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Capital-Gender Complementarity

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Abstract

Is capital more complementary to one of the genders? More specifically, which types of capital are complementary to which gender? This paper presents a first attempt at estimating capital-gender complementarities, at both aggregated and disaggregated levels. By employing a panel of 12 OECD countries covering the period of 1970-2005, I find that: a) at the aggregated level capital is, on average, more complementary to male labor; b) at the disaggregated level (non) ICT capital is more complementary to (male) female labor, yet the magnitude of complementarity is higher for male labor; c) these patterns hold for different skill groups, and intensify with skill.

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1. INTRODUCTION

Is capital more complementary to one of the genders?[1] More specifically, which types of capital are complementary to which gender? These questions are fundamental for understanding the association between capital, gender, and productivity. Previous theoretical studies assumed that capital exhibits greater complementarity to female labor (e.g. Galor and Weil 1996);[2] however, very little attention, if any, has been devoted to the empirics of this, especially with regard to the dynamics of recent decades.[3] In this paper I undertake a first attempt at estimating capital-gender complementarities at both aggregated and disaggregated levels, through which I present new evidence on the link between capital, gender, and productivity.[4]

By employing a panel of 12 OECD countries covering the period of 1970-2005, I find that contrary to the assumption made in previous studies, at the aggregated level capital is rather more complementary to male labor. I offer a potential solution for this discrepancy through the subsequent analysis at the disaggregated level in which I find that (non) ICT capital is more complementary to (male) female labor;[5] I then further show that the magnitude of complementarity is higher for male labor, explaining the complementarity patterns observed at the aggregated level. Last, by further disaggregating the analysis to different skill groups, I find that these patterns are robust to skill level, yet intensify with skill.

2. ESTIMATING CAPITAL-GENDER COMPLEMENTARITIES

To estimate capital-gender complementarities I follow the standard methodology used in the empirical literature on capital-skill complementarity,[6] only applied to gender rather than skill. Thus, I employ a gender-based framework of Berman et al. (1994) and estimate a male labor share equation. Assuming capital is a quasi-fixed factor and that male and female labor are variable factors, if the variable cost function is trans-log and production exhibits constant returns to scale, cost minimization yields the following:

$$S = \alpha + \beta \log(\omega) + \gamma \log(k / y) \tag{1}$$

[1] The meaning of 'capital' in this paper is 'capital equipment', or rather the types of capital that labor uses in the production process. As for complementarity, I follow the definition set by Griliches (1969) and Krusell et al. (2000) for capital-skill complementarity, only for gender; i.e. capital is defined as being complementary to male labor if it exhibits a relatively greater elasticity of substitution with female labor.

[2] Galor and Weil (1996) present a mechanism that links fertility and growth in which they assume there are intrinsic differences in factor endowments of brains and brawns between the two sexes that favor females in their complementarity to capital. This assumed complementarity between capital and female labor is a critical feature in their mechanism; in this paper I provide some evidence which indicate that these complementarity patterns are relevant for ICT capital specifically, and may be rather different at the aggregate level, when focusing on capital equipment.

[3] Goldin (1990) argues that industrialization in the beginning of the 19th century was responsible for the dramatic increase in the relative wages of women at the time. However, she does not undertake a formal analysis of complementarities, and does not investigate the dynamics of recent decades which I show exhibit different patterns.

[4] Beaudry and Lewis (2014), Black and Spitz-Oener (2010), and Weinberg (2000) point at complementarity patterns between female labor and computers. Unlike them, I consider also other types of capital, as well as different aggregation levels and skill groups; in addition, I focus on both genders, showing some types of capital are rather complementary to male labor.

[5] ICT capital includes computing equipment, communication equipment, and software; non-ICT capital includes transport equipment and machinery.

[6] See Berman et al. (1994), Duffy et al. (2004), Michaels et al. (2014), and Ruiz-Arranz (2003).

where S denotes the share of wages paid to male labor out of total labor compensation (being a proxy for the demand for male labor), ω denotes the ratio of wages of male labor to those of female labor, k denotes capital, and y denotes total value added. The focus in this exercise is on the coefficient γ which gives an indication for the type and magnitude of complementarity; a positive (negative) outcome suggests complementarity to male (female) labor. Intuitively, holding the ratio of male to female wages constant, if capital intensity increases (decreases) the wage share then capital and male (female) labor are relative complements.

Thus, I employ an annual-based panel that covers 12 OECD countries over the period of 1970-2005, to estimate the following model for country i, at time t:[7]

$$S_{i,t} = \alpha + \beta \log(\omega)_{i,t} + \gamma \log(k / y)_{i,t} + \eta_i + \delta_t + \varepsilon_{i,t} \tag{2}$$

where η_i and δ_t are country and time fixed effects, respectively. All the data for this exercise come from the EU-KLEMS project (O'Mahony and Timmer, 2009),[8] which provides disaggregated data on capital stocks for five distinct capital groups: communication equipment, computing equipment, software, transport equipment, and machinery. To address the potential endogeneity of the measure of capital intensity I take an instrumental variable approach, using lagged values as instruments.[9] The identification assumptions are that the error terms in Equation (2) are not serially correlated and that the variables are weakly exogenous.

Thus, I start by estimating Equation (2) using total capital equipment (being an aggregation of the five groups). Results appear in Regression (1). The coefficient on capital intensity is positive and significant, implying strict complementarity to male labor. To the extent that they consider capital equipment, this result stands in contrast to the assumption made by Galor and Weil (1996); namely, that capital is more complementary to female labor. However, the results of the subsequent analysis at the disaggregated level offer a potential solution to this discrepancy, as I explain below. That said, I now estimate Equation (2) for each of the five abovementioned capital groups separately. Results appear in Regressions (2)-(6). The significance and sign of the coefficient of interest reveal that computing and communication equipment are complementary to female labor, while transport equipment and machinery are complementary to male labor.

To better realize the distinction, I aggregate the five sub-groups to two groups of ICT and non-ICT capital; the former includes computers, communication and software, whereas the latter includes transportation and machinery. Then, I estimate the following version of Equation (2) with the two aggregated groups together:

$$S_{i,t} = \alpha + \beta \log(\omega)_{i,t} + \gamma_1 \log(ICT / y)_{i,t} + \gamma_2 \log(non - ICT / y)_{i,t} + \eta_i + \delta_t + \varepsilon_{i,t} \tag{3}$$

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[7] This is a maximized unbalanced panel, limited by data availability. See Appendix 2 for a list of economies included, as well as for a detailed description of all variables.

[8] See Appendix 1 for descriptive statistics of all variables used in the regressions.

[9] Duffy et al. (2004) use the same instrumental variable approach to estimate capital-skill complementarity in aggregate production functions.

results for γ_1 and γ_2 appear in Regression (7). These show the clear complementarity distinction of ICT and non-ICT capital: the former (latter) is complementary to female (male) labor. Interestingly, however, the magnitude of complementarity is higher for male labor, such that non-ICT capital is twice as complementary to male labor as ICT capital is to female labor.[10] This potentially explains the complementarity patterns observed at the aggregate level because the share of non-ICT capital in total capital equipment is larger than that of ICT capital.[11]

Additionally, these results at the disaggregated level offer a potential solution for the discrepancy of the aggregate-level results and the abovementioned assumption made in Galor and Weil (1996). It is well documented that during the investigated period technical change was strongly biased towards ICT capital (e.g. Ruiz-Arranz 2003); such technical changes provide significant wage premium (see Acemoglu 2002, and Galor and Moav 2000, for the skill-related aspects of this). This, in turn, implies for the existence of gender-biased technical change (GBTC) patterns. Thus, even though the aggregate results indicate that capital is more complementary to male labor, it is potentially sufficient that ICT capital is complementary to female labor for the mechanism linking fertility and growth of Galor and Weil (1996) to remain applicable, through the GBTC channel.[12]

Next, let us realize whether the observed patterns are driven by a specific skill group. Hence, I disaggregate the analysis to three skill groups: high, medium, and low skill labor, defined as those having tertiary, upper secondary, and up to lower secondary education levels, respectively. Then, I estimate the following version of Equation (2), for skill-group j:

$$S^j{}_{i,t} = \alpha + \beta \log(\omega)^j{}_{i,t} + \gamma \log(k/y)_{i,t} + \eta^j{}_i + \delta^j{}_t + \varepsilon^j{}_{i,t} \tag{4}$$

This model is identical to (2), with the exception of being divided to skill groups; thus, in this case S^j denotes the share of wages paid to male labor in skill group j out of total labor compensation in that skill group. The same idea applies to ω^j which denotes the ratio of wages of male labor to those of female labor in skill group j. The capital intensity measure remains as before, as it is not dependent on skill group.

Hence, I estimate Equation (4) for each of the three skill groups separately; results for the high, medium and low skill labor appear in Tables (2), (3), and (4), respectively. Each of these tables replicates Table (1), and undertakes the same regressions in the same order, as presented there and described in-detail above. Results indicate that the same patterns described for the aggregated group remain to hold under each of the three sub-skill groups; i.e. capital is more complementary to male labor, whereas at the disaggregated level (non) ICT capital is more complementary to (male) female labor, with the magnitude being higher for male labor. Interestingly, however, the patterns intensify with skill level. In the high-skill group, both the aggregated and disaggregated measures of capital exhibit significantly higher complementarities

[10] This is consistent with observed links between capital and gender intensities at the industry level. For instance, the EUKLEMS data reveal that some of the most capital intensive industries (e.g. mining and quarrying) are also relatively more male intensive, while those that are least capital intensive (e.g. services) are relatively more female intensive.
[11] As documented in Appendix 1, the share of non-ICT capital in total capital equipment is eight times larger than that of ICT capital.
[12] Nonetheless, investigating this channel in greater detail is beyond the scope of this study, and is thus left for future work.

(each to the corresponding gender) than those derived under the other skill groups. Moreover, the difference in the magnitude of complementarity of ICT capital to female labor and non-ICT capital to male labor increases with skill, such that in the low-skill group that difference is practically zero, whereas in the high-skill group it is 0.04 (representing a difference of a 100%).

Last, one concern is that given the concurrent rise in female participation rates in the labor market and the share of ICT capital in total value added during the investigated period, the results may pick up a third, unobservable, factor (such as, for instance, better child care services) rather than complementarity patterns, despite the estimation technique taken and the inclusion of time fixed effects. To better address that, I test a restricted sample that includes the countries that had relatively little change in female participation rates during the period of interest. Specifically, I include those that have an average annual change in the share of female compensation in total compensation that is lower than the average of the total sample; these include: Austria, Czech Republic, Germany, Japan, Slovenia, and the United Kingdom. In all six the said average annual change is less than one tenth of a percentile (i.e. presenting virtually no change). Indeed, the female compensation share in the initial year and that in 2005 is left largely unchanged in these countries; as an example, Slovenia had a female compensation share of 57% in 1995, remaining the same in 2005.

Thus, I estimate Equation (2), replicating Table 1, using this restricted sample. Results appear in Table (5). As can be seen, all the main results hold, being qualitatively identical to those in Table (1), with occasionally greater magnitude. These results indicate the patterns are observed even when there is no apparent concurrent rise in both female participation rates and ICT share, hence pointing more clearly at capital-gender complementarity being the underlying mechanism at hand.

3. CONCLUSION

This paper makes a first attempt at estimating capital-gender complementarities, and presents results that may shed light on the association between capital, gender, and productivity. By employing a panel of 12 OECD countries covering the period of 1970-2005, I find that in contrast to assumptions made in previous theoretical work capital is rather more complementary to male labor. At the disaggregated level, however, I show that ICT capital (computing equipment, communication equipment, and software) is complementary to female labor, whereas non-ICT capital (transport equipment, machinery) is complementary to male labor, having a relatively stronger association in the latter case. Lastly, I find that these patterns hold under various skill groups, yet increase with skill.

These results provide new insights on the interaction between capital and gender, which touch upon various central issues in economics and policy. Nonetheless, it is important to note that these findings are confined to the specific sample of countries and years investigated in this study. Future research may extend this further in an attempt to better understand the underlying mechanisms that link capital and gender.

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TABLE 1. *Estimating capital-gender complementarities: all skill groups*
[Panel, 1-year intervals, period: 1970-2005]

Dependent variable: Compensation share of male labor out of total labor compensation	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total capital equipment	0.02*** (0.007)						
Computing equipment		-0.03*** (0.003)					
Communication Equipment			-0.01* (0.007)				
Software				-0.01 (0.007)			
Transport Equipment					0.02*** (0.006)		
Machinery						0.03*** (0.007)	
ICT Capital (Computers, Communication, Software)							-0.03*** (0.004)
Non-ICT Capital (Transport and Machinery equipment)							0.06*** (0.007)
Observations	303	303	303	303	303	303	303
R-squared	0.8579	0.7466	0.2859	0.8549	0.8604	0.8657	0.7302
Economies Included	12	12	12	12	12	12	12

Standard errors are robust, clustered at the country level, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance, respectively. Only CGC-level reported; however, all regressions include an intercept, relative wages, and time-country fixed effects. All regressions are estimated using IV-GMM, with lagged values as instruments. Only second stage results are reported; all first stage results report F-statistics higher than 1040 and a positive coefficient on the relevant instrument, significant at the 1%. For description, sources, and descriptive statistics of variables, as well as list of economies included in each regression, see Appendices 1 and 2.

TABLE 2. *Estimating capital-gender complementarities: high-skill labor*
[Panel, 1-year intervals, period: 1970-2005]

Dependent variable: Compensation share of high-skill male labor out of total high-skill labor compensation	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Total capital equipment	0.09*** (0.007)						
Computing equipment		-0.04*** (0.002)					
Communication Equipment			-0.03*** (0.006)				
Software				-0.05*** (0.006)			
Transport Equipment					0.09*** (0.006)		
Machinery						0.09*** (0.006)	
ICT Capital (Computers, Communication, Software)							-0.04*** (0.006)
Non-ICT Capital (Transport and Machinery equipment)							0.08*** (0.005)
Observations	303	303	303	303	303	303	303
R-squared	0.5476	0.8462	0.2961	0.4597	0.6793	0.7073	0.835
Economies Included	12	12	12	12	12	12	12

Standard errors are robust, clustered at the country level, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance, respectively. Only CGC-level reported; however, all regressions include an intercept, relative wages, and time-country fixed effects. All regressions are estimated using IV-GMM, with lagged values as instruments. Only second stage results are reported; all first stage results report F-statistics higher than 802 and a positive coefficient on the relevant instrument, significant at the 1%. For description, sources, and descriptive statistics of variables, as well as list of economies included in each regression, see Appendices 1 and 2.

TABLE 3. *Estimating capital-gender complementarities: medium-skill labor*
[Panel, 1-year intervals, period: 1970-2005]

Dependent variable: Compensation share of medium-skill male labor out of total medium-skill labor compensation	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Total capital equipment	0.02** (0.01)						
Computing equipment		-0.01*** (0.003)					
Communication Equipment			0.005 (0.007)				
Software				-0.01*** (0.004)			
Transport Equipment					0.04*** (0.009)		
Machinery						0.02** (0.01)	
ICT Capital (Computers, Communication, Software)							-0.02*** (0.004)
Non-ICT Capital (Transport and Machinery equipment)							0.04*** (0.008)
Observations	303	303	303	303	303	303	303
R-squared	0.7832	0.8371	0.7177	0.7586	0.4936	0.7936	0.6135
Economies Included	12	12	12	12	12	12	12

Standard errors are robust, clustered at the country level, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance, respectively. Only CGC-level reported; however, all regressions include an intercept, relative wages, and time-country fixed effects. All regressions are estimated using IV-GMM, with lagged values as instruments. Only second stage results are reported; all first stage results report F-statistics higher than 670 and a positive coefficient on the relevant instrument, significant at the 1%. For description, sources, and descriptive statistics of variables, as well as list of economies included in each regression, see Appendices 1 and 2.

TABLE 4. *Estimating capital-gender complementarities: low-skill labor*
[Panel, 1-year intervals, period: 1970-2005]

Dependent variable: Compensation share of low-skill male labor out of total low-skill labor compensation	(22)	(23)	(24)	(25)	(26)	(27)	(28)
Total capital equipment	0.02*** (0.004)						
Computing equipment		-0.01*** (0.001)					
Communication Equipment			-0.02*** (0.003)				
Software				-0.01 (0.006)			
Transport Equipment					0.01*** (0.004)		
Machinery						0.03*** (0.004)	
ICT Capital (Computers, Communication, Software)							-0.02*** (0.006)
Non-ICT Capital (Transport and Machinery equipment)							0.02*** (0.004)
Observations	303	303	303	303	303	303	303
R-squared	0.7738	0.295	0.1767	0.0998	0.7612	0.1986	0.2797
Economies Included	12	12	12	12	12	12	12

Standard errors are robust, clustered at the country level, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance, respectively. Only CGC-level reported; however, all regressions include an intercept, relative wages, and time-country fixed effects. All regressions are estimated using IV-GMM, with lagged values as instruments. Only second stage results are reported; all first stage results report F-statistics higher than 726 and a positive coefficient on the relevant instrument, significant at the 1%. For description, sources, and descriptive statistics of variables, as well as list of economies included in each regression, see Appendices 1 and 2.

TABLE 5. *Estimating capital-gender complementarities: all skill groups*
Restricted Sample
[Panel, 1-year intervals, period: 1970-2005]

Dependent variable: Compensation share of male labor out of total labor compensation	(29)	(30)	(31)	(32)	(33)	(34)	(35)
Total capital equipment	0.05*** (0.003)						
Computing equipment		-0.02*** (0.001)					
Communication Equipment			-0.06*** (0.003)				
Software				-0.01*** (0.001)			
Transport Equipment					0.05*** (0.001)		
Machinery						0.05*** (0.002)	
ICT Capital (Computers, Communication, Software)							-0.03*** (0.002)
Non-ICT Capital (Transport and Machinery equipment)							0.04*** (0.002)
Observations	128	128	128	128	128	128	128
R-squared	0.3595	0.6374	0.7527	0.0867	0.5571	0.489	0.719
Economies Included	6	6	6	6	6	6	6

Standard errors are robust, clustered at the country level, and appear in parentheses for independent variables. Superscripts *, **, *** correspond to a 10, 5 and 1% level of significance, respectively. Only CGC-level reported; however, all regressions include an intercept, relative wages, and time-country fixed effects. All regressions are estimated using IV-GMM, with lagged values as instruments. Only second stage results are reported; all first stage results report F-statistics higher than 393 and a positive coefficient on the relevant instrument, significant at the 1%. For description, sources, and descriptive statistics of variables, as well as list of economies included in each regression, see Appendices 1 and 2.

Appendix 1 – Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Compensation share of male labor out of total labor compensation	.6819678	.0690625	.5678701	.8167404
Compensation share of high-skill male labor out of total high-skill labor compensation	.7274253	.1147853	.5052185	.96245
Compensation share of medium-skill male labor out of total medium-skill labor compensation	.6754918	.0590028	.5667486	.8123074
Compensation share of low-skill male labor out of total low-skill labor compensation	.6777145	.0963429	.4764644	.8401698
Male to female wage ratio: general	1.421286	.3078133	.9018915	2.361535
Male to female wage ratio: high-skilled	1.339698	.2353371	.7459475	1.991947
Male to female wage ratio: medium-skilled	1.357686	.2606906	.9241627	2.030917
Male to female wage ratio: low-skilled	1.520955	.3455693	1.103661	2.712657
Share of total capital equipment out of total value added	.9409958	.7607812	.4630896	5.059054
Share of computing equipment out of total value added	.0335254	.04671	.0001045	.272006
Share of communication equipment out of total value added	.0481304	.0388873	.0002651	.275758
Share of software capital out of total value added	.0235255	.0178087	.0010025	.0884215
Share of transport equipment out of total value added	.2313736	.2146351	.0716256	1.337199
Share of machinery capital out of total value added	.6044409	.5568282	.1895115	3.657627
Share of ICT capital out of total value added	.1051814	.0659183	.0131546	.3590476
Share of Non-ICT capital out of total value added	.8358144	.7586934	.2721853	4.780551

Appendix 2 – Data

Countries in sample (Tables 1-4): Australia, Austria, Czech Republic, Denmark, Finland, Germany, Italy, Japan, Netherlands, Slovenia, United Kingdom, United States.

Countries in sample (Tables 5): Austria, Czech Republic, Germany, Japan, Slovenia, United Kingdom.

Variables: All variables cover the period of 1970-2005. This is a maximized unbalanced panel, limited by the availability of data. All variables are annually based. Data are provided by the EU-KLEMS project (O'Mahony and Timmer, 2009).

Skill definition: Definitions follow those employed in the EU-KLEMS project and are based on the ISCED one-digit classification. Low-skill corresponds to primary or lower secondary education (ISCED 1 or 2), medium-skill to upper secondary education (ISCED 3 or 4), and high-skill to tertiary education (ISCED 5 or 6).

List of variables:

Compensation share of male labor out of total labor compensation	The share of compensation given to male labor out of total labor compensation. This is measured for all labor types (Tables 1 and 5), high-skilled labor only (Table 2), medium-skilled labor only (Table 3), and low-skilled labor only (Table 4).
Male to female wage ratio	The natural logarithm of the ratio of average annual wages of male labor to those of female labor. This is measured for all labor types (Table 1 and 5), high-skilled labor only (Table 2), medium-skilled labor only (Table 3), and low-skilled labor only (Table 4).
Share of total capital equipment out of total value added	The natural logarithm of the share of total capital equipment out of total value added.
Share of computing equipment out of total value added	The natural logarithm of the share of computing equipment (as defined in the EU-KLEMS database) out of total value added.
Share of communication equipment out of total value added	The natural logarithm of the share of communication equipment (as defined in the EU-KLEMS database) out of total value added.
Share of software capital out of total value added	The natural logarithm of the share of software capital (as defined in the EU-KLEMS database) out of total value added.
Share of transport equipment out of total value added	The natural logarithm of the share of transport equipment (as defined in the EU-KLEMS database) out of total value added.
Share of machinery capital out of total value added	The natural logarithm of the share of machinery capital (as defined in the EU-KLEMS database) out of total value added.

Share of ICT capital out of total value added	The natural logarithm of the share of ICT capital out of total value added. ICT is an aggregate of the computing, communication, and software equipment sub-groups.
Share of Non-ICT capital out of total value added	The natural logarithm of the share of non-ICT capital out of total value added. Non-ICT is an aggregate of the transport and machinery equipment sub-groups.