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Height and cognition at work: Labor market productivity in a low income setting

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ABSTRACT

Taller workers earn more, particularly in lower income settings. It has been argued that adult height is a marker of strength which is rewarded in the labor market; a proxy for cognitive performance or other dimensions of human capital such as school quality; a proxy for health status; and a proxy for family background and genetic characteristics. As a result, the argument goes, height is rewarded in the labor market because it is an informative signal of worker quality to an employer. It has also been argued that the height premium is driven by occupational and sectoral choice. This paper evaluates the relative importance of these potential mechanisms underlying the link between adult stature and labor market productivity in a specific low income setting, rural Central Java, Indonesia. Drawing on twelve waves of longitudinal survey data, we establish that height predicts hourly earnings after controlling education, multiple indicators of cognitive performance and physical health status, measures of family background, sectoral and occupational choice, as well as local area market characteristics. The height premium is large and significant in both the wage and self-employed sectors indicating height is not only a signal of worker quality to employers. Since adult stature is largely determined in the first few years of life, we conclude that exposures during this critical period have an enduring impact on labor market productivity.

1. Human capital and labor market performance

There is abundant evidence that taller people live longer, are healthier, better educated and have higher standards of living (Deaton and Arora, 2009; Fogel, 2012; Strauss and Thomas, 1988). While the precise mechanisms underlying variation in the aggregate relationships across populations and over time is not clear (Deaton, 2007), within populations the fact that taller workers earn more has been widely documented, particularly in lower income settings.[1] This paper uses rich longitudinal survey data to investigate mechanisms that potentially underlie the association between height and productivity in the labor market in rural Indonesia, a rapidly-growing low income setting.

Adult stature is largely determined in early childhood and reflects the combined influence of the early childhood environment including nutrition, disease insults, and investments in health during pregnancy and the first few years of life (Martorell and Habicht, 1986), as well as the possibility of selective early life mortality in some contexts. In an important paper, Case and Paxson (2008a) point out height is but one dimension of human capital that captures very early investments and is likely to be correlated with other early childhood experiences as well as later life human capital investments, many of which are difficult to measure. Specifically, height is likely to be correlated with schooling attainment (Case et al., 2009), cognition (Case and Paxson, 2008a, 2008b), non-cognitive traits such as ambition and confidence (Persico et al., 2004), as well as an array of other markers of both the quantity and quality of health and human capital (Strauss and Thomas, 2008). Moreover, a portion of height is genetic and thus almost surely captures the role of family background and investments made across multiple generations. In low income settings, height may be a marker of strength that translates into greater productivity in physically demanding work. Disentangling that effect is complicated since workers likely self-select into occupations that reward their skills (Case et al., 2009)

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[1] See, among others: Behrman et al. (2013),Case and Paxson (2008a, 2008b), Gao and Smyth (2010), Hoddinott et al. (2008), Lundborg et al. (2014), Persico et al. (2004), Sohn (2015), Thomas and Frankenberg (2002), Thomas and Strauss (1997), Yamamura, Smuth and Zhand (2015) and Vogl (2014).

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and taller, stronger workers are also likely to have better cognitive skills (Vogl, 2014). It is possible that height is a signal of worker quality or used as a screening device by employers or customers (Sohn 2015; Yamamura et al., 2015).

This research investigates each of these potential explanations for the association between height and productivity in the labor market as indicated by hourly earnings. Rather than attempt to identify a single mechanism, height is treated as one measure ofhuman capital investments that is likely to be correlated with many others and we explore the relative contributions of the different explanations using data from a single study setting, Central Java, Indonesia. The Work and Iron Status Evaluation (WISE) was designed to provide the evidence necessary to address this question, and analyze the role of human capital in predicting success in both the formal and informal sectors. In addition to measuring height and education, WISE assesses several different domains of cognition, a battery of additional health markers, measures of family background, and multiple labor market outcomes including earnings, wages, and sectoral and occupational choice.

2. Conceptual framework

Height, cognition, health, family background and labor market behavior are examined within a framework that recognizes the multidimensionality and dynamics of human capital accumulation over the life course (Strauss and Thomas, 1988, 2008; Heckman, 2006). Given early childhood production functions for multiple types of human capital, parental choices concerning nutrition and other investments interact with environmental factors and child-specifc endowments to establish early levels of human capital. These parental choices reflect not only the prices and opportunity costs of differing investments, but also family background characteristics such as available resources and attitudes towards health and human capital. If different markers of human capital share common inputs, correlations between cognitive and physical development naturally arise at a young age due to parental choices geared toward maximizing their own expected future utility, that of the child and possibly the entire family.

As the individual transitions through adolescence, human capital development and skill acquistion continues through choices regarding investments in schooling and skill development along with early labor market experiences. Facing a labor market with multiple sectors and occupations with varying uncertain returns, the decision to remain in school, for example, will be a reflection of liquidity constraints, expectations and the opportunity cost of forgone work, all of which depend on both the individual's choices and parental investments over the life course.

Similarly, earnings in differing occupations and sectors may offer specific returns to different dimensions of human capital which may vary over the short and longer term. As individuals choose to sort across formal wage work and informal self-employment, for example, their comparative advantage is a reflection not only of human capital at that point in time, but of the human capital accumulation process throughout the life course. Individuals may continue to make health and cognitive investments as they age, with opportunities for further development dependent in part on their chosen sectors and occupations.

Thinking in this framework of a life-course production process for multiple dimensions of human capital illuminates several key relationships explored in this research. The well established correlation between height and labor market productivity could be due to a number of simultaneously determined factors. Attained height as an adult reflects one's early life health, disease and nutrition environments, and likely also captures other early life investments as well as family background characteristics including tastes for human capital of the next generation and both financial and non-financial resources. Similarly, shared inputs into the height, cognitive, and other human capital production functions may drive a relationship between physical and intellectual capacity. Finally, as the value of different traits may vary over time and differ depending on the sector and nature of work chosen by an individual, so too may the links between height, earnings, and additional human capital markers.

To empirically examine these relationships in the labor market, we exploit rich, longitudinal data on sectoral and occupational choice, and formal and informal earnings of males and their siblings in combination with high quality measures of a wide array of human capital markers.

3. The Work and Iron Status Evaluation

WISE, a large-scale longitudinal study conducted in Central Java, Indonesia designed to collect detailed information on human capital and labor market outcomes, is ideally suited to investigate the relationship between height, cognition, education, health, and labor market outcomes within a population. After a listing survey in late 2001, a population-representative sample of households living in Purworejo *kabupaten* was interviewed every four months beginning in 2002 and continuing through 2005. Longer-term follow-ups were conducted five and seven years after the start of the survey in 2007 and 2009. All twelve waves of the survey are included in this study.

The study area covers over 1800 km^2 in Central Java and almost 80% of the population of one million lives in rural areas, the vast majority of whom rely on agriculture for their living. Rice is the dominant crop. It is a relatively low income area. According to the 2006 SUSENAS, median household per capita expenditure in Indonesia was Rp 900,000 per month and Rp 580,000 in the study area. Part, but only part of this gap can be attributed to the fact that the study area is largely rural; focusing only on rural areas, median PCE is Rp 550,000 in the study area and Rp 770,000 in all rural areas of Indonesia.

As the analysis relies on following individuals over time, it is imperative that selective attrition does not contaminate inferences. Attrition is extremely low in WISE: 94% of households from the 2002 baseline were re-interviewed seven years later in the 2009 wave (see Thomas et al., 2015; for a more extensive discussion of tracking and attrition). We focus on 5304 men between the ages of 25 and 65 who reported any earnings during the survey period; there are over 38,000 person-wave observations in our panel sample.[2]

3.1. Hourly earnings

Labor market outcomes are measured with great care in WISE. Each household member age 15 and older is individually interviewed to obtain detailed information on work status, employer and occupation, tenure, nature of work (tasks), and earnings in each job. Hourly earnings from wage work are

[2] 7% of 25–65 year old men report they did not earn income during the study period and are not included in these analyses. As shown in column 1 of the Appendix A, these men are more likely to have difficulty running a kilometer, perform worse on two cognitive assessments and are lower weight than those who do report earnings in the survey. Conditional on all of these characteristics, the excluded men are very slightly better educated than those included in the analyses. There are no differences in the heights of those who do and do not report earnings in WISE. The analytical sample includes all person-wave observations in which a respondent earned any income. Restricting analyses to the balanced panel of males whose earnings are positive in every wave reduces the sample by 6% and does not affect the substance of our results or our inferences. Because this restriction raises the possibility of selectivity of the sample, we report results for all males who have earnings in any survey wave.

Table 1
Sample description.

		Individual Works in [. . .]		
	All (1)	Wage Sector Only (2)	Self-employed Sector Only (3)	Both Sectors (4)
Hourly earnings (Rp0,000)				
All work	0.35	0.50	0.40	0.29
	(0.03)	(0.02)	(0.10)	(0.01)
From work in wage sector	0.40	0.50		0.37
	(0.03)	(0.02)		(0.03)
From self-employment	0.44		0.40	0.48
	(0.05)		(0.10)	(0.06)
Height (cm)	161.63	163.70	160.59	161.47
	(0.09)	(0.21)	(0.17)	(0.12)
Raven's Test (% correct)	53.56	65.28	46.52	52.99
	(0.36)	(0.87)	(0.69)	(0.46)
Fluid Intelligence (% correct)	61.26	68.53	55.04	61.98
	(0.34)	(0.90)	(0.66)	(0.42)
Working memory: Immediate	4.62	5.26	4.26	4.62
(correct out of 10)	(0.02)	(0.05)	(0.04)	(0.03)
Working memory: Delayed	3.56	4.27	3.20	3.53
(correct out of 10)	(0.02)	(0.06)	(0.04)	(0.03)
Age	41.36	31.93	48.17	41.26
	(0.17)	(0.30)	(0.35)	(0.21)
Years of Education	8.25	10.63	7.23	7.93
	(0.06)	(0.12)	(0.11)	(0.08)
Body Mass Index	20.87	20.99	20.68	20.92
	(0.04)	(0.09)	(0.08)	(0.05)
Difficulty Running 1 km (%)	16.89	9.00	26.80	14.71
	(0.51)	(0.91)	(1.17)	(0.66)
Systolic BP (mm Hg)	125.18	123.59	127.88	124.36
	(0.25)	(0.51)	(0.55)	(0.33)
Pulse Pressure (mm Hg)	46.91	45.22	49.04	46.40
	(0.18)	(0.40)	(0.39)	(0.24)
N. Individual-Wave Obs.	38,430	4521	8576	34,274
N. Individuals	5304	1000	1429	2875

calculated as total earnings from work in the market sector during the previous four months divided by hours worked during the same time period. Similarly, hourly earnings from self-employment are calculated as net profits from self-employment during the prior four months divided by the number of hours worked during that time. Total hourly earnings are the sum of earnings from all jobs divided by the total number of hours worked in all jobs during the previous four months. The four-month periodicity of the survey waves in WISE is selected to coincide with the rice growing cycle, the dominant crop in the area.[3]

Means and standard errors of key variables are displayed in Table 1. Column 1 includes all workers and, in the other columns, the sample is stratified into those who only work in the wage sector (column 2), those who only work in the self-employed sector (column 3) and those who work in both sectors during the study period (column 4).

The first three rows of Table 1 report hourly earnings in Rp 10,000 (equivalent to approximately 1 USD in purchasing power parity terms at the time of the survey). The average male earns Rp 3500 per hour, those working only in the wage sector earn about Rp 5000 per hour and those working only in the self-employed sector earn about Rp 4000 per hour. Those who work in both sectors earn the least: Rp 2900 per hour on average. This reflects the fact that relative to those who never switch sectors, those who do switch sectors or work in both simultaneously during the study period earn less when they work in the wage sector (row 2) but more when they work in the self-employed sector (row 3). These switchers, who account for over half the workers, are extremely valuable for this research as they provide an opportunity to directly address selection bias when comparisons of the height premium are drawn between those who choose to work in the wage sector relative to those who are self-employed. There are at least two reasons that working in both sectors is common in these data. First, rice farming is the dominant activity in the area and plots are, on average, less than half an acre in size. Many farmers supplement income by working both on and off the farm during the year. Second, during the study period, there was considerable variation in weather that affected crop output with one year being a severe drought and, again, many farmers supplemented income by working off the farm.

[3] WISE collects self-reported net profits for the prior four months for those who are self-employed in a work and earnings module in the individual interview. In addition, in a separate household enterprise module, detailed information is collected about business revenues and expenditures for the prior four months. The match between the two sources of information on total net profits for all household members working in the enterprise is very close. Converting all estimates to hourly rates, average earnings per hour for those who work in a household business is Rp5,000 (se = Rp300) in the work and earnings module and the average net profit per hour for the same workers is Rp5,300 (se = 1100); the difference, Rp300 (se = 290) is not statistically significant. If the two estimates of hourly earnings are the same, a regression of one on the other will have a slope of unity. In the model with hourly earnings from the work and earnings module as the dependent variable, the slope is 1.019 (se = 0.002) and with profits as the dependent variable, the slope is 0.84 (se = 0.001) indicating that hourly earnings in the work and earnings module is measured with very little error and less error than the estimate based on profits calculated from the enterprise module. We have also estimated these models stratifying the sample by height and by cognitive scores; we find no evidence that measurement error is correlated with any of the human capital markers. We use the value of hourly earnings for self-employment and for wage work reported by the individual respondent in his work and earnings module.

3.2. Height

The height of every household member is assessed at each survey wave. Adult stature is fixed until older ages, when individuals begin to shrink and so each assessment in our study sample of males age 25–65 should be the same. To minimize the impact of measurement error, we use the mean of measured height.[4]

As shown in the fourth row of Table 1, the height of the average male in the sample is 161.6 cm with those who only work in the wage sector being positively selected, those who are only self-employed being negatively selected and those in both sectors falling between those two groups. This parallels the pattern observed for hourly earnings.

3.3. Measures of cognition

A key strength of WISE for this research is that cognitive achievement is assessed using three different, complementary instruments that have been well-validated and are designed to measure different domains of cognitive performance. In addition, each instrument was assessed in more than one survey wave so that it is possible to mitigate the impact of measurement error in the assessments.

First, the Raven's Colored Progressive Matrices pattern recognition test is designed to provide a non-verbal measure of abstract reasoning that has been interpreted as indicative of intelligence (Raven, 2000). The assessment, which does not require literacy or numeracy, involves identifying the missing part of a progression of designs from among six different options. The assessment, first developed in 1938 for clinical and general use in the U.K., is thought to be free of cultural bias and has been implemented in a very large number of studies across the globe. In WISE, different subsets of the Ravens test were administered three times to respondents age 15 and older; since performance on the assessment is unlikely to vary during adulthood, we use the average score on all the assessments in the models.

Second, an adaptation of the Philippines National Intelligence Test developed by Guthrie et al. (1997) is utilized to assess fluid intelligence. The test is similar to the Columbia Mental Maturity Scale and was originally designed for settings that are similar to the WISE study site. Like the Raven's test, the assessment is non-verbal and does not require literacy or numeracy; it differs from Raven's in that it uses images of familiar objects and activities of daily life in order for it to be more reflective of experience, logical thinking, and the ability to recognize real world patterns than the abstract Raven's matrices. Specifically, each respondent is shown a series of 5 images and asked to identify the odd man out among the 5: that is, the respondent has to identify the common elements that bind four of the images but are not shared by the fifth image. Fig. 1 illustrates a sample question. The assessment has been used in other population-based surveys including the Cebu Longitudinal Health and Nutrition Survey (see Mendez and Adair, 1999; Glewwe and King, 2001; Daniels and Adair, 2005). As with the Raven's assessment, performance on this instrument is unlikely to vary during adulthood and so we use the average score on four assessments to maximize the signal in the measurement.

Third, working memory is assessed using a word recall test in which each respondent is read ten common words in Indonesian from a predetermined list. The respondent is asked to repeat back the words in any order immediately and the number the respondent remembers without prompting is recorded as the immediate word recall. The survey continues with questions about health status and, after about five minutes, the respondent is asked to recall as many words from the list as possible. The number recalled is the delayed word recall. Working memory is a core executive function and is thought to play an important role in reasoning and decision-making and, is, therefore, potentially related to labor market success. In our models, we use the number of words recalled immediately and after a delay, averaging across surveys for the same respondents. The first time the assessment was conducted, the list of words read to the respondent was randomly assigned so that household members who are present for another members' assessment do not hear the words multiple times. Thereafter, the list of words was selected to assure that each respondent received a different assessment across waves. We use the average number of words recalled in assessments conducted in three waves of WISE. The assessment is used widely in studies of cognitive aging including, for example, the Health and Retirement Survey and related global studies in Europe and low income countries (McArdle et al., 2011; Lei et al., 2012).

Table 1 reports the within-person averages (and standard errors) for each of the cognitive assessments. The average male completed slightly over half the Ravens assessments correctly and more than 60% of the fluid intelligence assessments correctly. He remembered 4.6 of the 10 words immediately and one less word after a delay. For all of the assessments, the average is highest among those who specialize in the wage sector, lowest among those who are only ever self-employed. In order to draw comparisons across the assessments, in the regression models, all of the assessments are standardized to z-scores using the overall sample mean and standard deviation.

3.4. Additional health assessments

In addition to measures of the attained height of individuals, the survey includes several health markers that are potentially related to labor market productivity. First, body mass index (BMI), weight (in kg) divided by height (in m) squared, is an indicator of nutritional status that, unlike height, varies throughout the life course. While extreme values of BMI are predictive of mortality and morbidity, 8% of respondents in this sample are overweight (BMI > 25) and less than 0.5% are obese (BMI > 30). The BMI of the average male is 20.9 m/kg^2 and 17.3% have BMI < 18.5 and so, in this sample, lower BMI is indicative of poorer health while higher BMI is likely associated with elevated VO_2 max and work capacity. Higher BMI is therefore likely to be an indicator of physical strength and endurance that is potentially valued in the labor market.

Resting blood pressure is measured for each respondent in WISE using an Omron portable automatic blood pressure monitor with upper arm cuffs of different sizes. As in many developing country settings, there are high levels of undiagnosed hypertension in Indonesia (Frankenberg et al., 2016) and very few of the WISE respondents take medication to control hypertension. We examine systolic blood pressure (SBP) along with pulse pressure, the difference between systolic and diastolic blood pressure. Whereas systolic blood pressure is a measure of the maximum pressure on the arteries, pulse pressure is an indicator of the force that the heart generates each time it contracts. Elevated systolic and diastolic blood pressure are predictive of cardiovascular disease, and pulse pressure is also indicative of hardening of artery walls (e.g. Blacher et al., 2000; Franklin et al., 1999; Mattace-Raso

[4] Height is well measured in this study. For example, one assessment of the quality of measurement is to examine the distribution of the final digit (which is mm of height). It should be uniformly distributed across all integers from 0 to 9. Stacking on preferred digits (0 and 5, for example) would indicate poor measurement protocols. There is no evidence of such stacking. 9.9% of heights end in 0 mm and 11.2% end in 5 mm. Using the average of all measured heights for a respondent provides protection against transcription errors and line shifting in recording.

Fig. 1. Example of a question from the assessment of fluid intelligence.
Note: Each respondent is asked to circle the picture that does not belong with the others.

et al., 2004; Panagiotakos et al., 2005; Safar et al., 1987). The SBP of the average respondent is 125 mm Hg with 16% having SBP above 140 mm Hg, the standard cut-off for hypertension. Pulse pressure of the average respondent is 47 mm Hg and 12% have pulse pressure above 60 mm Hg which is thought to be a risk factor for elevated heart disease.

Each respondent also provides information on a battery of self-assessed Activities of Daily Living (ADLs). We focus on whether the respondent has difficulty running a kilometer to capture a key indicator of physical function that is likely related to strength and endurance. Seventeen percent of males report such difficulty, with fewer than one in ten of those who work only in the wage sector and more than one in four of those who work only in self-employment reporting difficulty running a kilometer.

4. Descriptive analyses

All of the human capital markers are likely to be positively correlated. However, it is possible that the correlations are so high that it will not be possible to isolate independent associations with productivity in the labor market. This issue is investigated in Table 2.

Panel A reports pairwise correlations and jackknife standard errors for (log) height and the four cognitive assessments (in z scores). Taller males score significantly better on each cognitive assessment. A 5% increase in height (which is about a standard deviation increase) is associated with about a quarter of a standard deviation increase in the Raven's and fluid intelligence scores and about a sixth of a standard deviation increase in the working memory assessments. Fig. 2 displays locally weighted smoothed scatterplots with a biweight kernel and 20% bandwidth of the relationship between each cognitive assessment and (the logarithm of) height in order to assess whether there are important non-linearities in these associations. There are not. In fact, all of the correlations are positive and statistically significant. The Ravens and fluid intelligence assessments are strongly correlated and the two working memory assessments are also strongly correlated which is consistent with the pairs capturing related domains of functioning.

Panel B of the table reports regressions relating height to the four cognitive assessments (in the first column) and the Raven's score to the other three cognitive assessments (in the second column). The regressions establish there is independent variation in the cognitive assessments that predicts height: all but delayed

Table 2
Correlations among human capital markers.

A. Pairwise correlations between height and cognitive assessments

	Cognitive assessments (z scores)			
	Raven's Prog Matrices	Fluid Intelligence	Working memory	
			Immediate	Delayed
	(1)	(2)	(3)	(4)
ln(height)	0.241	0.243	0.183	0.167
	(0.013)	(0.013)	(0.014)	(0.014)
Raven's score		0.550	0.405	0.394
		(0.010)	(0.011)	(0.011)
Fluid intelligence			0.418	0.395
			(0.012)	(0.012)
Working memory: Immediate				0.777
				(0.007)

B. Multivariable correlations between height and cognitive assessments

	ln(height)	Raven's score
	(1)	(2)
Raven's score	0.549	
	(0.066)	
Fluid intelligence	0.599	0.482
	(0.070)	(0.014)
Working memory: Immediate	0.257	0.128
	(0.091)	(0.018)
Working memory: Delayed	0.048	0.124
	(0.090)	(0.018)
R^2	0.079	0.345

Note: Sample is 5304 males. Cognitive scores are averages for each respondent across assessments and converted to z scores using the overall sample mean and standard deviation. Standard errors in parentheses robust to arbitrary forms of heteroskedasticity.

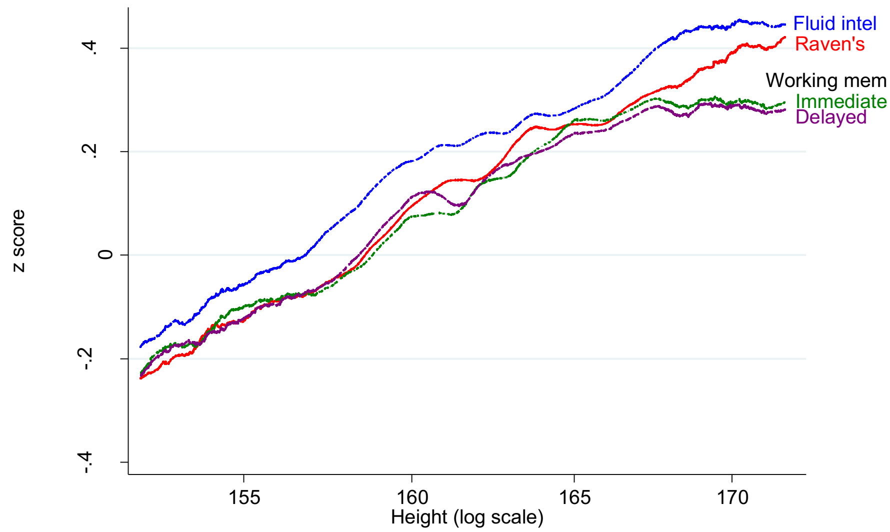

Fig. 2. Relationship between cognitive assessments and height.
Note: Locally weighted smoothed scatterplots with biweight kernel and 20% bandwidth

working memory predict ln(height), although only 8% of the variation in ln(height) is attributable to these markers. All three cognitive assessments are significant predictors of the Raven's score although only about one third of its variation is accounted for by the other assessments.

5. Human capital and earnings

We turn next to investigate how the association between hourly earnings and height varies in models that control education, cognition and health. Specifically, we estimate models that relate the logarithm of hourly earnings, $\ln(w_{ict})$, of individual i in community c during the 4 months prior to the survey interview at time t to individual human capital and demographic characteristics, taking into account time and local market effects:

$$\ln(w_{ict}) = \beta_0 + \beta_1 \ln(ht_i) + \beta_2 cog_i + \beta_3 age_{it} + \beta_4 ed_i + \beta_5 \theta_{it} + \mu_t + \mu_c + \varepsilon_{ict} \quad (1)$$

where $\ln(ht_i)$ is the logarithm of average measured height of individual i and cog_i is a vector of the four cognitive assessments, with the mean of each assessment for an individual expressed as a z score (subtracting the sample mean and dividing by the sample standard deviation for all male respondents). All models include age of the respondent (specified as indicator variables for each of five-year birth cohorts). We also control education, ed_i, measured as the number of years needed for an individual to complete the highest level of schooling achieved by the respondent and, in some of the models, we adjust for markers of health, θ_{it}, that are potentially related to height. The additional health indicators include the logarithm of BMI, whether the respondent reports having difficulty running 1 km, and the two blood pressure measures, SBP and pulse pressure. All of the health markers are time-varying. Wave fixed effects, μ_t, are included in all models to capture common aggregate conditions including seasonality as well as variation over time in prices and wages in the survey area. It is possible that part of the premium associated with each marker of human capital reflects sorting into different labor markets; to evaluate the importance of this possibility, we also add community-specific fixed effects, μ_c, to the model so that, in those models, comparisons are drawn between men within the same local labor market. All estimates of variance-covariance matrices allow for heteroskedasticity and take into account clustering at the person level; allowing for clustering at the *desa* (village) level does not change any inferences.

Table 3 reports results from estimating Eq. (1) using earnings for all male workers. We first establish the magnitude of the associations between earnings, height and cognition in the WISE sample. As shown in column 1, conditional on age and time effects, taller individuals earn more: on average, a 1% increase in height is

Table 3
Human capital and labor market productivity.

	ln(hourly earnings)				
	(1)	(2)	(3)	(4)	(5)
Height (logarithm)	3.636		1.874	1.942	1.763
	(0.345)		(0.304)	(0.299)	(0.286)
Cognitive assessments (z scores)					
Raven's progressive matrices		0.166	0.077	0.073	0.075
		(0.017)	(0.015)	(0.015)	(0.015)
Fluid intelligence assessment		0.164	0.056	0.049	0.036
		(0.017)	(0.016)	(0.016)	(0.015)
Working memory: Immediate		0.127	0.052	0.045	0.031
		(0.021)	(0.019)	(0.019)	(0.018)
Working memory: Delayed		0.045	0.028	0.026	0.024
		(0.020)	(0.018)	(0.018)	(0.017)
Completed education (years)			0.083	0.075	0.071
			(0.003)	(0.003)	(0.003)
Health indicators					
BMI (logarithm)				1.016	0.964
				(0.096)	(0.095)
(1) if difficulty running 1 km				−0.049	−0.040
				(0.024)	(0.023)
Systolic blood pressure				0.025	0.022
				(0.009)	(0.008)
Pulse pressure				−0.045	−0.055
				(0.011)	(0.010)
Local market fixed effects					Y
Joint tests (F-statistics)					
All human capital markers	111.2		252.4	170.1	129.7
Cognitive assessments		172.6	28.02	24.25	19.45
Health indicators				36.00	36.07
Sample size	38,430	38,430	38,430	38,430	38,430

Note: Standard errors in parentheses and all test statistics based on estimates clustered at the individual level and robust to arbitrary forms of heteroskedasticity. All models include flexible age controls and survey wave fixed effects.

associated with a 3.64% increase in hourly earnings. This is very close to the estimate of 3.71 for hourly earnings of Indonesian males based on the 2000 wave of the Indonesia Family Life Survey (IFLS) adjusting for the fact that the study area is largely rural and the height premium is larger in urban Indonesia. (The IFLS estimate is 3.62 for rural males and 4.07 for urban males. See also Thomas and Frankenberg, 2002; who use the 1993 and 1997 waves of IFLS and Sohn, 2015; who uses the 2007 wave of IFLS to investigate the relationships between earnings and human capital in Indonesia).

As shown in column 2, the cognitive assessments are also significant predictors of wages, both taken together and individually. Holding the other cognitive assessment scores constant, a standard deviation increase in the test score is associated with a 16% increase in hourly earnings for both the Raven's and fluid intelligence assessments. Working memory is an independent predictor of hourly earnings: a standard deviation increase in the number of words recalled is associated with a 12 and 5% increase in hourly earnings for the immediate and delayed assessments, respectively. As shown above, the cognitive assessments are all correlated and in models that do not control for other assessments, the estimated associations rise to between a 25 and 30% increase in hourly earnings which highlights the likely value-added for this research of multiple assessments that are designed to capture different domains of cognitive achievement.

Height, cognition and education are all included, along with age and wave effects, in the model reported in column 3 of the table. About one half of the height premium (in the first column) can be attributed to superior education and cognitive performance of taller men which is very similar in proportionate terms to the results reported for males in the U.K. and U.S. by Case and Paxson (2008a). The magnitude of the decline is much larger than in more advanced settings; it is 1.8 with a standard error of 0.2 which is statistically significant.

Somewhat more than half the association between the cognitive scores and earnings can be attributed to education and height with the vast majority of this effect being captured by education. The cognitive assessments remain statistically significant for all but the longer term working memory asssessment. Education is a significant predictor of hourly earnings with each year of education being associated with an 8% increase in earnings, holding height and cognition constant (Without those controls, the educaton premium is 10%).

Importantly, height continues to be a significant predictor of hourly earnings even after controlling education, cognition and age. It is possible that height is capturing non-linear effects of education: allowing the effect of education to differ for each year of education in the model in column 3 has an imperceptible impact on the coefficient on ln(height). In the model with education specified as linear in years, the estimated coefficient is 1.9 (with a standard error of 0.3) and it is 1.8 (s.e. = 0.3) in a semi-parametric specification with an indicator variable for each year of education.

It is also possible that height and education are complements. This would arise, for example, if height were a proxy for strength that is of greatest value to those with the least education. The evidence is not consistent with this interpretation. Restricting the sample to those males who completed primary school or less (about half the sample), the coefficient on ln(height) is 1.77 (s. e. = 0.4); the coefficient on the other half of the sample, who are better educated, is 1.94 (s.e. = 0.5). If the sample is restricted to those men who completed primary school (exactly 6 years of schooling), the coefficient on ln(height) is 1.99 (se = 0.4).

We have investigated whether there are important non-linearities in the relationships between height and productivity. Non-parametric estimates of the relationship between ln(hourly earnings) and ln(height) without controls, displayed in Fig. 3, indicates it is well approximated by the log–log model. Over and

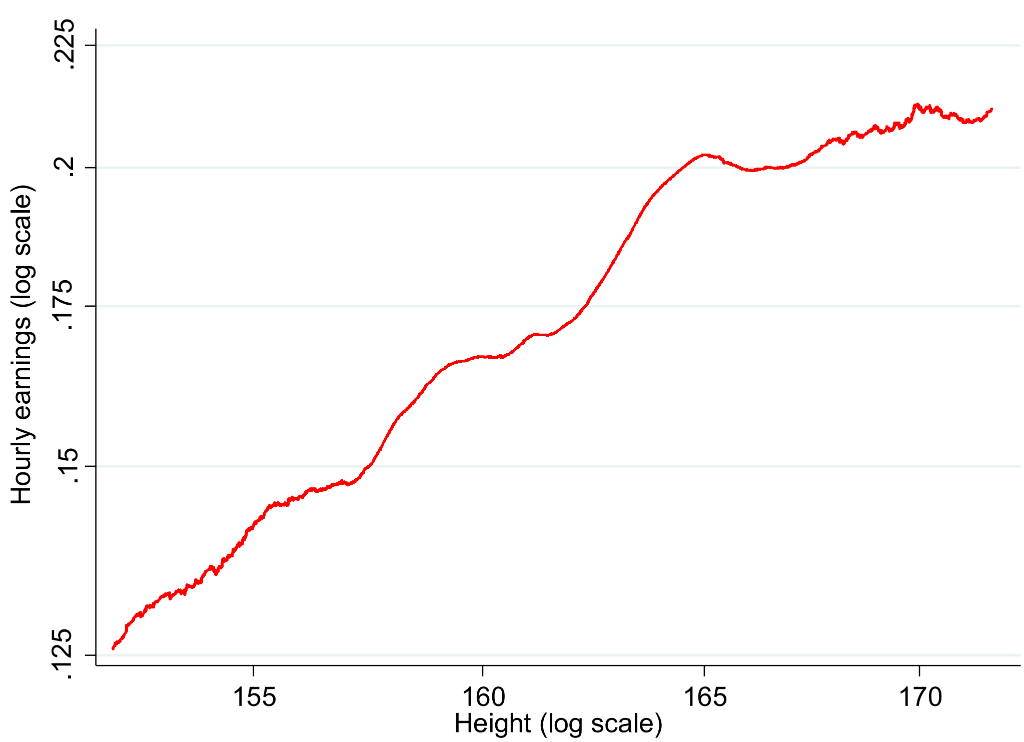

Fig. 3. Relationship between hourly earnings and height.
Note: Locally weighted smoothed scatterplots with biweight kernel and 20% bandwidth.

above this functional form, we do not find important non-linear effects of height in the multivariable regression models.[5]

In sum, variation in education and the four markers of cognitive achievement is able to explain no more than half the association between hourly earnings and height in our sample of Indonesian men. We conclude that height is not simply a proxy for cognition in this setting.

Taller people tend to be healthier. In these models, height may be serving as a proxy for other health markers including, for example, strength. Time-varying health status indicators are included in the model in column 4 and the estimated impact of height is slightly larger than in the model without health controls. As (the logarithm of) BMI rises, so do hourly earnings. This effect is primarily driven by the impact of weight, holding height constant.[6] Men who have difficulty with strenuous exercise earn less as do men with elevated pulse pressure. Elevated systolic blood pressure is positively associated with productivity after controlling weight and pulse pressure; this likely reflects the influence of a more sedentary lifestyle among those who have higher hourly earnings.

5.1. Local area markets

If markets are complete, the returns to human capital should be equalized across local area markets; since markets have been shown to not be complete in this study setting (LaFave and Thomas, 2016), we estimate the premium associated with each marker of human capital within local labor markets in column 5 of the table by including local market fixed effects in the model. The local market effects are statistically significant and while the height premium is about 10% smaller, indicating that taller people are more likely to work in markets where hourly earnings are higher, the height premium remains large, statistically significant and economically substantial. The difference between the uncontrolled height premium (in column 1) and the estimate adusting for education, cognition, other health indicators, age and local area markets is 1.9 (with a standard error of 0.2) which is statistically signigicant. In terms of hourly earnings in the model with all of these controls, a 10% height advantage is approximately equivalent to 2.5 years of additional education.

5.2. Sectoral choice

It is possible that employers use height as a signal of worker quality. It has also been suggested that customers use height as a signal of quality of services purchased from the self-employed (Sohn, 2015). In rural Central Java, the vast majority of the self-employed are rice farmers and the quality of their product is unlikely to be deduced from their height. If height is used as a signal in our setting, then height should be more highly rewarded in the wage sector than among the self-employed. To investigate this issue, Table 4 reports estimates from the model in the final column of Table 3 separately for the (logarithm of) hourly earnings from wages (in column 1) and from self-employment profits (in column 2). Height is not just a signal in the formal sector. In fact, the height premium is almost 20% higher in the self-employed sector relative to the wage sector. While this difference is not statistically significant, the higher premium in the self-employed sector is not consistent with employers discriminating against shorter workers.

It is possible that the gap is driven by measurement error in hourly earnings. There are at least two issues. First, it is possible that taller men are better able to report their self-employed earnings than shorter men; however, as noted above, we find no evidence that measurement error is correlated with height or cogntiive skills.

Second, it is not straightforward to attribute earnings from a household enterprise to individuals within the household (Beegle et al., 2003). In the survey, each individual reports his or her own earnings, including those who work in a household enterprise. In some cases, all earnings are reported by the "manager" of the enterprise and all other household members report themselves as unpaid family workers; in other cases, more than one individual in the household reports earnings from the enterprise. While, in principle, it would be possible to estimate a model to guide the allocation of earnings to individuals working in the household enterprise, we have chosen to use earnings as reported by each individual in the survey. This means that males who lead enterprises with more household labor will tend to have higher hourly earnings which shifts the mean for that individual but does not necessarily bias the estimates of the associations with height, cognition and other health markers. Those estimates will be biased if, for example, taller men tend to command more unpaid family labor or more productive unpaid family labor. There is only a modest association between the height of a man and the number of hours of unpaid family labor provided for the household enterprise; the coefficient on height in a model relating total hours of unpaid work over 4 months by household members to height of the manager of the enterprise is 0.98 (se = 1.85).

An alternative and direct approach to assessing the impact of unpaid family labor on our estimate of the height premium is to re-estimate the model of self-employed earnings, (displayed in column 2 of Table 4), first, attributing all enterprise income to the manager of the enterprise (so all other household workers earn nothing) and, second, assuming all household workers are equally productive and earn the same hourly rate. These estimates provide an upper and lower bound, respectively, on the height premium. The height premium for this sub-sample is 1.95 (se = 0.40), the upper bound is 2.03 (se = 0.47) and the lower bound is 1.72 (se = 0.36); none of these estimates is significantly different from each other and they are all greater than the estimated premium in the wage sector. We conclude measurement error cannot explain the higher estimated height premium in the self-employed sector.

In part, the greater height premium in the self-employed sector relative to the wage sector may reflect selection of workers into each sector (Heckman and Honore, 1990). We can directly evaluate the importance of such selection since over half the men report working in both sectors at some point during the study. The vast majority of these men switch sectors during the study, with many making more than one switch; other men hold multiple jobs and work in both sectors simultaneously. Panel B of Appendix A, Table A1 reports results from estimating a multinomial logistic regression of the probability of working in the wage sector, the self-employed sector or in both sectors. Odds ratios and associated standard errors relative to the excluded males who work in both sectors are reported in the table. Height is not a significant predictor of working in either sector alone, at a 5% size of test, and height does not predict sectoral choice. None of the cognitive assessments predicts sectoral choice. In contrast, better educated males are more likely to work in one sector, rather than both

[5] In addition to capturing non-linearity in the association between hourly earnings and height, the log–log specification has the advantage that it is unit-free and thus straightforward to compare across settings. Other studies have used adult height measured in inches or centimeters (Case and Paxson, 2008a and Vogl, 2014, respectively, for example). If height is measured in inches, the estimated coefficient and (standard error) is 0.057 (0.005) in column 1 and 0.028 (0.005) in column 5; this translates to a 3.63% and 1.76% change in wages for each percentage point change in height, respectively. These estimates are the same as those reported in Table 3 using height in logarithms. None of the substantive conclusions or inferences in this paper depends on the specification of height in logarithms.

[6] In a model that includes the logarithms of height, weight and height squared, the coefficient on ln(weight) is 1.0 (s.e. = 0.9) and the coefficient on the square of ln (height) is small and not statistically significant.

Table 4
Human capital and productivity in wage and self-employed sectors.

	ln hourly earnings from wage work (1)	ln hourly earnings from self-employment (2)	Self-employment premium rel to wages (3)
Height (logarithm)	1.658	1.952	0.331
	(0.284)	(0.364)	(0.539)
Cognitive assessments (z scores)			
Raven's progressive matrices	0.059	0.070	−0.002
	(0.015)	(0.020)	(0.030)
Fluid intelligence assessment	0.004	0.063	0.105
	(0.016)	(0.021)	(0.030)
Working memory: Immediate	0.035	0.024	0.077
	(0.020)	(0.024)	(0.036)
Working memory: Delayed	0.011	0.021	−0.030
	(0.019)	(0.022)	(0.034)
Completed education (years)	0.067	0.057	0.009
	(0.003)	(0.004)	(0.006)
Health indicators			
BMI (logarithm)	0.825	1.026	0.344
	(0.104)	(0.123)	(0.200)
(1) if difficulty running 1 km	−0.031	−0.001	0.030
	(0.025)	(0.028)	(0.035)
Systolic blood pressure	0.024	0.007	−0.005
	(0.009)	(0.011)	(0.014)
Pulse pressure	−0.041	−0.044	0.004
	(0.010)	(0.014)	(0.017)
(1) if self-employment earnings			−2.893
			(2.870)
Local market fixed effects	Y	Y	
Individual fixed effects			Y
Joint tests (F-statistics)			
All human capital markers	104.9	56.91	4.40
Cognitive assessments	9.917	12.05	5.46
Health indicators	21.67	20.85	0.95
Sample size	21,119	26,252	17,856

Note: Standard errors in parentheses and all test statistics based on estimates clustered at the individual level and robust to arbitrary forms of heteroskedasticity. All models include flexible age controls and survey wave fixed effects.

sectors, and most likely to work in the wage sector, suggesting that education is rewarded differently in the two sectors. There is also evidence that the additional health markers predict sectoral choice.

To interpret the height premia in the wage work and self-employed sectors, we exploit the fact that more than half the men work in both the wage and self-employed sector to assess the extent to which selection explains differences in human capital premia across sectors. The final column of Table 4 reports estimates of a model for this sub-sample of males that includes individual fixed effects and interacts each covariate with an indicator for whether the male's earnings are from self-employment. The coefficient estimates reflect the premium (or discount) received by that male in the self-employed sector relative to the wage sector. There is no difference in the effect of height on the productivity of the same individual whether his earnings are from the wage or self-employed sector. Nor is there a difference in the return to education although both fluid intelligence and (immediate) working memory have larger premia in the self-employed sector. Neither of those attributes is easily observed and so may be more difficult for an employer to reward. There is also a higher premium associated with BMI in the self-employed sector that likely reflects the effect of strength over and above height.

We conclude that selection does not drive the estimated height premia in the self-employed and wage sectors. However, it is possible that selection operates at the level of occupational rather than sectoral choice. This issue is directly addressed in the next sub-section.

5.3. Occupational choice

Occupational choice has been shown to depend on education, cognitive skills and height. Vogl (2014) argues that occupational sorting plays a key role in explaining the relationship between height, cognition, and earnings in Mexico. We investigate this issue directly exploiting the fact that WISE records detailed descriptions of each individual's tasks which have been classified into specific occupations at the two digit level.

As a first step, we investigate whether height and the other human capital attributes are associated with selecting into occupations in which strength is likely to be rewarded, specifically, agriculture, production work such as masonry and manual transportation operation (which is mostly bicycle rickshaws). These occupations account for 65% of the sample. The first column of Table 5 reports coefficients from a linear probability model with an indicator for working in one of these occupations as the dependent variable. Males who are taller, more educated, and score higher on Raven's exams are less likely to work in occupations that likely reward strength.

Second, we re-estimate the models of hourly earnings including occupation fixed effects. Occupations have been aggregated into the following categories: professional, teachers, administrative, clerical, sales, services, agriculture, manual production, transport operation, military, and students. Results are reported in columns 2 through 4 of Table 5 which add occupation fixed effects to the specifications reported in the final column of Table 3 and the first two columns of Table 4, respectively. The occupation fixed effects

Table 5
Occupational choice, productivity and human capital.

	Occupation choice	Occupation fixed effects		
	LPM	Productivity and Human Capital		
	Occupation that likely rewards strength (1)	ln hourly earnings (2)	ln hourly earnings from wage work (3)	ln hourly earnings from self-employment (4)
Height (logarithm)	−0.427	1.577	1.582	1.718
	(0.158)	(0.262)	(0.265)	(0.344)
Cognitive assessments (z scores)				
Raven's Score	−0.016	0.061	0.056	0.065
	(0.008)	(0.013)	(0.014)	(0.019)
Fluid Intelligence Score	−0.002	0.034	0.010	0.055
	(0.008)	(0.014)	(0.014)	(0.020)
Work memory: Immed	−0.016	0.014	0.027	0.007
	(0.009)	(0.017)	(0.018)	(0.022)
Work memory: Delayed	−0.013	0.018	0.007	0.018
	(0.009)	(0.016)	(0.018)	(0.021)
Completed education (years)	−0.032	0.046	0.040	0.042
	(0.002)	(0.003)	(0.003)	(0.004)
Health indicators				
Log BMI	−0.386	0.730	0.666	0.783
	(0.046)	(0.089)	(0.099)	(0.118)
(1) if difficulty run 1 km	−0.028	−0.057	−0.047	−0.021
	(0.009)	(0.022)	(0.024)	(0.027)
Systolic blood pressure	−0.011	0.011	0.015	0.002
	(0.004)	(0.008)	(0.008)	(0.010)
Pulse Pressure	0.028	−0.035	−0.030	−0.027
	(0.004)	(0.009)	(0.009)	(0.013)
Joint tests (F-statistics)				
All human capital markers	100.00	63.63	44.67	33.71
Cognitive assessments	6.83	13.58	9.08	9.55
Health indicators	32.21	22.06	15.36	12.55
Sample size	38,430	38,430	21,119	26,252

Note: Standard errors in parentheses and all test statistics based on estimates clustered at the individual level and robust to arbitrary forms of heteroskedasticity. All models include flexible age controls, survey wave fixed effects, and local market fixed effects. Columns 2 through 4 include occupation fixed effects.

are statistically significant, but they explain only a small part of the height premium. Occupational selection is slightly more important among the self-employed, for whom the height premium is reduced by 12%, than those in the wage sector, for whom the height premium is reduced by less then 5%. Occupational choice does not explain the height premium in this setting.[7]

5.4. Family background

All of the dimensions of human capital that we have examined – height, cognition, education, and health – have been shown to be related to earnings of males in rural Indonesia. There is at least one key difference between height and all the other human capital markers: height is largely determined in the first few years of life and depends critically on inputs during that period. All the other markers of human capital likely depend not only on those inputs but also inputs through the rest of childhood and adolescence, as well as adulthood in some cases.

In an effort to investigate the role family background plays in the relationships described above, we adopt two complementary approaches. First, we include controls for parental human capital and, second, we estimate models that include family fixed effects. These approaches exploit several features of the design of WISE. First, all adults report the education of their parents in the survey, whether or not the parent is alive, so that controlling parental education does not impose any selection rule on the sample. Second, when a respondent moves out of a baseline household, the respondent is followed to his/her new location and interviewed there. (Attrition in WISE is less than 2%.) Third, when a person joins a household, he or she is interviewed (and measured) as part of the survey. As a result of the second and third design features, there are a large number of adult siblings in the study sample although it is important to recognize that they are not a random sub-sample of the population.

Our first approach, reported in column 1 of Table 6, extends the model of hourly earnings [1] by including parental education (which is recorded for all respondents in WISE). Overall, the effects of own human capital are little affected. The estimated return to own education is reduced by about 10%, as is the effect of the Raven's score. The height premium is not reduced.

A complementary strategy is to examine differences between siblings who have shared genetic and environmental backgrounds. To assess the selectivity of this sample for interpretation of the link between human capital and hourly earnings, the model in the first column is estimated with the reduced sample of siblings and displayed in the second column. The differences in the effects of cognition and education in the two models are modest and they are slightly smaller in the sibling sample; the height premium is slightly larger in the sibling sample (but the difference is not statistically significant). A key genetic trait shared by the siblings is parental height which is also a powerful predictor of child height.

[7] Panel C of Appendix A, Table A1 repeats these analyses without controlling other dimensions of health which may be correlated with unobserved factors that also affect occupational choice. The estimated effects of height, and our conclusions, are not substantially affected.

Table 6
Family background, human capital and labor market productivity.

	All males	Males w/at least one sibling in sample		
	Include parental education (1)	Include parental education (2)	Include parental education & height (3)	Include mother fixed effects (4)
Height (logarithm)	1.780	1.938	1.953	1.313
	(0.285)	(0.473)	(0.535)	(0.732)
Cognitive assessments (z scores)				
Raven's Score	0.069	0.059	0.060	0.122
	(0.015)	(0.022)	(0.022)	(0.048)
Fluid Intelligence Score	0.039	0.034	0.034	−0.015
	(0.015)	(0.022)	(0.022)	(0.068)
Work memory: Immed	0.030	0.017	0.014	−0.026
	(0.018)	(0.028)	(0.028)	(0.059)
Work memory: Delayed	0.023	0.030	0.031	0.071
	(0.017)	(0.027)	(0.027)	(0.080)
Completed education (years)	0.066	0.056	0.056	0.015
	(0.003)	(0.005)	(0.005)	(0.008)
Health indicators				
Log BMI	0.946	0.590	0.583	0.381
	(0.095)	(0.144)	(0.144)	(0.440)
(1) if difficulty run 1 km	−0.035	0.080	0.079	0.105
	(0.023)	(0.042)	(0.042)	(0.041)
Systolic blood pressure	0.022	0.007	0.008	0.018
	(0.008)	(0.014)	(0.014)	(0.013)
Pulse pressure	−0.053	−0.049	−0.050	−0.046
	(0.010)	(0.015)	(0.015)	(0.013)
Joint tests (F-statistics)				
All human capital markers	106.90	30.79	30.53	4.12
Cognitive assessments	17.79	6.46	6.42	2.23
Health indicators	34.31	8.95	8.94	5.39
Parental characteristics	16.48	6.68	3.47	
Sample size	38,430	11,789	11,789	11,789

Note: Standard errors in parentheses and all test statistics based on estimates clustered at the individual level and robust to arbitrary forms of heteroskedasticity. All models include flexible age controls, survey wave fixed effects, and local market fixed effects. Columns 1 through 3 include parental characteristics. Column 4 includes mother fixed effects.

Parental heights are included in the model in column 3: the estimated own height premium is not substantially changed indicating that the estimated height premium is not driven by intergenerational transmission.

The model reported in the final column of the table includes a fixed effect for each mother in order to take into account genetic and background characteristics that are shared among siblings. (Divorce and remarriage is very uncommon in Central Java and so this approach amounts to including parent fixed effects in the model.) Identification depends on differences between siblings in human capital and labor market outcomes. These differences are much smaller than those in the sample overall. A substantial part of the height premium is driven by shared background although hourly earnings are 1% higher for each percentage difference in height between brothers. This effect is significant at a 10% size of test. Differences in education and the Raven's score are also significant predictors of differences in the earnings of siblings. These siblings differences likely reflect differences in the environment, resources and parental investments during the child life, with the height differences driven by exposures in the first few years of each child's life.

6. Conclusions

This research has established that, in rural Indonesia, over and above height, multiple dimensions of human capital are rewarded in the labor market for males. These include educational attainment, several different indicators of cognitive performance, and other dimensions of health status. After controlling these indicators of human capital, we have shown that taller men are more productive as measured by hourly earnings in both the wage and self-employed sectors, and that this premium is greater among those who select to work in the self-employed sector. We have also shown that while height does predict occupational choice, taller men earn a premium within occupations. To wit, in our study setting, height does not appear to be a proxy for strength, cognition or other dimensions of health and human capital, to the extent they are well-measured in our study. This contrasts with evidence from more advanced economies where the height premium in the labor market tends to be much smaller in magnitude and where there is compelling evidence that height is a proxy for cognition (Case and Paxson, 2008a).

Since taller (or longer) infants and young children are less likely to die and taller people tend to live longer, in principle, it is possible that the association between height and hourly earnings observed in this Indonesian setting is driven by mortality selection. However, given the magnitude of the estimated height premium, the levels of infant and child mortality experienced by the cohorts included in this research and the fact that older males are not included in the study, mortality selection is unlikely to be an important contributing factor. Bozzoli et al. (2009) draw the same conclusion in a broader context.

Even after controlling for a rich set of cognition and health markers, it is possible that there are other dimensions of cognition and health that are not controlled that are correlated with height and earn a premium in the labor market. Studies indicate that part of the height premium reflects the influence of non-cognitive skills such as confidence, emotional control, and other pro-social skills, although there is relatively little empirical evidence on the magnitude of these effects in developing countries (Persico et al., 2004; Lindqvist and Vestman, 2011; Lundborg et al., 2014; Schick and Steckel, 2015).

We present one approach to addressing this limitation by comparing the height premium between siblings. This approach takes into account all shared dimensions of family background, including shared genetic traits, as well as other dimensions of human capital including health, cognitive skills and non-cognitive skills that are shared. In these models, adjusting for a broad array of human capital markers, about one-quarter of the height premium can be attributed to factors that are shared within a family. Height continues to have an independent and statistically significant impact on productivity after adjusting for the shared characteristics of siblings.

This is, perhaps, not entirely surprising. Not only are taller men happier, healthier and more productive, but they likely benefited from a reduced burden of infection and inflammation during the first few years of life that construed many benefits (Crimmins and Finch, 2006). More generally, the height of an adult reflects the combination of the disease, nutrition and health services environment, resource availability and choices of parents made during the first few years of the individual's life. Our results indicate that these early life investments have long lasting effects on health and well-being even after taking into account shared experiences of siblings as well as other human capital investments over the life course. The impacts of these early life experiences are likely to be especially important in low resource settings and they are not likely to be fully captured by the choice of type of work of an individual in adulthood or by even more extensive measures of cognitive performance, educational attainment, and health status measured in adulthood than those that are used in this study. The evidence presented in this paper suggests that in low resource settings like Indonesia, investments that improve early life nutrition outcomes, such as improved access to food and diet quality, greater access to and higher quality health services along with reduced exposure to disease, are likely to have a substantial economic pay-off over the entire life course.

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Appendix A.

See Table A1.

Table A1
Sample selection, sectoral choice and occupational choice excluding health status.

	A. Selection into the sample	B. Sectoral choice		C. Adjusting for occupational choice		
	Linear probability model	Multinomial logit (Odds ratios relative to both sectors)		Effects of human capital on ln(hourly earnings) without controlling health		
	Pr (no earnings) (1)	Only wage sector (2)	Only self-employed sector (3)	All (4)	From wages (5)	From self-employment (6)
Height (logarithm)	−0.03	1.02	1.01	1.52	1.51	1.64
	(0.09)	(0.01)	(0.01)	(0.26)	(0.27)	(0.35)
Cognitive assessments (z scores)						
Raven's Score	−0.03	1.06	0.91	0.06	0.06	0.07
	(0.01)	(0.06)	(0.05)	(0.01)	(0.01)	(0.02)
Fluid Intelligence Score	−0.01	0.99	0.96	0.04	0.01	0.06
	(0.01)	(0.07)	(0.06)	(0.01)	(0.01)	(0.02)
Work memory: Immed	−0.01	1.06	0.91	0.02	0.03	0.01
	(0.01)	(0.09)	(0.06)	(0.02)	(0.02)	(0.02)
Work memory: Delayed	−0.01	1.09	1.11	0.02	0.01	0.02
	(0.01)	(0.09)	(0.07)	(0.02)	(0.02)	(0.02)
Completed education (years)	0.01	1.11	1.04	0.05	0.04	0.04
	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)
Health indicators						
BMI (logarithm)	−0.06	0.45	1.11			
	(0.03)	(0.17)	(0.36)			
(1) if difficulty run 1 km	0.04	1.38	1.22			
	(0.01)	(0.21)	(0.12)			
Systolic blood pressure	0.01	1.02	1.00			
	(0.01)	(0.01)	(0.01)			
Pulse pressure	0.01	0.99	0.99			
	(0.01)	(0.01)	(0.01)			
Observations	5741	5304		38,430	21,119	26,252

Note: Estimates of standard errors in parentheses are robust to arbitrary forms of heteroskedasticity; clustered at community level (columns –3) or individual level (columns 4–6). All models include flexible age controls and community fixed effects. Models in columns 4 through 6 also include survey wave and occupation fixed effects.

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