies within a worker across years. The time-invariant component u_{ij} captures factors such as preferences for autonomy, tolerance for the risks of self-employment, latent entrepreneurial ambition, and family norms surrounding business ownership. Workers with stronger preferences for self-employment may sort into occupations with higher business-skill content and remain in those occupations longer in anticipation of future entry. This creates a positive correlation between BX_{it} and u_{ij} for self-employment options, so the estimated effect of business skills may reflect both the direct role of skills and the influence of these time-invariant preferences.

The time-varying component v_{ijt} captures changes in a worker's plans or circumstances over the career. For example, a worker who becomes interested in self-employment later in life may intentionally move into a more business-intensive occupation before entering. In this case, within-person changes in skills may still be correlated with unobserved changes in the attractiveness of self-employment. This distinction parallels work on returns to occupational tenure (Kambourov and Manovskii, 2009) and task-specific human capital (Gathmann and Schönberg, 2010), where workers sort into occupations or tasks based on match quality.

C.1 Individual fixed effects

One way to address the time-invariant component u_{ij} is to estimate the entry model using individual fixed effects. This approach would identify the relationship between skills and entry using within-person changes in BX_{it} and SX_{it} as workers move across occupations over their careers. Because time-invariant individual characteristics are absorbed, the estimates would no longer be driven by correlation between skills and preferences for self-employment.

I estimate a conditional logit model following Chamberlain (1980). This approach avoids imposing a distributional assumption on the individual effects and allows u_{ij} to be arbitrarily correlated with the observed covariates. A conditional rather than unconditional approach is necessary because estimating individual-specific intercepts in a nonlinear model introduces the incidental parameters problem.

Fixed effects, however, do not address the time-varying component v_{ijt}. A worker who becomes interested in self-employment at age forty and then shifts toward business-intensive occupations would still generate within-person variation in BX_{it} that is correlated with her evolving plans. Thus, fixed effects address one form of occupational sorting but not changes in occupational choices that occur in anticipation of self-employment. This motivates the instrumental variables approach described next.

C.2 Instrumental variables

A second approach is to use an instrumental variables strategy that isolates variation in BX_{it} and SX_{it} arising from local labor market conditions rather than workers' own occupational choices. I construct a shift-share instrument based on the industrial composition of the worker's county of residence at labor market entry, following Jara-Figueroa et al. (2018).

The intuition is that local labor markets differ in the occupations they offer. A county whose economy is concentrated in manufacturing exposes workers to a different set of occupational opportunities—and therefore a different trajectory of skill accumulation—than a county with a larger service sector or a concentration of professional industries. Workers with similar initial characteristics may accumulate different skills because they begin their careers in different local labor markets.

I construct the instrument as follows. For each county c, I use the 1975 County Business Patterns to calculate the share s_{kc} of employment in each two-digit industry k. I then compute the average business-skill content of each industry using the 1980 Census, denoted $\overline{BX}_k$, by assigning each occupation its business-skill score from Section 3.4 and averaging across workers employed in industry k. The instrument for worker i, whose county of residence at labor market entry is $c(i)$, is:

$$Z_{ict}^{BX} = \sum_k s_{kc(i),1975} \cdot g_{kt} \cdot \overline{BX}_k, \tag{C1}$$

where g_{kt} is national cumulative employment growth in industry k from 1975 to year t. The instrument captures whether a worker's initial local industry mix was exposed to national growth in industries with high business-skill content. A parallel construction yields Z_{ict}^{SX} for specialized skills.

The validity of this approach requires that the initial industrial composition of a worker's county affects self-employment entry only through the skills accumulated through employment. Two concerns remain. First, local economic conditions may directly affect self-employment decisions. For example, limited wage opportunities may encourage workers to enter self-employment regardless of their accumulated skills. I therefore control for the county unemployment rate at labor market entry to absorb part of this channel. Second, workers may sort across counties based on entrepreneurial preferences. Using county of residence at labor market entry, rather than at the time of the self-employment decision, reduces this concern, and I restrict the sample to individuals who remain in the same county during the period used to construct the instrument.