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The role of Human Capital in preindustrial societies: Skills and Earnings in eighteenth-century Castile (Spain)

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THE ROLE OF HUMAN CAPITAL IN PRE-INDUSTRIAL SOCIETIES: SKILLS AND EARNINGS IN EIGHTEENTH-CENTURY CASTILE (SPAIN)*

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ABSTRACT

Using the Ensenada Cadastre, a unique database on Castilian households circa 1750, we measure the effect of human capital on the structure of male labor earnings. Human capital is proxied by individual indicators of basic skills (literacy and numeracy) and of occupational skills. We employ a Mincerian regression approach and find that, on average, workers with greater skills earned more than otherwise similar workers with lesser skills. This finding is robust to the inclusion of additional controls for age, household composition, job characteristics, and place of residence. Estimated returns were larger for urban than for rural workers and were strongly heterogeneous across activity sectors. The richness of our data set reveals that higher-skilled workers not only reaped positive rewards in their main jobs but also were more likely to diversify and increase their earnings through "by-employment". However, not all workers benefited to the same degree from increased human capital. Quantile regression analysis shows that earnings disparities between workers with different skills were much smaller at the lower than at the upper end of the earnings distribution. This evidence indicates that, in pre-industrial Castile, human capital contributed to earnings (and income) inequality.

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1. INTRODUCTION

At what stage of the economic development process did human capital begin to play a significant role? This is an open and widely discussed question in the economics literature. Much of the debate has focused on exploring the contribution of education to the Industrial Revolution. The modern literature on economic growth provides a formal framework in which that link can be explained (Nelson and Phelps, 1966; Galor and Moav, 2004; Galor, 2005), yet empirical findings remain controversial. Early evidence based on literacy rates concludes that human capital requirements were minimal at the first phases of the British Industrial Revolution (Sanderson, 1972; Schofield, 1973; Mitch, 1993; Allen, 2003; Clark, 2005; McCloskey, 2010). However, studies based on more accurate databases and on indicators of advanced skills (e.g., book production, presence of knowledge elites, schooling rates) suggest that human capital accumulation had a significant effect on the economic performance of Britain prior to 1800 (Mokyr, 2002; Baten and van Zanden, 2008; Mokyr, 2010; Mokyr and Voth, 2010), on the catch-up of technological follower nations (Becker et al. 2011), and on the divergence between countries in the North Sea region and those near the Mediterranean (van Zanden, 2009a; Pleijt and van Zanden, 2013; Fouquet and Broadberry, 2015). The recent contribution of Squicciarini and Voigtländer (2015) reconciles those findings. Using a rich data set for France, these authors show that—whereas average working skills raise the productivity for a given technology (i.e., in the cross section), it is upper-tail knowledge that fosters technological change and, hence, growth.

As the link between human capital and economic growth becomes better understood, there is increasing interest in the mechanisms through which human capital conditioned individual outcomes and behavior in pre-industrial societies. Exploring this connection would help us understand why some nations accumulated higher stocks of human capital than others. There is consistent evidence that, in contemporaneous economies, skills and formal education enhance the odds of individuals engaging in different types of jobs, increase the income returns to labor, and are a key component of the individual's living standard and quality of life (Hanushek and Woessman, 2008). But did such links exist in pre-industrial societies? Empirical research on this question is scarce and fragmented owing to the difficulty of finding data that combine, at the individual level, not only income (and/or other labor outcomes) but also human capital indicators. Moreover, the literature focuses mainly on Britain and the first follower nations; much less is known about the role

of human capital in regions that were latecomers to industrialization (one exception is Reis, 2004).

The prevailing view of the pre-industrial world is of one in which both the incomes and the private returns to skills were low (Clark, 2005), and where the use of basic skills, such as literacy, were more an indicator of hierarchy—deriving from wealth or occupational status—than an important input in the production process (Lane, 1996, Goldin and Katz, 1998; Mokyr, 2001). So in such a world, market signals did not motivate the acquisition of skills. Yet other authors (e.g., Reis, 2005) argue that an individual's ability to read, write, and count generated a utility stream even in rural contexts: such ability played a role in acquiring, consolidating, and signaling social status and also generated utility through its role in the *transactions technology* required of certain occupations. In the same vein, Nilsson, Pettersson, and Svensson (1999) find evidence of literacy's usefulness in farming and trading activities in Sweden. Numeric skills have been also associated with workers' productivity in agriculture (Tollnek and Baten, 2012) and in the naval sector (van Lottum and Poulsen, 2012; van Lottum and van Zanden 2014). Still other studies suggest that basic schooling eased the acquisition by textile workers of on-the-job skills (Bessen, 2000; 2012).

Our paper contributes to this literature by analyzing the relationship between different types of skills and workers' labor earnings in eighteenth-century Castile. The analysis is based on data from the Ensenada Cadastre, a unique database collected around 1750 that offers information on income sources, demographic characteristics, and occupations of Castilian household heads. Previous research on the relationship between human capital and earnings in pre-industrial Spain derives skill premia as the ratio of wages for skilled to unskilled work in certain occupations (mainly building craftsmen) and selected cities (e.g., Allen, 2001; Álvarez-Nogal and Prados de la Escosura, 2007; van Zanden, 2009b; Llopis and García-Montero, 2011; Andrés and Lanza, 2014). Although such empirical evidence is extremely useful for tracing long-run trends and establishing comparisons across countries, it yields few insights on the role of human capital in shaping individual earnings. Furthermore, the cited works provide no evidence on whether or not *other* types of skills (e.g., literacy and numeracy) had a differential effect on workers' earnings. To the best of our knowledge, this paper is the first to provide a micro-level analysis of earning returns—from different dimensions of human capital—in eighteenth-century Castile.

The Ensenada Cadastre has several advantages in comparison with other historical sources that make it especially suitable for our analysis. First, it offers information on signatures and ages reported by household heads that allows us to build indicators for their literacy and numeracy skills; in addition, we use reported occupational titles to classify workers into occupational skill levels by applying the HISCO/HISCLASS scheme (van Leeuwen, Maas, and Miles, 2002; van Leeuwen and Maas, 2011). Second, for each household head, the Ensenada Cadastre provides information on different sources of labor earnings; hence we can distinguish between earnings from a person's main job and earnings obtained through by-employment or subsidiary jobs. Earnings diversification through by-employment was common in proto-industrialized economies, and it was a path out of poverty for manyespecially rural—households (Shaw-Taylor, 2009; Saito, 2010). In settings characterized by such labor diversification, measuring the skill premium in terms of earnings from only the main job would underestimate human capital's true effects (Jollife, 1998; 2004). A third advantage of the Ensenada Cadastre is due to its census-like nature. We can therefore take a closer look at the heterogeneity of returns to skills in both rural and urban areas and also across all activity sectors. That approach will yield a more accurate picture of the role of human capital in Castilian pre-industrial society.

In this paper we make three main contributions. First, we use a sample of male workers and quantify the average returns to both basic and occupational skills via a Mincerian approach (Mincer, 1974). The results support our hypothesis that better skills increased workers' total earnings. We document this positive link for occupational skills in both rural and urban areas as well as for literacy and numeracy in urban areas. Although we cannot assess causality in the relationship, our rich information data set makes it possible to show the robustness of this association to the inclusion of explanatory variables not incorporated in the previous literature.

Second, we explore the pathways through which skills affect earnings. In line with studies of contemporaneous developing economies, we find that better-qualified workers achieved higher earnings in their main jobs—and were also more likely to engage in by-employment—than were less qualified workers. This result indicates that, even in pre-industrial societies, human capital enhanced an individual's ability to accommodate change, to engage in different types of work, and to improve resource allocation (Nelson and

Phelps, 1966; Welch, 1970). In our sample, however, the relevance of these two pathways is clearer for urban than for rural workers.

Our third contribution is to analyze whether there is significant variation in returns to basic and occupational skills for workers located in different parts of the earnings distribution. Using unconditional quantile regression (Firpo, Fortin, and Lemieux, 2009), we find that better-off workers obtain greater rewards from both basic and occupation-specific skills than do workers at the bottom of the earnings distribution. That is, skills not only exhibited a pure "location shift" effect on workers' earnings but also increased earnings dispersion and therefore earnings inequality. The latter effect is relevant to our study because research has shown labor income inequality to be the second leading contributor (after inequality in land yields) to household income inequality in Castile—especially in urban locations (Nicolini and Ramos Palencia, 2015). Hence our findings support the literature that views human capital formation as a driver of income inequality in pre-industrial societies (Williamson, 1985; van Zanden, 1995; 2009b).

The paper proceeds as follows. Section 2 briefly reviews the historical and economic context of mid-eighteenth-century Castile. In Section 3, we describe the Ensenada Cadastre's main features, our sample selection, and the procedures used to build the main variables needed for our descriptive analysis. Section 4 presents the empirical model. In Section 5 we estimate the returns to skills for average rural and urban workers; we also assess the heterogeneity of returns across activity sectors and identify the earnings components through which skills affect earnings. In Section 6, we apply unconditional quantile regression to analyze the heterogeneity of skill effects across the entire earnings distribution. Section 7 concludes.

2. HISTORICAL CONTEXT

Eighteenth-century Spain was a stagnant and backward economy in Western Europe (Álvarez-Nogal and Prados de la Escosura, 2007; 2013). The dualistic economic model configured during the seventeenth century favored the coastal areas (the northern coast, Catalonia, and Valencia) and Madrid to the detriment of the old Crown of Castile (Yun, 2004). This center–periphery division favored an increasing urbanization in the coastal provinces and Madrid as well as a progressive de-urbanization in the interior, trends that extended from 1700 to 1900 (Grafe, 2012, p. 215). According to Reher (1990, pp. 37–43),

only 6.6% of the population in North Castile lived in urban locations whereas, in Central Castile (including Madrid), the urbanization rate reached 26.6%—that is, higher than the 25% urbanization rate overall for Spain.

The former Crown of Castile was, in essence, an agricultural society. So in 1750, the primary sector accounted for 58.2% of Castilian income while the secondary (manufacturing) and tertiary (service) sectors contributed 12.3% and 29.5%, respectively (Grupo 75, 1977, p. 169). More than 80% of land was devoted to the cultivation of cereals (Llopis, 2002, p. 128), and there were noticeable north—south differences in landownership patterns. The south (current Castile La Mancha, Extremadura, Murcia, and Andalusia) was characterized by large properties, a significant amount of landless day laborers, high seasonal unemployment, and very low wages. In the north (current Castile and León), most land property consisted of low-productive small farms whose size made them unprofitable (Herr, 1988, p. 82; Ruiz, 2008, p. 293). During this period, increasing food prices and a tax system weighted unfairly against small landowners further eroded peasants' real wages, pushing many of them to engage in proto-industrial manufacturing activities for subsistence (Yun, 1987; Ramos Palencia, 2010).

Textile activities were, by far, the most important source of employment in the secondary sector. More than half the workers not engaged in agricultural activities participated in the textile sector; a quarter of them worked in construction and the rest had different professions, among which the metal sector was prominent (Ruiz, 2008, p. 291). The picture that emerges is that of Castile as a locally oriented manufacturing system in which rural industries producing low-skill manufactures co-existed with craft guilds production and with some factories producing both textiles and pottery.

The Castilian crisis in the seventeenth century had a negative effect on labor force quality because the emphasis on education declined. Spanish literacy rates evolved from levels similar to those of France and England in the sixteenth century and in the first third of the seventeenth century to a period of stagnation during 1620–1640 and 1730–1740, when they lagged Spain's relative position in terms of overall human capital (Bennassar, 1985). The collapse of rural primary schools, which followed declines in municipal resources, had dramatic effects on the population's reading and writing skills. According to Amalric (1987), by the mid-eighteenth century a mere 22% of locations in northern Castile had a

teacher or were within reach of a school. In all the other towns and villages, it was practically impossible to acquire reading and writing skills. Estimates based on signatures suggest total literacy rates of 20%–30% by the mid-eighteenth century (Soubeyroux, 1985, p. 165; Allen, 2003, p. 415), as compared with 40%–60% for England. Numeracy indicators based on "age heaping" (A'Hearn, Baten, and Crayen, 2009, p. 801; Tollnek and Baten 2012) report similar conclusions. Although the literacy rate rose starting in 1740 and until the Napoleonic Wars, the education gap between Spain and other Western European countries (England, the Netherlands, France, and Germany) remained and then extended into the eighteenth century and onward.¹

The Castilian crisis resulted also in a decline of incentives to incorporate technological advances and thus in a lack of stimulus to upgrade workers' occupational skills. In the textile industry, foreign fabrics displaced domestic production of fine cloth. That development forced local artisans into weaving common textiles, which had two ill effects: first, it lowered Spain's standing with respect to other nations in Northern and Western Europe; second, it reduced the average level of transferable skills (La Force, 1964b). Castile remained competitive in woolens but not in manufactures (García Sanz, 1994). In cities, craft guilds regulated entry to certain occupations as well as the promotion from apprentice to journeyman and master. For example, the ordinances of the textile Guild of La Puebla in Palencia required—to become a craft master—four years of apprenticeship, one year as a journeyman, and the creation of a masterpiece that proved the candidate's skill and dexterity. It is possible that neither literacy nor numeracy figured prominently in this process, since most working skills were learned orally and by direct observation.

Perhaps the most salient initiative to make technological improvements in Castilian domestic industry was the creation of Royal Factories, which were devoted mainly to producing fine textiles with imported technology and skills (La Force, 1964a; 1964b). After the War of Spanish Succession, the Bourbons promoted these publicly funded factories to reduce Spain's dependence on foreign imports and to facilitate the diffusion of technology in the regions where these factories were located. For the most part, Castilian artisans rejected the new sophisticated methods. Craft guilds opposed to interference from foreign artisans could force them, even the high-qualified craftsmen, to undergo a training process

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¹ In 1860, when the first census to include literacy information was collected, Spain was far behind the vast majority of European countries (Tortella, 1994); at that time, three fourths of all Spaniards were illiterate.

before receiving permission to open a workshop or could impose high fees for being admitted to the guild. Such resistance—when combined with the inexperience of managers, the low demand for fine textiles, and the competition from more advanced countries (e.g., France and England)—hindered the diffusion of new textile technologies outside the Royal Factories.

3. DATA

3.1. The Cadastre of Ensenada

In 1746, the King Fernando VI ordered the assessment of a fiscal reform in the Crown of Castile that replaced the complex collection of various taxes by a direct single tax (contribución única) on income. This reform entailed eliminating the current exemptions for ecclesiastical institutions and the aristocracy.² Implementation of the new tax system required officials to make a full record of the properties and sources of personal income in all the cities, towns, and villages of Castile. Between 1750 and 1756, more than 1,000 judges, 6,000 assistants, and 90,000 experts collected information from all the properties—urban and rural—and sources of personal income of about 7 million people in the 22 Castilian provinces (Camarero, 1999). This census is known as the Ensenada Cadastre (or EC).

For each location, the census is organized into two data sources: Respuestas Generales and Respuestas Particulares.³ The book of Respuestas Generales offers aggregated information on the sociodemographic and economic structure of the corresponding town/city. The Respuestas Particulares comprises several documents that gather information at the household level. The Memoriales collects the original statements drafted by household heads on their properties (land, livestock, buildings, etc.) and earnings sources; these statements also provide information on household composition (servants, employees, apprentices, etc.). Each statement had to be signed by the head of household or by another person if the former was illiterate. Once the information had been checked and, if needed, corrected by supervisors, it was compiled (separately for the clergy and lay households) into two different books: (i) the Household Heads Books (Libros de Cabeza de Familia), which included

² Although Fernando VI approved the single tax in 1757, the downfall of La Ensenada—due to pressures from the British and the anglophile lobby of the Spanish Court in 1754 as well as to opposition from those who stood to lose their fiscal privileges—caused the tax reform impulse to wither away (Ruiz, 2008, pp. 280–85).

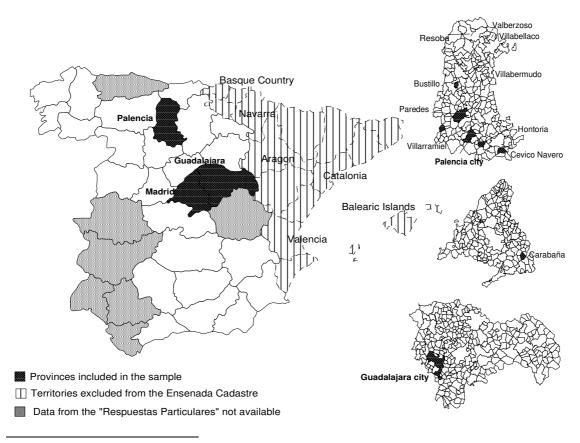
³ This name was suggested by Matilla (1947) as a counterpart to the Respuestas Generales.

the name of the family head and all members who live in the same house (spouse, children, relatives, servants, and/or apprentices) along with their respective ages and professions; and (ii) the *Finance Books (Libros de Hacienda)*, which contain the annual gross income from rural and non-rural properties, livestock, entrepreneurial activities, and labor.⁴ There is no longer any record of the *Respuestas Particulares* for eight provinces (about 23% of Castilian households) (see Map 1). The EC is nonetheless considered, within Spanish historiography, as one of the higher-quality sources of data on the eighteenth century.

3.2. Sample selection

Our analysis is based on a sample of twelve Castilian locations from three provinces of north and central Castile: Guadalajara, Madrid and Palencia. See Map 1. Table A in the Appendix reports the total population (including clergy) of these locations, distance to the nearest city, and the predominant economic activity. The sample's composition is heterogeneous in terms of local economy and individuals' socioeconomic conditions.

MAP 1 NORTHERN CENTRAL SPAIN (PALENCIA, MADRID, AND GUADALAJARA), c. 1750



⁴ Measures were taken to prevent fraud, with public readings of the findings at each locality. Intendants from other provinces were called when the local intendants were not trustworthy. To detect implementation errors, test inquiries were held in one locality within each province. See Camarero (1999, pp. 7–33).

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The two urban locations⁵ included in our sample, Palencia and Guadalajara, were important textile-producing locations that differed significantly in how they organized production. In Palencia, production was based on a craft guilds system that regulated industries and trades; wool and linen were the most important textile products. Larruga (1787)—chronicler and Spanish politician—described Palencia as "the most industrious province of Castile". Guadalajara City was heralded as a leading manufacturing center of Spain's enlightenment thanks to the Royal Factory, a company created by the State in 1719 and financed by the Treasury. This textile factory incorporated looms, hammers, wool laundry, and fabric dying and it operated outside the guild network (La Force, 1964a). The factory provided employment (directly or indirectly) to nearly three fourths of the local population. Guadalajara Royal Factory produced the high-quality woolen cloth demanded by the Court and regularly destined for royal cavalrymen, the king's guard, and royal servants. However, these products "competed poorly with the cheaper, lighter and more colorful [fabrics] from mixtures of silk, wool, cotton, and flax manufactured in England" (La Force, 1964b).

The sampled rural locations can be organized into two groups according to the predominant economic activity. The first group includes two villages (Villarramiel and Villabermudo) with proto-industrial economies consisting of artisan households devoted to home production of rough fabrics (textiles) combined with agrarian and commerce activities. Villarramiel was an important rural trading network for textiles that even exported manufactured woolen and leather goods to Portugal and Spanish America. In contrast, Villabermudo was a small mountain village that focused on trading goods from its local cheap textile industry. The second group of rural locations subsisted mostly on agricultural, livestock, and/or forestry activities. This group includes small agricultural towns of fewer than 100 inhabitants in mountain areas (e.g., Villabellaco, Resoba) and also medium-sized towns such as Paredes de Nava, which has about 3,400 inhabitants and is located near Palencia City.

Data were hand-collected from the Respuestas Particulares. They include information on the 5,278 households that composed the census of the selected locations. Because the planned tax reform intended to exempt female-headed households and households headed by individuals aged more than 60, in some locations the EC intendants did not collect

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⁵ Following Vries (1984), Reher (1990), Malanima (2009), and Álvarez-Nogal and Prados de la Escosura (2013), we classify as "urban" those towns with at least 5,000 inhabitants.

complete information on the labor earnings from those households. We therefore confine our analysis to male household heads between the ages of 18 and 59. Our data set *excluded* individuals with no known occupation, paupers reporting zero income, and disabled people who did not state an occupation; we also excluded rentiers (*Hacendados*) because they do not report a specific occupation. After applying these restrictions, the final sample amounts to 3,657 male household heads for whom we observe age, main occupation, household composition, and income (including sources).

3.3. Earnings measures

The Ensenada Cadastre provides detailed information on the sources and amounts of annual household income. These sources can be organized (Nicolini and Ramos Palencia, 2015) into the following categories: a) income derived from buildings and non-land properties (e.g., houses and mills in the countryside); b) income derived from land; c) income from livestock; d) net rents from credit operations, financial assets, and so forth; and e) labor earnings.

The analysis is restricted to annual labor earnings of household heads. In our sample, this income source accounts for almost 88% (on average) of the total household head's income and constitutes the *only* source of income for nearly 54% of our sample households. An advantage of the EC is that it allows us to identify two labor earnings components. The first of these is earnings from the household head's main job, which we compute as follows. For wage earners (or, more generally, workers who work on a daily pay scheme), the Ensenada Cadastre reports a measurement of potential annual earnings by multiplying daily earnings and the number of working days per year. Daily earnings vary according to occupation, category (master, journeyman, or apprentice), and place of residence. With regard to working days, the Ensenada Cadastre imputes 120 days annually to agricultural laborers, 180 days to workers in secondary and tertiary sectors, and 250 to servants. For other occupational groups—including commerce workers, professionals (e.g., notaries, surgeons), and other self-employed workers (e.g., butchers, innkeepers, mule drivers)—the Ensenada Cadastre collects the gross profits generated by their respective professional activities.

The second component consists of annual earnings due to by-employment; such earnings derive from commerce or trade, farming on rented land, and other by-occupations. As in

other proto-industrial economies (see e.g. Shaw-Taylor, 2009; Saito, 2010; Keibek and Shaw-Taylor, 2013), labor diversification was a livelihood strategy that allowed Castilian households (especially in rural areas) to reduce seasonal and inter-annual consumption risks. Where such diversification occurs, estimating the human capital premium based solely on income from the individual's main job will understate the value of human capital to those who are engaged in several income-earning activities (Jolliffe, 1998; 2004). Our analysis will therefore focus on total earnings as the *sum* of earnings from a main job and complementary earnings from by-employment, although we also examine the differential effects of human capital indicators on each of these two earnings components.

3.4. Human capital indicators

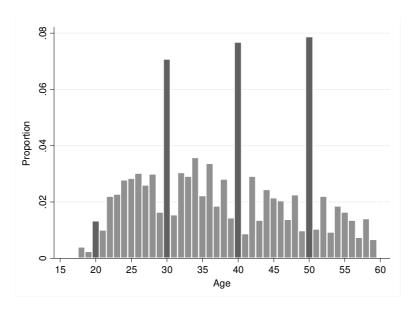
We consider two dimensions of human capital: basic skills (measured through indicators of literacy and numeracy) and occupational skills acquired through on-the-job training. Household heads' literacy is proxied by their ability to sign the Cadastre statement (i.e., rather than delegation of signing to a third person). Although the ability to sign may reflect no more than wealth or hierarchical position, some authors argue against the likelihood that, in pre-industrial societies, those who signed could neither read nor write (Schofield, 1968; 1973). This indicator has the additional advantage of being easily comparable across time and space (see Reis, 2005, for further discussion).

Numeracy, or the ability to count, is proxied by the accuracy of age reporting. The tendency to "heap" age at certain numbers—often a multiple of 5—suggests low numeracy skill, which is a widely used indicator of human capital in the economic history literature (A'Hearn et al. 2009; Crayen and Baten, 2010; Hippe and Baten, 2012). In our sample, men exhibit a pattern of age heaping at numbers ending in 0 but not in 5 (see Figure 1).⁶ For that reason, in the empirical analysis we view reporting an age *not* ending in 0 as indicative of numeracy. Nonetheless, in the descriptive analysis we also account for levels of numeracy that are based on age heaping at numbers ending in 5.

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⁶ About 9.2% of individuals in our sample report ages ending in 5. This is the expected frequency in a population *without* heaping in ages ending in five. In contrast, 27.5% of those in our sample report ages ending in 0, which exceeds by far the natural frequency of such ages in a population without heaping at those multiples.

FIGURE 1
AGE-HEAPING PATTERN IN THE SAMPLE



Note: The figure plots the proportion of individuals in our sample reporting each age. *Source:* Authors' calculations from the Ensenada Cadastre, circa 1750. Sample of 3,657 male household heads between 18 and 59 years of age.

Occupational skills are assigned according to the HISCO/HISCLASS classification scheme documented by van Leeuwen et al. (2002) and van Leeuwen and Maas (2011). To apply this scheme, we first matched each of more than a hundred occupations in our database to a 5-digit code from HISCO via the mapping available on its website. Next, we used the HISCLASS scheme to map occupations into the skill level required to perform it: unskilled, low, medium, or high. These levels are based on the general educational development and specific vocational training required by each occupation. An unskilled occupation requires no more than 30 days of training, so this category includes day laborers, farm helpers, and street vendors. Low-skill occupations require from a month to a year of training; professions such as quarryman, knitter, cloth weaver, and concierge are included in this category. Medium-skill occupations require from one to ten years of training; examples include cooper, bread baker, plumber, and potter. Finally, high-skill occupations are defined as those requiring more than ten years of training. In this category we consider, among others, lawyers, physicians, and general managers.

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⁷ See http://historyofwork.issg.nl/

Farmers (*labradores*) are an important yet heterogeneous occupational category that includes farmers without land, farmers with semi-subsistence small landholdings, and farmers with larger landholdings. According to the HISCLASS categories, general farmers are medium-skilled workers whereas small-subsistence farmers are low-skilled workers. To distinguish between these two categories, we employ complementary information (from the Ensenada Cadastre) on land property yields and net profits from hired land. We classify farmers as semi-subsistence if their net profit from own or hired land is no more than 500 reales annually. This threshold corresponds to the estimated subsistence level for an average four-member family. Then we classify as medium-skilled those farmers who work either own or hired lands for which the net yields *exceed* that level. Only 9% of general farmers fall into this latter category.

Finally, we follow van Leeuwen and Maas (2011) in applying some further corrections to account for the career status of workers as master, journeyman, or apprentice. More specifically: if an occupation is classified as low-skilled but the household head is labeled as a master, then he is "promoted" to a medium skill level. Apprentices are downgraded one skill level vis-à-vis the level corresponding to their respective occupations.

3.5. Descriptive overview

Table 1 reports the composition of rural and urban subsamples, in terms of human capital indicators, while conditioning on sector of activity. We classified household heads as being workers in either the primary, secondary, or tertiary sectors in accordance with their reported main jobs and with reference to the Cambridge group's PST system (Wrigley, 2005). Given the importance of textile activities in Castile, the secondary sector is further split into textile production and other secondary activities, which include construction and other manufactures. Literacy is measured as the percentage of men in our sample who

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⁸ For each household head, the EC intendants imputed gross annual income from land with reference to land area and quality as well as to the type of crop cultivated (Matilla, 1947, pp. 77–86; Camarero, 2004). In the case of hired land, the rent payed to the landowner was discounted.

⁹ Yun (1987, pp. 463–64) estimates a net income of 300 reales as the minimum subsistence level for a family of 3½ members. Donézar (1996, pp. 338–41) calculates 500 net reales to secure a minimum subsistence for a peasant *and* his family. Since the EC offers information on gross annual income from land, we apply a 50% discount rate to convert it into net income (and thus follow Matilla, 1947, p. 109; Grupo 75, 1977, p. 173). So to classify a landowner farmer as medium-skilled, his gross profits from land must exceed 1,000 reales.

¹⁰ It is important to remark that the picture we obtain corresponds to the human capital map not for the whole male population of sampled locations but only for the heads of households. In fact, we expect these rates of literacy and skilled population to be biased upward with respect to those for the total male population because our sample includes neither servants (who do not have their own household) nor household heads more than 60 years old.

signed the Cadastre statements. For numeracy, we report two indicators. To facilitate comparisons with other studies, we first provide the ABCC Index¹¹ proposed by A'Hearn et al. (2009). This index ranges between 0 and 100 and estimates the percentage of individuals who report their age correctly—that is, without heaping at age numbers ending in 0 or 5. We follow the convention of many other studies and compute this index for men aged 23 to 62 years. Our second indicator for numeracy is the percentage of household heads who reported ages ending in 0. As explained previously, our data reveal a clear pattern of age heaping at ages ending in 0 but not in 5 (see Figure 1). Hence, our individual indicator of numeracy distinguishes between individuals who report an age ending in 0 and individuals reporting other ages.

TABLE 1
BASIC AND OCCUPATIONAL SKILLS BY ACTIVITY SECTOR

| Basic skills | | | | Occupational skills | | | | |
|-------------------|-----------|------------|------------------------|-----------------------|------------------------|---------------------------|-------------------------|-------|
| Activity sector | Signature | ABCC index | Age not ending in zero | Un- skilled (%) | Low- skilled (%) | Medium- skilled (%) | High- skilled (%) | N |
| Rural | | | | | | | | |
| Primary | 39.7% | 78.4 | 74.3% | 55.6 | 34.3 | 10.1 | 0.0 | 834 |
| Secondary | 52.8% | 80.9 | 74.8% | 1.0 | 64.7 | 34.3 | 0.0 | 286 |
| Textile | 54.7% | 84.3 | 78.2% | 1.7 | 94.4 | 3.9 | 0.0 | 179 |
| Other | 49.5% | 75.7 | 69.2% | 0.0 | 14.9 | 85.1 | 0.0 | 107 |
| Tertiary | 75.6% | 85.2 | 84.9% | 1.2 | 44.2 | 22.1 | 32.5 | 86 |
| All rural workers | 45.4% | 80.5 | 75.2% | 38.8 | 42.2 | 16.7 | 2.3 | 1,206 |
| Urban | | | | | | | | |
| Primary | 23.7% | 79.6 | 75.0% | 81.0 | 13.5 | 5.5 | 0.0 | 695 |
| Secondary | 47.3% | 76.2 | 74.3% | 26.7 | 38.0 | 35.3 | 0.0 | 1,415 |
| Textile | 43.2% | 74.9 | 73.4% | 43.5 | 40.0 | 16.5 | 0.0 | 850 |
| Other | 53.6% | 78.0 | 75.7% | 1.4 | 35.0 | 63.6 | 0.0 | 565 |
| Tertiary | 83.0% | 85.8 | 80.0% | 4.4 | 21.7 | 30.5 | 43.4 | 341 |
| All urban workers | 45.6% | 79.7 | 75.3% | 39.0 | 28.8 | 26.1 | 6.0 | 2,451 |
| Total Sample | 45.5% | 80.0 | 75.3% | 39.5 | 34.5 | 21.2 | 4.8 | 3,657 |

Notes: For the sake of comparison with other studies, the ABCC index has been computed for male household heads aged between 23 and 62 years. The classification of workers into primary, secondary, and tertiary activities follows the Cambridge group's PST system (Wrigley, 2005); levels of occupational skills were assigned following the HISCO/HISCLAS scheme.

Source: Authors' calculations from the Ensenada Cadastre sample of male household heads between 18 and 59 years of age. The sampled urban locations are Palencia City and Guadalajara City; sampled rural locations include Villarramiel, Paredes de Nava, Carabaña, Cevico Navero, Hontoria, and three mountain villages (Resoba, Valberzoso, and Villabellaco).

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¹¹ The ABCC index is a version of the Whipple Index, $WI = [(n_{25} + n_{30} + \dots + n_{60})/(\frac{1}{5} \times \sum_{i=23}^{62} n_i)] \times 100$, where n_i denotes the number of individuals whose age equals i. The formula is: ABCC = $[1-(WI-100)/400] \times 100$. The index ranges from 0 (lowest level of numeracy) to 100 (highest level).

Just over 45% of the men in our sample are classified as literate (last row of Table 1), with negligible differences between rural and urban workers. That level of literacy is consistent with other estimates for the second half of the eighteenth century in Spain (e.g., Soubeyroux, 1985). This rate also does not differ significantly from the male rates in other European regions during the same period, such as southern France or Parma, Italy, although it lies below the literacy levels in England, Holland, and Germany. With regard to numeracy, the ABCC index for our sample is near 80; this is lower than the index for Denmark (90), the United Kingdom (93), and France (89) but is similar to the index for Austria and Belgium (see A'Hearn et al., 2009).

The highest literacy rates correspond to workers in the tertiary sectors, with percentages of 75.6% and 83% in rural and urban locations (respectively), followed by workers in the secondary sector and then those in the primary sector. There is a sizable gap in literacy rates between tertiary- and primary-sector workers: about 36 (resp. 49) percentage points among rural (resp. urban) workers. Numeracy also is most prevalent among tertiary-sector workers. When conditioning on sectors, we observe important differences in basic skill levels between rural and urban workers. In the primary and secondary sectors, basic skills were more widespread in rural locations than in cities. In the primary sector, for example, workers' literacy in rural locations (39.7%) is significantly higher than the rate for urban workers (23.7%). Textile workers in towns and villages were likewise more literate and numerate than in cities. This result is not surprising when one considers that rural workers engaged in proto-industrial textile production and were frequently involved in trading home-produced goods, which required these basic competencies. That being said, the difference runs in the opposite direction for workers in other secondary sectors and for workers engaged in tertiary activities.

Table 1 also classifies men according to their occupational skill level. As workers, 39.5% of men in our sample are considered to be unskilled, 34.5% are low skilled, 21.2% are medium skilled, and 4.8% are high skilled. Pleijt and Weisdorf (2016) apply the same HISCO/HICLASS scheme and find that, in the period 1750–1799, about 59% of English

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¹² Using a wide range of notarial documents from different Castilian locations, Soubeyroux (1985) finds that about 32% of men were able to sign by 1750–1759 and 44% by 1787–1805. According to Reis (2005, p. 202), male literacy rates were 44% in southern France, 45% in Parma (Italy), and 73% in Holland. Schofield (1973) reports a literacy rate of 64% for England.

¹³ We compare our results with the ABCC values reported by A'Hearn et al. (2009) for individuals who were born during the period 1675–1724.

workers were either unskilled or low skilled—a percentage far below the 74% for our Castilian sample.

Urban workers in our sample are, on average, more qualified than their rural counterparts: 32% of them are medium- or high-skilled workers, compared with 19% in rural villages. A common finding for both rural and urban locations is the presence of larger shares of skilled workers in tertiary-sector activities than in other sectors. However, the skill composition of the primary and secondary sectors is more heterogeneous. The high prevalence of "day laborer" and "farm helper" as occupational titles of urban workers explains the larger share of unskilled workers in the primary sector (81%) and in textile production (43.5%) than observed at rural locations. In the sampled rural villages, semi-subsistence farmers are an important part of the agricultural workforce; their proto-industrial textile activities (which have low training requirements) help to balance the number of unskilled and low-skilled workers in the primary and secondary sectors.

100% 81.8% 77,3% 77,3% 71,6% 61.9% 60% 52,1% 40% 23.9% 20% 0% Unskilled Low skilled Medium skilled High skilled ■ Literacy (% signatures) ■ Numeracy (% reporting non-zero ended age)

FIGURE 2
BASIC SKILLS BY OCCUPATIONAL SKILL LEVELS

Note: This graph displays the percentage of men in our sample who are classified as literate and numerate within each occupational skill level (unskilled, low, medium, or high). Occupational skills are based on the HISCO/HISCLASS classification scheme presented by van Leeuwen et al. (2002) and van Leeuwen and Maas (2011).

Source: Authors's calculations from the Ensenada Cadastre, circa 1750. Sample of 3,657 male household heads between 18 and 59 years of age.

An interesting aspect that emerges from our data is that workers with higher occupational skills had, on average, higher literacy and numeracy indicators (see Figure 2). The percentage of men who could sign their names ranges from 23.9% for household heads with unskilled occupations to 52% for low-skilled workers, 62% for the medium skilled,

and 99.4% for workers in high-skilled occupations. Similarly, the percentage of men who did *not* report an age ending in 0 ranges between 71.6% for unskilled workers and 81.8% for high-skilled workers. This high correlation between basic competencies and occupational skills underscores the importance of controlling for both types of human capital when measuring their individual effects on workers' earnings.

TABLE 2

LABOR EARNINGS BY ACTIVITY SECTOR

| | Earnings from | | Total labor (in rea | | | |
|-----------------|----------------------|--------|------------------------|--------|-------------------|-------|
| Activity sector | Mean (S.D.) | Median | Mean (S.D.) | Median | By- employment | N |
| Rural | | | | | | |
| Primary | 535.62 (292.12) | 480 | 583.54 (360.03) | 480 | 15.46% | 834 |
| Secondary | 656.30 (268.60) | 540 | 869.43 (563.59) | 800 | 54.19% | 286 |
| Tertiary | 1291.13 (1185.26) | 900 | 1496.95 (1357.95) | 1,070 | 23.25% | 86 |
| Total rural | 618.11 (461.01) | 480 | 716.47 (596.71) | 500 | 25.21% | 1,206 |
| Urban | | | | | | |
| Primary | 522.34 (748.71) | 420 | 531.15 (522.34) | 420 | 1.01% | 695 |
| Secondary | 638.59 (474.80) | 540 | 762.22 (721.80) | 540 | 21.06% | 1,415 |
| Tertiary | 2076.84 (2470.01) | 1,100 | 2258.62 (2719.60) | 1,460 | 9.38% | 341 |
| Total urban | 805.73 (1179.93) | 540 | 904.89 (1338.78) | 540 | 13.75% | 2,451 |
| Total Sample | 743.86 (1005.40) | 492 | 842.75 (1151.65) | | | 3,657 |

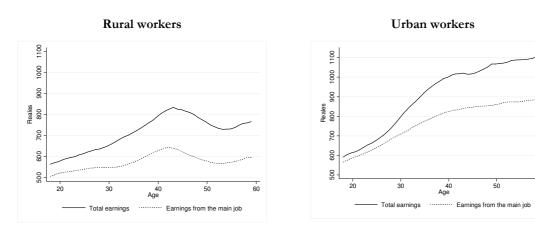
Source: Authors' calculations from the Ensenada Cadastre sample of male household heads between 18 and 59 years of age. The sampled urban locations are Palencia City and Guadalajara City; sampled rural locations include Villarramiel, Paredes de Nava, Carabaña, Cevico Navero, Hontoria, and three mountain villages (Resoba, Valberzoso, and Villabellaco).

Table 2 offers a descriptive overview of male labor earnings in our sample. We distinguish between earnings from the main job and total labor earnings, where the difference between these two measures is earnings from by-employment. The prevalence of this labor diversification strategy is also evident from the table. Two salient features of these data are the wide dispersion of earnings across and within sectors and the low standard of living of some Castilian population subgroups. Workers in tertiary activities were by far the best remunerated in their main jobs, with median earnings of 900 and 1,100 reales in rural and

urban locations, respectively. Workers in the primary sector had the lowest median remuneration, 420–480 reales, which barely reached the subsistence level for a four-member family (see footnote 12).

By-employment was more frequent in rural villages (25%) than in cities (13.7%). Although workers flowed both ways between sectors, secondary-sector workers were the most likely (54.2% in rural villages) to seek by-employment and primary-sector workers were the least likely to do so. ¹⁴ Subsidiary jobs for manufacturers consisted mainly of agricultural activities and trafficking in home-produced goods. On average, by-employment adds about 100 reales of annual earnings, which barely moves the median of main job earnings. Yet it is notable that, for rural manufacturers and workers in the urban tertiary sector, by-employment increased average annual earnings by 200 reales.

FIGURE 3
NON-PARAMETRIC ESTIMATES OF AGE—EARNINGS PROFILES



Note: These graphs plot kernel-weighted local polynomial smoothing of log earnings as a function of age. Source: Authors's calculations from the Ensenada Cadastre, circa 1750. Sample of male household heads between 18 and 59 years of age. The rural subsample consists of 1,206 men from the following villages: Bustillo, Carabaña, Cevico Navero, Hontoria, Paredes de Nava, Resoba, Valberzoso, Villabellaco, Villabermudo, and Villarramiel; the urban subsample includes 2,451 men from Palencia City and Guadalajara City.

Figure 3 plots the age-earnings profiles in our sample. We observe an increasing pattern of earnings at the main job from age 18 to age 40, which is consistent with continuous on-the-

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¹⁴ For agricultural workers, we have modified the earnings structure presented in the Cadastre. We consider net profits from hired land as part of earnings from the main job—and not as a component of earnings from by-employment (the classification used for other workers). This correction ensures that, for agricultural workers, earnings from the main job account for earnings from the on-farm job while earnings from by-employment arise from off-farm labor.

job training for workers up to that age. For rural workers, the decreasing profile from age 40 onward may reflect the reduced productivity—in what is predominantly agricultural employment—resulting from lower levels of physical strength and health. For urban workers, earnings at older ages do not decline but they do increase at a lower rate. Note that this pattern resembles the age—earnings profiles seen in contemporaneous economies (Heckman et al., 2006). This figure also illustrates the increasing gap, with age, between earnings from the main job and total earnings; that trend reflects the growing relevance of earnings from by-employment at older ages. We remark that these complementary earning sources help smooth the decline in earnings from the main job at those ages.

4. EMPIRICAL MODEL

The usual way of measuring returns to human capital is the Mincer equation (Mincer, 1974). In its original formulation, this model assumes that schooling is the main source of human capital or skill differentials. That assumption does not hold in pre-industrial societies, where wide segments of the population had no access to formal education and where skills derived mainly from on-the-job training. Here we shall adopt the conceptual framework proposed by Hanushek et al. (2015). In particular, we specify a Mincer-type earnings equation that accounts for human capital via measured skills instead of schooling; thus,

$$\ln Y_i = \beta_0 + S_i' \beta_1 + \beta_2 E_i + \beta_3 E_i^2 + X_i' \beta_4 + u_i.$$
 (1)

Here Y_i denotes the annual earnings of individual i, for whom S_i is the vector of skill indicators; E_i is years of experience or seniority and is proxied by the individual's age; the term X_i is a vector, which includes a set of observable factors (other than skills and age) that explain individual earnings; and u_i is the error term. We consider three types of skills. Literacy is measured through a dummy variable that takes the value 1 if the individual is able to sign (and value 0 otherwise), and numeracy is proxied by an indicator variable set equal to 1 only if reported age does *not* end in 0. Occupational skills are measured using a set of dummy variables that classify individuals into three categories: unskilled workers, low-skilled workers, or medium/high-skilled workers. The parameter vector β_1 is the earnings gradient associated with these skills. Although we use the phrase "returns to skills", our estimates do not measure the *internal* rate of return to skills because that would require accounting for the cost of acquiring those skills.

In our sample, the percentage of urban workers (67%) far exceeds the urbanization rate in eighteenth-century Castile.¹⁵ To the extent that skills were remunerated differently in urban versus rural areas—as suggested by several authors (Vries and van der Woude, 1997; Clark, 2005, p. 1316)—using the pooled sample to estimate the earnings equation could result in misleading conclusions about the average effects of skills. We therefore estimate model (1) separately for urban and rural workers.

Before presenting the results, we should discuss some issues relevant to the interpretation of our estimates. Since the dependent variable in these regressions is total labor earnings, it follows that returns to skills should capture two overlapping effects: on productivity and on access to complementary earning sources. A key concern here is the extent to which earnings reported in the Cadastre reflect the labor productivity of household heads. The literature identifies different sets of influences in the fixing of wages that need not be related to workers' productivity; examples of such influences include the payment of efficiency wages, institutional constraints on the wage-setting process or requirements to observe seniority, and notions of justice regarding what a worker under certain personal circumstances (e.g., with family responsibilities) "should" earn (Huberman, 1996; Rosés, 1998; Reis, 2005). The method used by EC intendants to register earnings from the main occupation involved a mixture of market-based and institutionally assessed productivity, so the Cadastre provides an estimate of potential earnings rather than actual earnings. This reduces the likelihood that earnings reflect payment of efficiency wages. Furthermore, the average age-earnings profiles shown in Figure 3 support neither that hypothesis nor any positive consequences of seniority, since earnings decline at older ages (along with health and productivity). Furthermore, the inclusion of age and other additional variables—such as family composition, job characteristics, and controls for locations as explanatory variables (vector X_i in the model)—enables our estimates to account for these possible confounds.

Even so, there are sources of unobserved heterogeneity for which we cannot control and that may therefore bias our estimates. One possible drawback often discussed is that individuals with greater *unobserved* skills (e.g., innate ability) are more likely to acquire human capital and to obtain higher earnings. This likelihood would bias upward the estimated

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¹⁵ See Section 2.

effect of human capital. Another potential problem is reverse causality. Since information on basic competencies (e.g., literacy and numeracy) is contemporaneous with measures of individual earnings, it may be that the causal link runs in the opposite direction. In other words, individuals in highly remunerated jobs might tend to improve these basic skills; conversely, individuals in poorly remunerated jobs that do not require literacy and numeracy may lose those skills (if they had been previously acquired). The third problem is related to measurement errors associated with our indicators of human capital, especially in the case of basic skills, which would exert a downward bias on their estimated effects. In applications involving contemporaneous data sets, these issues are addressed by adding measures that proxy for unobserved ability (for instance, family background variables are used by Card, 1999) or by using instrumental variables—neither of which is possible with our data set. These limitations preclude us from deriving causal interpretations of the estimated effects presented next.

5. RESULTS

5.1. Average returns to skills

Table 3 presents ordinary least-squares (OLS) estimates of coefficients for the age terms and skill indicators corresponding to different specifications of model (1). The dependent variable is (the log of) total earnings. Columns [1]–[4] display estimates for the rural sample, while columns [5]–[8] report estimates for the urban sample. In order to analyze the robustness of estimates and to investigate channels that could explain the association between skills and earnings in pre-industrial Castile, we sequentially add controls for family composition variables, job characteristics, and location variables. Thus the specifications in Table 3 differ with regard to the variables included in vector X_i . We also include tests for the joint significance of added regressors. To facilitate interpreting the effects of occupational skills, we computed the incremental effects of moving (upward) between adjacent skill levels. Descriptive statistics of the set of explanatory variables used in the analysis are given in Table B in the Appendix. For the sake of brevity, we restrict our comments to the estimated coefficients for skill indicators. Table C in the Appendix reports the full set of estimated coefficients for specifications [4] and [8].

TABLE 3
RETURNS TO SKILLS: OLS ESTIMATES OF TOTAL EARNINGS EQUATIONS

| | RURAL | | | URBAN | | | | |
|---|-----------------------|----------------------|----------------------|-----------------------|-----------------------|-----------------------|----------------------|-----------------------|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] | [8] |
| Age | 0.031*** (0.011) | 0.023** (0.011) | 0.025** (0.010) | 0.028*** (0.009) | 0.027*** (0.009) | 0.026*** (0.009) | 0.022*** (0.008) | 0.028*** (0.008) |
| (Age) ² | -0.0004*** (0.000) | -0.0003** (0.000) | -0.0003** (0.000) | -0.0003*** (0.000) | -0.0003*** (0.000) | -0.0003*** (0.000) | -0.0002** (0.000) | -0.0003*** (0.000) |
| Basic skills | | | | | | | | |
| Literacy | -0.034 (0.030) | 0.041 (0.029) | 0.010 (0.027) | 0.011 (0.025) | 0.248*** (0.024) | 0.246*** (0.024) | 0.159*** (0.024) | 0.157*** (0.023) |
| Numeracy | 0.031 (0.030) | 0.026 (0.030) | 0.035 (0.027) | 0.034 (0.024) | 0.040 (0.026) | 0.041 (0.026) | 0.039 (0.025) | 0.034 (0.024) |
| Occupational skills | , , | , , | , , | , , | , , | , , | , , | , , |
| Low vs. Unskilled | 0.356*** (0.029) | 0.345*** (0.029) | 0.188*** (0.031) | 0.347*** (0.038) | 0.454*** (0.023) | 0.449*** (0.023) | 0.406*** (0.027) | 0.568*** (0.034) |
| Medium/high vs. Low | 0.335*** (0.048) | 0.336*** (0.048) | 0.359*** (0.066) | 0.290*** (0.064) | 0.477*** (0.035) | 0.474*** (0.035) | 0.378*** (0.041) | 0.251*** (0.043) |
| Control variables | | | | | | | | |
| Household composition | No | Yes | Yes | Yes | No | Yes | Yes | Yes |
| Job characteristics | No | No | Yes | Yes | No | No | Yes | Yes |
| Location dummies | No | No | No | Yes | No | No | No | Yes |
| F-test [p-value] for joint significance of added controls | | 12.09 [0.000] | 32.38 [0.000] | 49.54 [0.000] | | 4.83 [0.000] | 14.28 [0.000] | 112.52 [0.000] |
| Adj. R ² | 0.214 | 0.231 | 0.344 | 0.490 | 0.383 | 0.386 | 0.434 | 0.466 |
| $N^{'}$ | 1,206 | 1,206 | 1,206 | 1,206 | 2,451 | 2,451 | 2,451 | 2,451 |

Notes: The dependent variable is (log of) total earnings. Columns [1] and [5] report the results of baseline regressions. Household composition includes a dummy variable for civil status (married = 1, otherwise = 0) and the number of children aged 12 or more. Job characteristics include a dummy for manual/non-manual job and a set of dummies that classify workers into seven groups: agriculture, husbandry/forestry, textile production, construction, other manufactures, commerce/transport, and professional services. Location dummies distinguish between Palencia City and Guadalajara City in the urban sample and distinguish among Villarramiel, Paredes de Nava, Carabaña, Cevico Navero, Hontoria, and three mountain villages (Resoba, Valberzoso, and Villabellaco) in the rural sample. Robust standard errors are given in parentheses. Based on specifications [4] and [8], we performed a χ^2 test for equality of coefficients between rural and urban subsamples. The *t*-statistic values [*p*-values] are: literacy, 19.34 [0.000]; numeracy, 0.00 [0.999]; low-skilled versus unskilled, 18.93 [0.000]; medium/high-skilled versus low-skilled, 0.26 [0.607].

Source: Author's calculations from the Ensenada Cadastre, circa 1750. Sample of male household heads between 18 and 59 years of age.

^{*}p < 0.10, **p < 0.05, ***p < 0.01

Columns [1] and [5] display the baseline specifications, which include only age terms and skill indicators as covariates. The resulting concave earnings—age relationship is consistent with the experience or seniority effect observed in contemporaneous economies. In both the rural and urban subsamples, the turning point—that is, the age at which total labor earnings reaches its maximum—is near age 50. Once we control for age effects, the effects of literacy and numeracy on rural workers' earnings are not statistically significant. However, literacy is positive and significantly associated with urban workers' earnings. In particular, workers able to sign earned 28% more, on average, than otherwise similar workers who could not sign. Occupational skills are associated with greater earnings than are basic skills. In cities, a low-skilled worker earned 57% more (on average) than an unskilled worker of similar age, literacy, and numeracy. The estimated return to this skill level is 10 percentage points higher in urban than in rural locations. The incremental reward associated with moving from the low to the medium/high skill level is likewise greater in urban than in rural locations, with respective magnitudes of 60% and 40%.

Specifications [2] and [6] in Table 3 add controls for household composition through (i) an indicator variable for whether or not the household head is married and (ii) a count variable for the number of children aged 12 or more. Of course, a household's subsistence needs are increasing in the number of its members. Yet the presence of more household members increases household labor supply and hence also the likelihood that the earnings from by-employment, which the EC attributes to the household head, are at least partially generated by other family members. According to Humphries and Sarasúa (2012) and Hernández (2013), child labor rates in mid-eighteenth century Castile were high. For example, more than a third of 12-year-olds worked in remunerated activities, with boys usually working in agriculture and girls in textile production. Our results confirm that the two variables on household composition are jointly significant in the explanation of total earnings. However, their inclusion has hardly any effect on the estimated coefficients for skills indicators.

In specifications [3] and [7], we add a set of dummy variables that classify workers into seven industries according to their main jobs: agriculture, husbandry/forestry, textile

¹⁶ Coefficient estimates are converted to percentage changes using the standard transformation in semi-logarithmic specifications: $(e^{\beta} - 1) \times 100$, where β is the corresponding coefficient.

production, construction, commerce/transport, or professional services. We also include a dummy for whether the job is manual (blue-collar) or non-manual (white-collar). When putting an occupation into one of these two categories, we followed the HISCO/HISCLASS criterion (van Leeuwen and Maas, 2011). Only 4.8% of household heads in rural villages—and only 11% in cities—are classified as non-manual workers. In the rural subsample, adding this new set of covariates practically halves the return to low skill (though the other coefficients remain similar). In the urban subsample, controlling for these job characteristics reduces the estimated return to literacy and to medium/high skill by about 10 percentage points each, although the returns remain statistically significant. These results suggest that the self-sorting of more qualified individuals into non-manual jobs and industries with better wages explains some of the positive association between skills and earnings. Nonetheless, that the skill effects remain statistically significant leaves room for causal explanations.

Finally, in specifications [4] and [8] we add indicators for the place of residence; in this way we account for local market conditions and for any *geographical* sorting of more able individuals into locations with higher wages. In the rural subsample, small mountain villages (Valberzoso, Villabellaco, and Resoba) are grouped into a one category. Although estimated coefficients for unskilled labor remain similar in magnitude and significance when geographical indicators are incorporated into the regressions, estimated returns to the low-skilled labor of urban (resp. rural) workers increases by as much as 76% (resp. 41%). In contrast, the estimated return to medium or high skill (as compared with low skill) declines to 28% in urban locations and 34% in rural areas; this rural–urban difference in returns is not statistically significant, however. These results suggest that workers were concentrated in locations featuring wages commensurate with their skills. The key result is that, even after controlling for place of residence, estimated returns to skills remain both statistically significant and of sizable magnitude.

In sum, our estimates indicate that workers' skills are significantly associated with higher labor earnings. Our finding that this association is stronger for urban than for rural workers is consistent with previous literature. These empirical results also indicate that workers in pre-industrial Castile were rewarded more for their occupational skills than for being literate or numerate. Although our econometric analysis does not disentangle the channels (causal or not) through which a household head's skills affect his earnings, the association

between better skills and higher earnings is robust to the inclusion of other covariates. We therefore conclude that neither in rural nor in urban locations is this relationship explained by the selection of more highly skilled workers into industries, locations, or types of occupations (manual or not) characterized by higher wages.

5.2. Returns heterogeneity across activity sectors

So far, we have assumed that returns to skills were similar across activity sectors. However, the economics literature has cast doubt on this assumption. The magnitude of returns may differ across sectors because of interactions between the relative supply and demand of skills and/or because of differences in the elasticity of substitution between skilled and unskilled workers (Katz and Murphy, 1992; Johnson, 1997). Even sectors that are similar in these respects may reward skills differently owing to disparities in wage-setting criteria or, more generally, in institutional setups (e.g., guilds' regulations).

To assess heterogeneity in the returns to skills, we re-estimate the regression models for total earnings while interacting skill indicators with dummies for the activity sector (primary, secondary, or tertiary) in which the worker's main job is classified. These models incorporate the full set of explanatory variables included in specifications [4] and [8] of Table 3. In Table 4 we summarize the estimated skill effects for urban and rural workers.

We find that tertiary-sector workers obtained greater returns to basic skills than did other workers. In urban locations, the return to literacy ranges from 9.3% in the primary and secondary sectors to almost 73% in the tertiary sector (after we control for the other explanatory variables). In rural villages, literacy is associated with higher earnings only for workers in the tertiary sector. Given the high percentage of literate workers in the tertiary sector (see Table 1), our estimates likely reflect that literacy was a highly valued skill in these activities. Interactions between numeracy and activity sectors offer new results: the returns to numeracy are positive and statistically significant for urban workers engaged in primary- and tertiary-sector activities, with respective values of 6.3% and 31%; however, the effect of numeracy on other workers remains insignificant in the re-estimation.

TABLE 4
HETEROGENEITY OF RETURNS TO SKILLS
ACROSS ACTIVITY SECTORS

| Age 0.026*** (0.009) (0.008) (Age)² -0.0003*** (0.000) Basic skills -0.024 (0.023) (0.034) Literacy -0.024 (0.023) (0.034) × Secondary 0.040 (0.057) (0.042) × Tertiary 0.374** (0.181) (0.136) Numeracy 0.033 (0.063** (0.021) (0.030) × Secondary -0.038 (0.021) (0.030) × Secondary -0.038 (0.059) (0.041) × Tertiary -0.010 (0.235) (0.121) Occupational skills Unskilled Low vs. Unskilled 0.354*** (0.036) (0.034) × Secondary -0.241 (0.301) (0.044) × Tertiary 0.351 (0.069) (0.059) (0.013) Medium/high vs. Low 0.335*** (0.069) (0.069) (0.0652) (0.199) Medium/high vs. Low 0.335*** (0.070) (0.138) × Secondary -0.387*** (0.070) (0.138) × Secondary -0.387*** (0.146) × Tertiary 0.321 (0.121) Control variables Household composition Job characteristics Yes Yes Location dummies Yes Yes R² 0.521 (0.515) 0.515 N 1,206 2,451 <th>_</th> <th>Rural</th> <th>Urban</th> | _ | Rural | Urban |
|---|---------------------|----------|----------|
| (Age)² -0.0003*** (0.000) -0.0002*** (0.000) Basic skills Literacy -0.024 (0.023) (0.034) × Secondary 0.040 (0.057) (0.042) × Tertiary 0.374** (0.181) (0.136) Numeracy 0.033 (0.063*** (0.021) (0.030) × Secondary -0.038 (0.059) (0.041) × Tertiary -0.010 (0.235) (0.121) Occupational skills 0.059) (0.041) X Secondary -0.241 (0.036) (0.034) × Secondary -0.241 (0.301) (0.044) × Tertiary 0.351 (0.069 (0.652) (0.199) Medium/high vs. Low 0.335*** (0.135) (0.146) × Secondary -0.387*** (0.135) (0.146) × Tertiary 0.321 (0.135) (0.146) × Tertiary 0.321 (0.121) Control variables Yes Household composition Job characteristics Yes Yes Location dummies Yes Yes Location dummies Yes Yes | Age | 0.026*** | 0.020** |
| (0.000) (0.000) (0.000) | | (0.009) | (0.008) |
| Basic skills Literacy | $(Age)^2$ | | |
| Literacy | | (0.000) | (0.000) |
| (0.023) (0.034) | Basic skills | | |
| × Secondary 0.040 (0.057) (0.042) × Tertiary 0.374** (0.181) (0.136) Numeracy 0.033 (0.021) (0.030) × Secondary -0.038 (0.059) (0.041) × Tertiary -0.010 (0.235) (0.121) Occupational skills Low vs. Unskilled 0.354*** (0.036) (0.034) × Secondary -0.241 (0.301) (0.044) × Tertiary 0.351 (0.069) (0.652) (0.199) Medium/high vs. Low 0.335**** (0.070) (0.138) × Secondary -0.387*** (0.135) (0.146) × Tertiary 0.321 (0.199) (0.243) Control variables Household composition Job characteristics Yes Yes Yes Yes Yes Yes Location dummies R² 0.521 0.515 | Literacy | -0.024 | 0.093** |
| (0.057) (0.042) × Tertiary (0.181) (0.136) Numeracy (0.033 (0.03** (0.021) (0.030) × Secondary (0.059) (0.041) × Tertiary (0.235) (0.121) **Occupational skills** Low vs. Unskilled (0.354*** (0.036) (0.034) × Secondary (0.036) (0.034) × Secondary (0.301) (0.044) × Tertiary (0.301) (0.044) × Tertiary (0.301) (0.044) × Tertiary (0.652) (0.199) Medium/high vs. Low (0.335*** (0.199) Medium/high vs. Low (0.335*** (0.138) × Secondary (0.135) (0.146) × Tertiary (0.135) (0.146) × Tertiary (0.135) (0.146) **Control variables** Household composition Yes Yes Yes Household composition Yes Yes Yes Location dummies Yes Yes Yes Yes Yes Yes Yes Yes Yes Y | | (0.023) | (0.034) |
| X Tertiary | × Secondary | | |
| Numeracy | | (0.057) | (0.042) |
| Numeracy 0.033 (0.063** (0.021) (0.030) × Secondary -0.038 (0.059) (0.041) × Tertiary -0.010 (0.235) (0.121) Occupational skills 0.354*** (0.036) (0.034) × Secondary -0.241 (0.301) (0.044) × Tertiary 0.351 (0.069 (0.652) (0.199) Medium/high vs. Low 0.335*** (0.146) × Secondary -0.387*** (0.135) (0.146) × Tertiary 0.321 (0.199) (0.243) Control variables Household composition Yes Yes Yes Yes Yes Location dummies R2 0.521 (0.515) | × Tertiary | | |
| (0.021) (0.030) × Secondary (0.059) (0.041) × Tertiary (0.235) (0.121) **Occupational skills** Low vs. Unskilled (0.354*** (0.036) (0.034) × Secondary (0.36) (0.034) × Secondary (0.301) (0.044) × Tertiary (0.301) (0.044) × Tertiary (0.351 (0.069) (0.199) **Medium/high vs. Low (0.335*** (0.199) (0.199) **Medium/high vs. Low (0.070) (0.138) × Secondary (0.135) (0.146) × Tertiary (0.135) (0.146) × Tertiary (0.199) (0.243) **Control variables** Household composition Yes Yes Yes Location dummies Yes Yes Yes Yes Yes Yes Yes Yes Yes Y | | (0.181) | (0.136) |
| $\begin{array}{cccccccccccccccccccccccccccccccccccc$ | Numeracy | | |
| (0.059) (0.041) × Tertiary | | (0.021) | (0.030) |
| × Tertiary -0.010 (0.235) 0.205* (0.121) Occupational skills 0.354*** (0.036) 0.149*** (0.034) × Secondary -0.241 (0.301) 0.521*** (0.044) × Tertiary 0.351 (0.069) 0.069) (0.652) (0.199) Medium/high vs. Low 0.335*** (0.199) × Secondary -0.387*** (0.135) -0.821*** (0.135) × Tertiary 0.321 (0.146) -1.213*** (0.199) Control variables Household composition Yes Yes Job characteristics Yes Yes Location dummies Yes Yes R² 0.521 0.515 | × Secondary | | |
| (0.235) (0.121) Occupational skills Low vs. Unskilled 0.354*** 0.149*** (0.036) (0.034) × Secondary -0.241 0.521*** (0.301) (0.044) × Tertiary 0.351 0.069 (0.652) (0.199) Medium/high vs. Low 0.335*** 1.607*** (0.070) (0.138) × Secondary -0.387*** -0.821*** (0.135) (0.146) × Tertiary 0.321 -1.213*** (0.199) (0.243) Control variables Household composition Yes Yes Job characteristics Yes Yes Location dummies Yes Yes R² 0.521 0.515 | | ` , | ` , |
| Occupational skills Low vs. Unskilled 0.354*** 0.149*** (0.036) (0.034) × Secondary -0.241 0.521*** (0.301) (0.044) × Tertiary 0.351 0.069 (0.652) (0.199) Medium/high vs. Low 0.335*** 1.607*** (0.070) (0.138) × Secondary -0.387*** -0.821*** (0.135) (0.146) × Tertiary 0.321 -1.213*** (0.199) (0.243) Control variables Yes Yes Household composition Yes Yes Job characteristics Yes Yes Location dummies Yes Yes R² 0.521 0.515 | × Tertiary | | |
| Low vs. Unskilled 0.354*** 0.149*** (0.036) (0.034) × Secondary -0.241 0.521*** (0.301) (0.044) × Tertiary 0.351 0.069 (0.652) (0.199) Medium/high vs. Low 0.335*** 1.607*** (0.070) (0.138) × Secondary -0.387*** -0.821*** (0.135) (0.146) × Tertiary 0.321 -1.213*** (0.199) (0.243) Control variables Household composition Yes Yes Yes Location dummies Yes Yes Location dummies Yes Yes | | (0.235) | (0.121) |
| $ \begin{array}{cccccccccccccccccccccccccccccccccccc$ | Occupational skills | | |
| $\begin{array}{cccccccccccccccccccccccccccccccccccc$ | Low vs. Unskilled | 0.354*** | 0.149*** |
| (0.301) (0.044) × Tertiary (0.351 (0.069) (0.652) (0.199) Medium/high vs. Low (0.335*** (0.199) × Secondary (0.070) (0.138) × Secondary (0.135) (0.146) × Tertiary (0.135) (0.146) × Tertiary (0.199) (0.243) Control variables Household composition Yes Yes Job characteristics Yes Yes Location dummies Yes Yes R2 (0.521 (0.515) | | (0.036) | (0.034) |
| $\begin{array}{cccccccccccccccccccccccccccccccccccc$ | × Secondary | | 0.521*** |
| $ \begin{array}{c} (0.652) & (0.199) \\ \text{Medium/high vs. Low} & 0.335^{***} & 1.607^{***} \\ (0.070) & (0.138) \\ \times \text{Secondary} & -0.387^{***} & -0.821^{***} \\ (0.135) & (0.146) \\ \times \text{Tertiary} & 0.321 & -1.213^{***} \\ (0.199) & (0.243) \\ \hline \\ \textit{Control variables} \\ \text{Household composition} & \text{Yes} & \text{Yes} \\ \text{Job characteristics} & \text{Yes} & \text{Yes} \\ \text{Location dummies} & \text{Yes} & \text{Yes} \\ \hline \\ \textit{R}^2 & 0.521 & 0.515 \\ \hline \end{array} $ | | (0.301) | (0.044) |
| | × Tertiary | | |
| $ \begin{array}{cccccccccccccccccccccccccccccccccccc$ | | (0.652) | (0.199) |
| $ \begin{array}{cccccccccccccccccccccccccccccccccccc$ | Medium/high vs. Low | | |
| $(0.135) \qquad (0.146)$ $\times \text{ Tertiary} \qquad 0.321 \qquad -1.213^{***}$ $(0.199) \qquad (0.243)$ $Control \ variables$ $\text{Household composition} \qquad \text{Yes} \qquad \text{Yes}$ $\text{Job characteristics} \qquad \text{Yes} \qquad \text{Yes}$ $\text{Location dummies} \qquad \text{Yes} \qquad \text{Yes}$ $R^2 \qquad 0.521 \qquad 0.515$ | | (0.070) | (0.138) |
| \times Tertiary 0.321 $-1.213***$ (0.199) (0.243) Control variables Household composition Yes Yes Job characteristics Yes Yes Location dummies Yes Yes R^2 0.521 0.515 | × Secondary | | |
| $(0.199) \qquad (0.243)$ $Control \ variables$ $Household \ composition \qquad Yes \qquad Yes$ $Job \ characteristics \qquad Yes \qquad Yes$ $Location \ dummies \qquad Yes \qquad Yes$ $R^2 \qquad 0.521 \qquad 0.515$ | | ` ' | ` , |
| Control variablesHousehold compositionYesYesJob characteristicsYesYesLocation dummiesYesYes R^2 0.5210.515 | × Tertiary | | |
| $ \begin{array}{cccc} \text{Household composition} & \text{Yes} & \text{Yes} \\ \text{Job characteristics} & \text{Yes} & \text{Yes} \\ \text{Location dummies} & \text{Yes} & \text{Yes} \\ \hline R^2 & 0.521 & 0.515 \\ \end{array} $ | | (0.199) | (0.243) |
| Job characteristicsYesYesLocation dummiesYesYes R^2 0.5210.515 | Control variables | | |
| Location dummies Yes Yes R^2 0.521 0.515 | | | |
| R ² 0.521 0.515 | J | | |
| | Location dummies | Yes | Yes |
| N 1,206 2,451 | | | |
| | N | 1,206 | 2,451 |

Notes: Reported values are OLS estimates; the dependent variable is (log of) total earnings. The coefficients for literacy, numeracy, and occupational skills measure returns to each of these skills for the reference category (i.e., the primary sector). All models include the set of explanatory variables used in specifications [4] and [8] of Table 3. Robust standard errors are given in parentheses.

Source: Authors' calculations from the Ensenada Cadastre, circa 1750. Sample of male household heads between 18 and 59 years of age.

*p < 0.10, **p < 0.05, ***p < 0.01

With regard to occupational skills, we uncover some diverging patterns for rural and urban workers. In rural villages, the positive earnings differential between low-skilled and

unskilled workers does not differ significantly among sectors. In cities, however, achieving a low level of skill was (on average) better rewarded in the secondary sector than in the primary and tertiary sectors; we find in particular that the return to low skill is 52 percentage points higher for secondary-sector workers than for primary-sector workers. At the same time, moving upward from the low to the medium/high skill level was most rewarded in the primary sector—a result that holds in both rural and urban locations. Note that the group of primary-sector workers classified as medium-skilled consists mostly of farmers with larger landholdings and/or rented lands. Hence the returns to working at this level reflect a mixture of returns to better farming-specific skills and to greater availability of land, which helps explain its magnitude.

Another finding of interest is that medium-skilled secondary-sector workers earned significantly higher amounts than did low-skilled workers—but in cities only, not in rural villages. Given the importance of textiles for total Castilian employment, one would expect this result to be driven by the industry's different features in the sampled locations. During the period under study, Royal Factories in the cities co-existed with guild production in rural villages. That rural manufactures required little skill and were technically backward would explain the greater substitutability of low- and medium-skilled workers and thus the small reward for rural textile workers upgrading their skills. Yet for urban workers in our sample, the estimated higher returns to medium skill are probably driven by the combination of (a) guild restrictions in Palencia City and (b) the comparatively higher technical requirements of the textile factory in Guadalajara. Even in cities, however, the returns to medium skill were considerably lower than those estimated for the primary sector.

5.3. Returns to skills in different earnings components

About 17.5% of urban workers and 25% rural workers reported some form of byemployment (see Table 2). It follows that the positive association between skills and total earnings could operate through increased productivity in workers' main occupation and/or through increased access to and earnings from by-employment. In this section, we evaluate the relevance of these pathways by estimating separate models for each earnings component.

TABLE 5
SKILL EFFECTS ON EARNINGS COMPONENTS

| | | RURAL | | | URBAN | | | |
|---------------------------|---------------------|---------------------|---------------------|----------------------|--|---------------------|--|--|
| | Earnings from | selection model) | Earnings from | employmen | Earnings from by- employment (Heckman selection model) | | | |
| | main job (OLS) | Selection | Earnings level | main job (OLS) | Selection | Earnings level | | |
| Age | 0.009 (0.010) | 0.093** (0.043) | 0.120** (0.049) | 0.023*** (0.008) | 0.044 (0.030) | 0.061 (0.054) | | |
| (Age) ² | -0.0001 (0.000) | -0.001* (0.001) | -0.002** (0.001) | -0.0003** (0.000) | -0.0004 (0.000) | -0.0005 (0.001) | | |
| Basic skills | | | | | | | | |
| Literacy | -0.005 (0.027) | -0.146 (0.125) | 0.186 (0.131) | 0.122*** (0.021) | 0.030 (0.087) | 0.621*** (0.096) | | |
| Numeracy | 0.006 (0.023) | -0.146 (0.138) | 0.278* (0.150) | 0.031 (0.024) | 0.009 (0.092) | -0.013 (0.152) | | |
| Occupational skills | | | | | | | | |
| Unskilled | Ref. | Ref. | Ref. | Ref. | Ref. | Ref. | | |
| Low-skilled | 0.279*** (0.033) | 1.788*** (0.247) | -0.409 (0.720) | 0.486*** (0.032) | 0.270** (0.133) | 2.116*** (0.222) | | |
| Medium/high-skilled | 0.596*** (0.055) | 1.660*** (0.271) | -0.451 (0.722) | 0.632*** (0.047) | 1.071*** (0.128) | 1.828*** (0.178) | | |
| Control variables | | | | | | | | |
| Household composition | Yes | Yes | Yes | Yes | Yes | Yes | | |
| Job characteristics | Yes | Yes | No | Yes | Yes | No | | |
| Location dummies | Yes | Yes | Yes | Yes | Yes | Yes | | |
| \mathbb{R}^2 | 0.429 | | | 0.418 | | | | |
| LR test for $\varrho = 0$ | | 0.60 | | | 0.0 | | | |
| N | 1,206 | 1,206 | 304 | 2,451 | 2,451 | 337 | | |

Notes: Total earnings and earnings from the main job are in logarithms. All models include the set of explanatory variables used in specifications [4] and [8] of Table 3. Robust standard errors are given in parentheses. LR = likelihood ratio; Ref. = reference category.

Source: Authors' calculations from the Ensenada Cadastre, circa 1750. Sample of male household heads between 18 and 59 years of age.

We began by re-estimating the semi-logarithmic specifications [4] and [8] in Table 3 while using earnings from the main job as our dependent variable. Results are presented in Table 5. Next we modeled earnings from by-employment through a Heckman sample selection specification that separates the binary decision to engage in supplementary occupations from the (log of) earnings that those occupations generate. This specification accommodates any correlation between the unobserved factors that explain both outcomes. To identify the model, we need at least one variable that (i) has a nonzero coefficient in the *selection* equation (engagement in by-employment) and (ii) can be excluded from the complementary *earnings* equation. For this purpose, we use a set of dummies for

^{*}p < 0.10, **p < 0.05, ***p < 0.01

industries in which the household head's main job is performed. We anticipate that the main job's particular activity will affect the decision to engage in by-employment but will not affect the level of earnings achievable at the latter—especially when we condition on age and skills. For example, the seasonality of agriculture may incentivize workers to seek by-employment via such textile activities as spinning and weaving; all else held constant, though, their main job has little effect on how much income these subsidiary activities generate. That by-employment usually occurs outside the worker's main occupational sector makes our exclusion strategy more credible. The second and third (resp., fifth and sixth) columns of Table 5 report maximum likelihood estimates of this selection model for rural (resp., urban) samples. In both samples, activity sector indicators are jointly significant in the selection equations.

The estimates reported previously in Table 3 established that, for urban workers, being literate had a positive and significant effect on total earnings. In Table 5, we see that this effect is due mainly to the increase in earnings from the main job. Moreover, although urban literate workers were not more likely to engage in by-employment than their illiterate counterparts, when the former did so they earned significantly more. This finding could be explained by the predominance of commercial activities (presumably based on home-produced goods) among the main types of by-employment reported by urban workers. In rural locations—where textile production was, jointly with trade, an important source of by-employment—literacy affected neither the probability of by-employment nor the magnitude of complementary earnings. Yet for rural workers we do estimate a positive and significant effect of numeracy on earnings from subsidiary occupations, for those who select into them, although the effect is significant only at the 10% level.

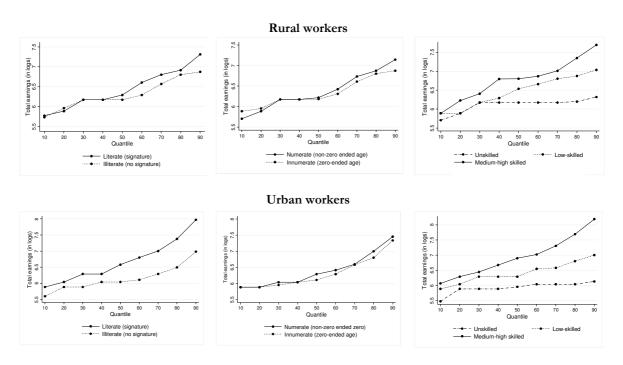
In line with our previous findings, the association between occupational skills and the components of workers' earnings is stronger for urban than for rural workers. In fact, we find that the occupational skill levels of urban workers affect the entire earnings structure. Thus, ceteris paribus, workers with higher occupational skills earn more at their main job, are more likely to access by-employment, and (when so engaged) earn more than workers with lower skills. For rural workers we also find significant earnings rewards to upgrading occupational skills in the main job, although these rewards are of lower magnitude than those accruing to urban workers who similarly upgrade their skills. Finally, rural workers at any skill level are more likely to engage in by-employment than otherwise similar unskilled

workers. Note, however, that the remuneration from these complementary labor activities does not vary significantly as a function of occupational skills.

6. SKILLS AND EARNINGS INEQUALITY

The evidence for a positive association between skills and earnings is based on estimated returns to skills for an average worker—that is, a worker exhibiting the sample's average characteristics. An interesting question is whether better skills improved earnings similarly for workers in the lower versus the upper tail of the earnings distribution. The answer to this question bears crucial implications for inequality. If a certain skill was better rewarded at the top of the earnings distribution (where high-ability individuals are expected) than at the bottom, then this form of human capital contributed to income inequality in eighteenth-century Castile. But if a given skill is more valued instead at the bottom of the conditional earnings distribution (for the worse-off) than at the top, then that skill actually compresses the earnings distribution.

FIGURE 4
PERCENTILES OF TOTAL EARNINGS BY SKILL LEVEL



Source: See source note for Figure 3.

Figure 4 illustrates descriptive evidence suggesting that dispersion of earnings distributions increases with workers' qualification levels. In particular, we observe that the earnings

gap—between workers with higher and lower occupational skills—increases toward the upper part of earnings distributions. A similar pattern is observed when we compare earnings distributions for literate and illiterate workers, especially in cities. The pattern is less evident for numeracy.

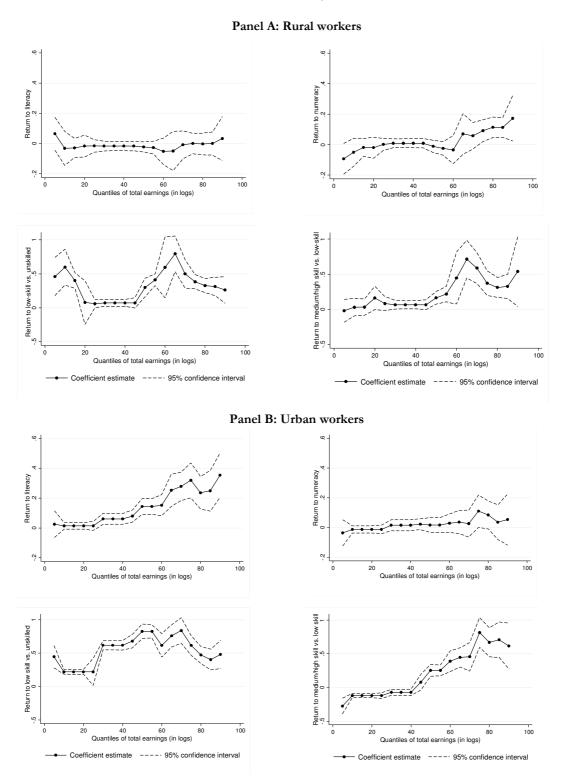
When quantifying the heterogeneity of returns to skills across an earnings distribution, the usual econometric approach is to employ conditional quantile regression (Koenker and Bassett, 1978; 1982). That technique models the effect of covariates (e.g., skills) on the individual's position (quantile) within a virtual distribution in which all individuals are assumed to have the same observed characteristics. The problem with this approach is that deriving conclusions with respect to the unconditional distribution of income (which is our aim) requires "integrating out" these effects for the distribution of skills, which is not a straightforward task. Here, we implement the unconditional quantile regression method proposed by Firpo et al. (2009) to estimate the effects of basic and occupational skills on the distribution of workers' unconditional earnings.¹⁷ This technique allows for measuring the effect of covariates on the quantile where the individual is placed in the unconditional earnings distribution, which is the most suitable way to assess distributional effects.

Figure 5 displays the main estimation results. We plot estimated skill effects for the 5th to 95th quantiles together with their 95% confidence intervals based on standard errors computed from 400 bootstrap replications. The coefficient estimates measure the marginal changes (by quantile) in response to a marginally increased probability of having the corresponding skill. Panel A displays results for rural workers and Panel B for urban workers. All regressions include as additional covariates quadratic age terms, controls for household composition, and dummies for manual/non-manual jobs, industry, and location.

_

¹⁷ The estimation is carried out using Stata's *rifreg* routine. Let $q(\tau)$ denote the τ th quantile of the distribution of Y_i (log earnings). The method proposed by Firpo et al. (2009) consists of estimating a regression in which the dependent variable is the recentered influence function (RIF) of the quantile. The RIF is defined as follows: RIF_i($q(\tau)$) = $q(\tau)$ +[(1(log(Y_i) $\geq q(\tau)$)-(1- τ)]/ $f(q(\tau)$), where 1(.) is the indicator function and $f(q(\tau))$ is the earnings density evaluated at the τ th quantile. Estimating a regression of RIF_i($q(\tau)$) on a linear function of the explanatory variables is, in practice, equivalent to estimating a linear probability model for whether individual log earnings are above or below $q(\tau)$. Firpo et al. (2009) show that the expected value of RIF_i($q(\tau)$) is the unconditional quantile. We can therefore interpret estimated coefficients for the explanatory variables as average effects on the unconditional quantile.

 ${\bf FIGURE~5}$ RETURNS TO SKILLS: UNCONDITIONAL QUANTILE REGRESSION ESTIMATES.



Notes: These graphs plot unconditional quantile regression coefficients of skill indicators estimated by the RIF-based OLS procedure proposed in Firpo et al. (2009). The 95% confidence intervals are based on bootstrap standard errors (400 replications). Besides skill indicators, all quantile regressions include as regressors the set of variables included in specification [4] of Table 3.

Source: See source note for Figure 3.

Overall, our results reveal heterogeneity in the effects of skills across the earnings distribution, with some differences among skills and between urban and rural locations. Let us start with the estimated returns to basic skills. For urban workers, the estimated return to literacy is almost null at the low end of the earnings distribution but increases to become statistically significant starting at the 30th quantile; the return reaches nearly 0.35 log points at the top quantile. For rural workers, literacy has practically no effect in any part of the earnings distribution. The opposite holds for numeracy: the return to this basic skill is nil for urban workers yet positive and significant for rural workers located at the upper part of the earnings distribution. In short: literacy contributed to labor earnings inequality in cities; and numeracy had a similar (though less pronounced) effect in rural locations.

With regard to occupational skills, the estimated earnings gap between low-skilled workers and unskilled workers (who are otherwise similar) is positive and increases until the 70th quantile; at that point the earnings gap shrinks, though more dramatically in the rural than in the urban sample. A common finding for both rural and urban workers is that, in the lower part of the earnings distribution, the earnings gap between unskilled and low-skilled workers is higher than the earnings gap between low-skilled workers and medium/high-skilled workers. This result suggests that qualifying as a low-skill worker involved tasks that complemented the innate ability of workers at the low end of the earnings distribution better than did the requirements for higher occupational skill levels. The opposite holds when moving from low skill to medium/high skill. In that case, the return is positive and statistically significant from the 50th quantile onward and follows an increasing pattern, which suggests that the better-off workers—because of their innate ability or social status—were more able to exploit the occupational skills associated with this category.

Unraveling what causes the estimated heterogeneity in returns to skills is certainly not easy. On the one hand, the significance of basic skills at the upper end of the earnings distribution might simply reflect differences in the level of literacy and numeracy captured by our indicators—that is, rather than any heterogeneity of effects corresponding to similar skill levels. In this regard, we must concede that the ability of poorer household heads to sign could reflect only the roughest of literacy skills whereas, for richer household heads, that ability reflects more advanced writing and reading skills. Unfortunately, we cannot test this hypothesis. On the other hand, occupations carried out by individuals at the low end of the earnings distribution might be of lower prestige than other occupations, requiring no

greater skill, carried out by individuals at the high end of that distribution. We have explored this hypothesis by augmenting the quantile regressions with an additional set of dummy variables that control for the social class into which individuals can be allocated according to their main job; this classification is derived from the scheme proposed by van Leeuwen and Maas (2011).¹⁸ We found that the pattern of estimated effects of skill indicators across the earnings distribution does not differ significantly from the pattern seen in Figure 5.

7. CONCLUSIONS

This paper offers new insights on extant empirical evidence concerning the role of human capital in pre-industrial societies. Using information from the Ensenada Cadastre—a unique database on mid-eighteenth century Castilian households—we explore the relationship between basic and occupational skills and male workers' earnings. The analysis is carried our separately for rural and urban workers.

Overall, we find that the distribution of basic and occupational skills among Castilian male household heads were closely associated with the distribution of total labor earnings. Male workers with better skills had, on average, higher earnings. This association is robust to the inclusion of controls for age, family composition, job characteristics, and location of residence. Furthermore, our results highlight that measuring skill premia on the basis of one only source of earnings (the household head's main job) may underestimate the benefits of skills for pre-industrial households. The reason is that some of the positive effect on total earnings, especially for urban workers, is transmitted via access to and earnings from by-employment. Earnings diversification through subsidiary occupations was frequent in pre-industrial societies (Saito, 2010).

Our estimates uncover substantial heterogeneity in the returns to skills. Returns to occupational skills generally were larger in magnitude than returns to literacy and numeracy, and the difference favored urban more than rural workers. In the sampled cities, returns to basic skills were mainly driven by the positive effect of literacy and numeracy on workers'

¹⁸ Van Leeuwen and Maas (2011, p. 57) classify occupations into 12 social class levels: (1) higher managers; (2) higher professionals; (3) lower managers; (4) lower professionals, and clerical and sales personnel; (5) lower clerical and sales personnel; (6) foremen; (7) medium-skilled workers; (8) farmers and fishermen; (9) lower-skilled workers; (10) lower-skilled farm workers; (11) unskilled workers; (12) unskilled farm workers. Estimation results of unconditional quantile regressions that incorporate controls for social class are not presented here (in order to save space) but are available from the authors upon request.

earnings in primary- and tertiary-sector activities. These results are consistent with studies that point to the relevance of counting skills in commerce or trading activities and in agriculture (Nilsson et al., 1999; Reis, 2005; Tollnek and Baten, 2012). In contrast, for secondary-sector workers (among whom textile production predominated) we find that possessing basic skills yielded negligible rewards. Along these lines, Becker et al. (2011) emphasize that the basic education acquired in Prussian schools yielded significant rewards only in non-textile industries. As regards occupational skills, the greatest earnings gap between unskilled and low-skilled workers is found in the urban secondary sector. However, secondary-sector workers obtained significant rewards from moving up to a medium-skill level in cities—but not in rural villages (despite the scarcity of these skills). This finding is likely explained by the backwardness of rural proto-industrial manufacturing and, more generally, by the subservience (in manufacturing production) of formal education to manual dexterity and to the skills acquired through on-the-job training. We were surprised to find that the highest reward for a medium/high skill level was achieved by workers in the primary sector. This result is mainly driven by the earnings patterns of medium-skilled farmers. Because development of higher occupational skills in agriculture was related to the availability of land, it is difficult to disentangle the effects of land availability and skills. Even so, this result is not surprising for an agricultural-based society that ended up arriving late to industrialization.

A final noteworthy result is that having better skills exerted not only pure "location shift" effects but also unequalizing effects on the earnings distribution. Quantile regression analysis reveals that the average positive effects of skills on workers' earnings actually *mask* the combination of large returns to skills for the better-off and low or nonexistent returns for workers at the low end of the total earnings distribution. This pattern is especially marked in cities and indicates that, in eighteenth-century Castile, human capital accumulation may well have driven earnings (and hence income) inequality.

It will be no simple task to determine how much the positive association (reported here) between skills and earnings reflects the existence of incentives for human capital accumulation. First of all, we are not measuring net returns to skills because we do not account for the private costs of education and training. In the second place, our estimates—despite their suggestiveness—do not allow conclusions about whether or not the effects are causal; this shortcoming follows from our inability to correct for sources of

bias (e.g., the mediating effect of unobserved ability). Yet some room remains for the possibility of a causal account, given (i) the robustness of our estimated associations between skills and earnings to different specifications and controls and (ii) a sectorial heterogeneity in returns to skills that coheres with the known structure and characteristics of the Castilian economy.

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APPENDIX

TABLE A
DESCRIPTION OF SAMPLED LOCATIONS

| | | Number of | | |
|------------------|-------------|-------------|--|--------------------------|
| Location | Province | inhabitants | Main economic activity | Distance to nearest city |
| Palencia City | Palencia | 9,402 | Industrial; guild of La Puebla | |
| Guadalajara City | Guadalajara | 5,238 | Industrial; Royal Manufactures: Real Fábrica de Paños (1719–1822) | |
| Paredes de Nava | Palencia | 3,311 | Farming activities | 22 km to Palencia |
| Villarramiel | Palencia | 1,422 | Rural industrial; "putting out" system | 34 km to Palencia |
| Carabaña | Madrid | 740 | Farming activities | 54 km to Guadalajara |
| Cevico Navero | Palencia | 499 | Forestry activities; charcoal | 38 km to Palencia |
| Villabermudo | Palencia | 283 | Rural industrial; "putting out" system | 74 km to Palencia |
| Hontoria | Palencia | 272 | Farming activities | 22 km to Palencia |
| Resoba | Palencia | 217 | Farming activities (mountain) | 120 km to Palencia |
| Bustillo | Palencia | 140 | Farming activities | 59 km to Palencia |
| Villabellaco | Palencia | 116 | Farming activities (mountain) | 103 km to Santander |
| Valberzozo | Palencia | 103 | Farming activities (mountain) | 92 km to Santander |

Note: Reported values for inhabitants are authors' calculations from "Vecindario de Ensenada 1759" (Madrid, 1991).

TABLE B SUMMARY OF DESCRIPTIVE STATISTICS

| | RUI | RAL | URI | URBAN | |
|----------------------------|-------|-------|-------|-------|--|
| Variable | Mean | S.D. | Mean | S.D | |
| Age | 38.19 | 10.50 | 37.63 | 10.29 | |
| Basic skills | | | | | |
| Literacy | 0.453 | | 0.456 | | |
| Numeracy | 0.722 | | 0.753 | | |
| Occupational skills | | | | | |
| Unskilled | 0.388 | | 0.390 | | |
| Low | 0.422 | | 0.288 | | |
| Medium-high | 0.190 | | 0.322 | | |
| Household composition | | | | | |
| No. children >12 years old | 0.730 | 1.09 | 0.475 | 0.849 | |
| Married | 0.907 | | 0.906 | | |
| Job characteristics | | | | | |
| Agriculture | 0.584 | | 0.267 | | |
| Husbandry/forestry | 0.110 | | 0.017 | | |
| Textile | 0.148 | | 0.369 | | |
| Construction | 0.024 | | 0.049 | | |
| Other manufactures | 0.065 | | 0.163 | | |
| Professional services | 0.040 | | 0.087 | | |
| Commerce/transport | 0.031 | | 0.047 | | |
| Non-manual | 0.048 | | 0.110 | | |
| Location | | | | | |
| Palencia | | | 0.620 | | |
| Guadalajara | _ | | 0.380 | | |
| Paredes de Nava | 0.406 | | _ | | |
| Villarramiel | 0.223 | | _ | | |
| Villabermudo | 0.045 | | | | |
| Carabaña | 0.101 | | _ | | |
| Cevico Navero | 0.085 | | _ | | |
| Bustillo | 0.023 | | | | |
| Hontoria de Cerrato | 0.044 | | _ | | |
| Mountain | 0.071 | | _ | | |
| Sample size | 1,206 | | 2,451 | | |

Source: Authors' calculations from the Ensenada Cadastre, circa 1750. Sample of male household heads between 18 and 59 years of age.

TABLE C
OLS ESTIMATES OF TOTAL EARNINGS EQUATIONS

| | RURAL | URBAN |
|---------------------------------|-----------------------|----------------------|
| Age | 0.028*** (0.009) | 0.028** (0.008) |
| (Age) ² | -0.0003*** (0.000) | -0.0003** (0.000) |
| Basic skills | (0.000) | (0.000) |
| Literacy | -0.011 (0.030) | 0.157*** (0.023) |
| Numeracy | 0.034 (0.024) | 0.034 (0.024) |
| Occupational skills Unskilled | Ref. | Ref. |
| Low-skilled | 0.347*** (0.038) | 0.568*** (0.034) |
| Medium/high-skilled | 0.637*** | 0.819*** |
| Household composition | (0.059) | (0.047) |
| No. children >12 years old | 0.044*** (0.016) | 0.056*** (0.017) |
| Married | -0.019 | 0.036 |
| I. b. al. and a sixting | (0.041) | (0.045) |
| Job characteristics Agriculture | Ref. | Ref. |
| Husbandry/forestry | 0.393*** | 0.302*** |
| Textile | (0.047) 0.287*** | (0.103) 0.069*** |
| Construction | (0.051) -0.017 | (0.026) 0.083 |
| Other manufactures | (0.080) 0.134 | (0.059) -0.050 |
| Other manufactures | (0.091) | (0.054) |
| Professional services | 0.397* (0.236) | 0.025 (0.142) |
| Commerce/transport | 0.433*** (0.131) | 0.180* (0.104) |
| Non-manual | -0.085 (0.207) | 0.533*** (0.132) |
| Location | (0.207) | |
| Palencia Cuadalaiara | _ | Ref. -0.310*** |
| Guadalajara | | (0.029) |
| Paredes de Nava | Ref. | _ |
| Villarramiel | -0.170*** (0.047) | _ |
| Villabermudo | -0.607*** (0.061) | _ |
| Carabaña | -0.541*** (0.046) | _ |
| Cevico Navero | -0.001 | _ |
| Bustillo | (0.083) -0.471*** | _ |
| Hontoria de Cerrato | (0.068) -0.163** | _ |
| Mountain | (0.066) -0.611*** | _ |
| | (0.047) | |
| \mathbb{R}^2 | 0.500 | 0.470 |

Notes: The dependent variable is (log of) total earnings. Estimated coefficients are from specifications [4] and [8] in Table 3. All regressions include a constant term. Robust standard errors are given in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01