MACRO-INSTITUTIONAL INSTABILITY AND THE SKILL PREMIUM FORMATION

Serena Masino[1]
University of Manchester and CGBCR
serena.masino@manchester.ac.uk

This paper investigates the impact of macroeconomic and political instability on the skill premium formation, in a 69 country panel in which all levels of development are represented. The results suggest a negative impact of instability on the skill premium, which is defined as the ratio of unskilled to skilled wages. Such impact is mediated by a decrease in the wage of skilled occupations that is closely linked to lower levels of R&D investment. The latter is often a consequence of unstable macro-institutional environments and the cause of two resulting phenomena: the decline of skilled labour's productivity and the decrease in demand for skilled labour. Such outcomes highlight the desirability of stable macro-institutional environments in order to prevent the shrinkage of the skill premium. In fact, ultimately, the latter is likely to lead to low human capital accumulation levels as well as brain drain.

Keywords: Skill Premium, Wage Ratio, Political Instability, Macroeconomic Volatility, Innovation

JEL Classification: C33, J24, J31, O11

1. INTRODUCTION

An extensive literature exists surrounding the role of innovation for growth, and the interaction between skilled labour and productive capital (Romer, 1990; Helpman and Grossman, 1991; Aghion and Howitt, 1992; Grossmann, 2007). In this literature, skilled labour is shown to be key to the growth process as its existence complements and augments the productivity of innovative capital. For a skilled workforce to exist, however, some level of skill premium - defined as the difference between skilled and unskilled wages - must be in place. This will act as an incentive that induces individuals to acquire the necessary level of skills (Kimura and Yasui, 2007; Agenor and Canuto, 2012). Failure to allow the skill premium to take shape will likely lead to lower human capital accumulation levels and brain

[1] Dept. Economics, University of Manchester, M13 9PL Manchester UK - 00447505019161

drain, which, ultimately, slow down the pace of both innovation and development. The scope of this paper is the analysis of the impact that macroeconomic and political instability have on the unskilled to skilled wage differential, in light of the importance that a stable macro-political environment has for the skill premium to take shape.

In practice, instability affects two main determinants of skilled wages: the demand for a skilled workforce and the productivity of skilled labour. With regards to the first, the literature has extensively shown that macro-institutional instability lowers the incentives to innovate faced by entrepreneurs (Isham and Kaufmann, 1999; Rafferty, 2003a; Rafferty and Funk, 2008; Aghion *et al.*, 2008; Bohva-Padilla *et al.*, 2009, Aghion et al., 2010; Masino, 2012). It follows that a reduction in innovative investment will translate into lower skilled labour's employment and retribution (Rodrik, 1999; Spagat, 1995). With regards to the second determinant just mentioned above, namely, the productivity of skilled labour: this can be lowered by instability either directly or indirectly.

It is straightforward to see how timing and quality of education can be directly affected in contexts where disruptions caused by social unrest exist (see Rubio, 1998 and Hofstetter, 1998). In addition, the productivity of skilled labour can also decrease indirectly, as a consequence of reduced productivity of the tangible and intangible capital skilled labour works with (Olson et al., 2000; Fosu, 2002).[2] To see why this is the case, consider that innovative investment entails higher than average set-up costs and longer maturity horizons. These two characteristics make it inherently risky and create a range of inaction in the presence of uncertainty (Bernanke, 1980). Moreover, uncertainty often leads governments to pursue sub-optimal short-term policies, which translate into high probability of policy reversal (Rodrik, 1989; Fanelli and Frenkel, 1995; Guillaumont et al., 1999). In other words, volatile and mixed signals sent by institutions with regards to property right enforcement, fiscal and monetary policy objectives, or incentive and tax regimes, can lead to misallocation of private investment efforts (Aryeetey, 1994; Alesina et al., 1996; Isham and

2 Tangible capital refers to physical capital, e.g. machinery. Intangible capital defines non-physical capital, e.g. software

Kaufmann, 1999; Fosu, 2003). If all these elements shift the investment composition towards less risky, short-term projects, lower levels of innovation will result in decreased overall productivity of tangible and intangible capital. And, as a result of the complementarity existing between skilled labour and productive capital (Griliches, 1969; Mincer, 1985; Krusell et al., 2000; Lindquist, 2004), skilled labour's productivity will also decrease, together with its marginal wage. In this respect, Mincer (1985) argues that, as the ratio of 'new' capital per worker increases so does the skilled wage differential, as a reflection of capital-skill complementarity.

The literature on the skill premium and that surrounding the unskilled to skilled wage differential has focused, in the past, mainly on factors that change the distributional structure of wages. Such as trade composition effects (Parteka, 2010); labour union strength (Kraft, 1994; Ziliak et al., 1999), cyclicality of output (Nissim, 1984; Keane and Prasad, 1993; Kraft, 1994), skill-capital complementarity (Krusell et al., 2000; Lindquist, 2004). While these factors will be tested in my model as determinants of the unskilled/skilled wage ratio, only a limited number of studies exists that examines the decrease in the skill premium as a consequence of instability. Moreover, all of these studies do so in an indirect way. For example, in Mincer (1985) the focus is not on instability *per se*, but rather on the interdependency between economic growth and human capital. Mincer argues that it is innovative investment what drives the wage differential in favour of skilled wages, so that only innovative societies can maintain high skill premia. On the other hand, while more openly referring to the negative relationship between macro-political instability and the wage differential, Spagat (1995) retains a purely theoretical focus in his analysis. Finally, Isham and Kaufman (1999) use a micro-dataset to explore the relationship between the quality of the macro-institutional environment and factors' productivity. They argue that political volatility and lack of timely policy adjustment considerably lower factors' productivity.

Thus, what motivates my work is the attempt to fulfill a gap exiting in the empirical literature on the relation between macro-political instability and the skill premium. My findings lend evidence to the hypothesis that unstable environments result in lower skilled wages in the sample of countries considered. Because insufficient skill premium is what ultimately leads to low human capital accumulation and brain drain, the empirical outcomes of this study highlight the importance of stable macro-political environments for knowledge-based development. The rest of the paper is structured as follows: the model and data specifications are outlined in the next section. Section 3 and 4 present the results and the robustness analysis. Section 5 summarises the main findings, outlines some policy implications and draws some conclusions. Finally, all data sources as well as the technical notes are contained in Appendix A and B.

2. MODEL AND DATA

The panel used for this analysis includes 449 observations in total, when the benchmark specification outlined in equation (1) below is estimated. The sample contains 69 countries representing all levels of development,[3] and covers 20 years, from 1983 to 2002. All data sources appear in Appendix A. The regression specification is as follows:

$$y_{it} = a_i + \sum_{j=1}^{j} \beta_j X_{j,i} + \sum_{l=1}^{l} \theta_l MacroInstab_{l,it} + \varepsilon_{it} \tag{1}$$

The skilled premium is measured by the dependent variable as the ratio between unskilled and skilled wage rates. The source for the raw occupational wage data measured in $US is the 2004's *ILO October Inquiry* database. Freeman and Oostendorp (OWW, 2004) have normalised these data using country-specific calibration. The data normalized in such manner refer to average monthly wage rates and are recorded for a number of occupations. The dependent variable uses the normalised OWW data as a base to create the mean ratio of unskilled to skilled wages. Mean wage data are calculated by

[3] The country list is available in Appendix A

averaging occupational observations by year, on a country by country basis. The detailed procedure implemented to transform the original OWW micro-dataset into a macro-dataset of aggregate mean ratios is described in detail in Appendix B.

The vector of controls, $X_{j,i,}$ broadly reflects the choice of wage ratio determinants found in the literature. It includes GDP per capita in log form (*LogGDPpc*) to control for the level of development; the interaction (*LogGDPpcHI*) between GDP and an HI dummy, which takes the value of 1 for developed countries,[4] to verify whether in developed countries a supplementary skill premium exists. An indicator of brain drain of the skilled population aged 25 and above, *BrainDrain*, is included to verify whether emigration of skilled workforce leads to a scarcity premium for the skilled people who stay. The average years of tertiary education, *AvgTertiary25*, are included to account for the higher salary that additional years of education should lead to. An index of worker rights protection, *WorkerRights*, is included to proxy for the strength of trade and labour unions. The share of high-tech exports (*HighTechExp*) has been included to assess the wage distribution effects of trade composition: higher technological content of exports should indicate greater need for skilled workforce and possibly higher skill premia (Parteka, 2011).

With regards to the *MacroInstab* vector in equation (1): two measures of political instability and one of output instability are considered. Output instability, *LogGDPpcCoV*, is measured as the coefficient of variation of GDP per capita (in log form). The institutional instability variables are a measure of internal armed conflict and a measure of parliamentary fractionalisation. *Conflict* is meant to capture contexts where socio-political unrest takes the form of openly conflicting factions. Instead, parliamentary fractionalisation (*PoliticalFract*) is measured by the probability that two deputies within the parliament pertain to different party-groups. Because none of the developed countries in the sample used experiences internal armed conflict during the time span considered, the political fragmentation variable seems more appropriate in their case. Caution should however be placed in interpreting the results generated by this variable, since, in principle, low political fragmentation can

4 According to the World Bank's Atlas Classification System.

be the result of a dictatorship. This would the case if, for example, the probability of finding two deputies of different parties was zero because parties were not allowed to exist. To correct for this, I model the impact of the type of institutional background explicitly, with the inclusion of an additional variable, *Democracy*, which measures the degree of checks and balances enforcement. In this way, once the political setting effect is dealt with, the residual impact of *PoliticalFract* is that captured by parliamentary fractionalisation.

The model is going to be estimated using GMM dynamic panel data techniques. In particular, the System-GMM estimator developed by Arellano and Bover (1995) is adopted. This is preferred to the Difference-GMM estimator (Arellano and Bond, 1991) for two sets of reasons. Firstly, differencing leads to loss of useful long-run cross-country information (Klomp and de Haan, 2009). Secondly, the Difference-GMM estimator satisfactorily solves the endogeneity problem by instrumenting the differenced predetermined/endogenous variables with their available lags in levels. Unfortunately, however, lagged levels are weak instruments for first-differences if the series are very persistent (Blundell and Bond, 1998). The latter is most likely the case for institutional variables such as the ones employed in this analysis (Klomp and de Haan, 2009). Under an additional set of assumptions, the System-GMM estimator can overcome these problems and increase efficiency. To be more specific, if the assumption that the regressors' first-differences are not correlated with the individual effects holds, lagged values of the first-differences can be used as instruments in the equation in levels. The estimation will then combine the set of moment conditions available for the first-differenced equations with the additional moment conditions available for the levels equation.

3. RESULTS

Before going into the detailed description of the results, please note that at the bottom of each table the serial correlation test is reported and the presence of serially correlated errors is always rejected in the entire estimation set. In addition, the lag interval used for each regression is always specified together with the Hansen-J statistic for the overidentification test of the instruments. The number of instruments should not be higher than the number of groups (Roodman, 2006). Equivalently, the Hansen-J statistic should lie in a range delimited by values lower than 0.9 and higher than 0.1, with values lower than 0.1 indicating that the null of valid overidentifying restrictions is rejected. Broadly speaking, more instruments convey additional useful information. However, too many instruments can create an upward bias in the results, by reducing standard errors and leading to over-acceptance of coefficient validity (Roodman, 2009). To avoid this, each regression is estimated with the lag interval that maximises the trade-off between the quantity of instruments used and the resulting degree of overidentification. The Hansen-J statistics reported confirms the validity of the chosen set of instruments in all cases. Finally, Dynamic Panel Data methods have been originally designed to estimate micro-panels with at least 1000 observations. While the panel considered in this analysis is relatively big in macro-panel terms, the 'small panel correction' option has been invoked. The results are consistently robust to the introduction of this restriction.

[*Table 2 about here*]

Column (1) of Table 2 presents the benchmark regression where only the control variables are included. Column (2), (3) and (4) add the macro-political instability indicators one at a time, and finally column (5) presents the benchmark specification in the most inclusive form.

Starting with column (1), the reduced form specification is estimated to check the validity of the wage ratio determinants chosen, before the components of the *MacroInstab* vector are added. In this specification, the level of development - proxied by GDP per capita in log form - has a positive impact on the wage ratio. This means that as development increases so do wages of unskilled workers. Something which can be viewed to represent the increased scope for redistribution richer societies commit to. On the other hand, the negative coefficient exhibited by the interaction between GDP and HI suggests that in richer societies the skill premium is still more pronounced. The brain drain has a negative effect on the wage ratio, indicating that, in this sample, skilled individuals who are left in the country of origin experience higher wages. In particular, a 1% point increase in the proportion of skilled individuals leaving the country leads to an increase of about 1% points in the skill premium. This may be capturing a scarcity premium effect. That is, the fewer skilled individuals are left in the country of origin, the higher the demand per individual and, as a result, the retribution. Or it may be capturing what part of the literature identifies as positive externalities produced by the brain drain. In particular, brain drain can increases remittances; it can also encourage outflows of FDI and transfer of knowledge by enhancing network effects; finally, it can foster human capital accumulation in the country of origin, via an ‘emulation’ effect (Docquier et al., 2010; Beine et al., 2011). However, it will be shown later on, in the robustness analysis, that when the scarcity premium effect is taken into account explicitly the impact of the brain drain on the skill premium turns negative. This is line with another part of the literature which shows that emigration of the skilled work-force leads to inability of the countries of origin to innovate and keep pace with technological progress (see Docquier et al., 2010; and Di Maria and Lazarova, 2012). As expected, an increase in the average level of tertiary education leads to an increase in the skill premium; specifically, one more year of tertiary education results in a 4.3% points increase in the skill premium. To see what this means is practice, consider that the average mean wage ratio in my sample is of around 0.57 (see Table 1 in Appendix A for descriptive statistics). That is, overall, the mean unskilled wage is equivalent to slightly more than half the mean skilled wage, on average. In this sample, one more year of tertiary education would bring the 0.57 mean wage ratio down to around 0.53. If, for example, the ratio of unskilled to skilled monthly wage was of $1710 to $3000, a drop in the ratio from 0.57 to 0.53 implies that the skilled wage grows to $3225 per month, that is, an increase of $225 as a consequence of an additional year of tertiary education. An increase in the coefficient of labour union strength, instead, raises unskilled wages. For example, moving from a regime in which workers’ rights are severely restricted to one where such restrictions are only partially in place reduces the skill premium by 6.2%points. This could be explained by the fact that unskilled labourers’ wages are more likely to be found around the minimum wage threshold, as a consequence they tend to rise when this threshold is increased via labour union bargaining or confrontation. These findings are supported by the results of Ziliak et al. (1999) and Kraft (1994). With regards to *HighTechExp*, except for the specification in column (2), there is no evidence of trade composition bearing explanatory power for the wage ratio determination, in the sample considered.

Columns (2), (3) and (4) include the institutional and macroeconomic and instability variables one at a time, on their own. When *PoliticalFract* is included, in column (2), *Democracy* is also included at the same time for the reasons explained above. *Democracy* has a small but positive impact on the skill premium. This suggests that, once the presence and strength of worker rights is controlled for, more democratic societies are the ones where the skilled premium may materialise more easily.[5] The latter hypothesis is confirmed by Feng's (2001) results. The inclusion of this institutional variable, allows qualifying the impact of parliamentary fractionalisation, as conveyed by *PoliticalFract.* Political fractionalisation is measured as the probability that two deputies in the parliament are from different parties. The fact that it appears in this sample with a negative coefficient lends evidence to the hypothesis that, when the parliament is fragmented, dialogue and the pace of reform are slower. This hinders swift political responses to signals emerging from society (see Isham and Kaufmann, 1999 for a similar argument). In column (3), *Conflict*, too, exhibits a negative coefficient. A finding confirmed by Rubio (1998) and Hofstetter (1998). For example, Rubio (1998) finds that, for the case of Colombia, where armed internal unrest has been long-lasting, the rate of kidnapping is among the most important determinants of low factor productivity. This is followed by the homicide rate, which also has secondary effects through the resulting demographic composition of the population. Hofstetter (1998), instead, finds that violence dampens the accumulation of skills and human capital, because of generalised loss of human lives and because of productive physical capital destruction. In column (4), output volatility is added to the reduced-form model. The use of GDP volatility to proxy for aggregate output uncertainty is well documented in the literature (Price, 1995; Aizenman and Marion, 1993). In addition, GDP volatility has been used before in the literature to assess the effects of output cyclicality on the skilled to unskilled wage ratio (Nissim, 1984; Keane and Prasad, 1993). Because skilled workers are more complementary with capital (Krusell et al., 2000) and aggregate volatility discourages innovative investment (Price, 1995; Aghion *et al.*, 2008; Rafferty

5 The inclusion of additional controls in the robustness analysis will reverse this result.

and Funk, 2008), it seems straightforward that the skill premium should fall as a consequence of aggregate output volatility, something which is confirmed by the results reported in Table 2, for this sample.

All three findings carry over to the benchmark specification in column (5), where all instability measures are included at the same time. To quantify the negative impact of political instability and real volatility, consider that a 10% point increase in the probability of finding two deputies of different parties in the legislature decreases the skill premium by 2.15% points. Further to this, moving from a situation of no internal conflict to one of minor armed conflict decreases the skilled premium by 8% points. Finally, a one standard deviation increase in the coefficient of variation of GDP per capita leads to a 1% point decrease in the skill premium. When the entire set of instability measures is included in the benchmark specification of column (5), the most significant impact variations in the control variables are the following: the coefficient magnitude of *BrainDrain* is now higher, indicating that a 1% point increase in the proportion of skilled individuals leaving the country leads to an increase of about 1.2% points in the skill premium. The impact of the average level of tertiary education has also increased, with a coefficient indicating that one more year of tertiary education leads to an increase of 11% points in the skill premium. The magnitude of the impact of worker rights protection is also higher. Specifically, in this sample, moving from a regime in which workers' rights are severely restricted to one where they are moderately protected reduces the skill premium by 11% points.

4. ROBUSTNESS ANALYSIS

The sensitivity analysis will test the robustness of the results obtained so far. This is done, in Table 3, by estimating the model with different lag structures in the instrumentation, first. Subsequently, to test the sensitivity of the dependent variable to different measurement specifications, the mean wage ratio is going to be substituted by the median wage ratio. In Table 4, instead, new variables are added to the benchmark model. Finally, in Table 5, all variables contained in the *MacroInstab* vector are substituted with others that proxy for the same underlying concept but are measured in different ways.

[*Table 3 about here*]

I focus, first, on Table 3 where column (1) repeats the benchmark specification for comparison purposes. The benchmark instrumentation set goes from lag 2 to lag 6. Column (2) and (3), instead, report the results of the benchmark regression when estimated with different lag structures: lags 2 to 5 in column (2), and lags 2 to 7 in column (3). All results carry over with no significant difference, apart from two elements: in column (2), *AvgTertiary25* loses its significance; and in column (3) the coefficient magnitude of output volatility is somewhat reduced. As anticipated, in column (4) the measurement of the dependent variable is changed and the median instead of the mean wage ratio is used. This is done as a robustness check due to the unbalanced structure of the raw wage data used to calculate the unskilled/skilled wage ratio.[6] Once again results remain broadly stable, but note that the magnitude of both *PoliticalFract* and *LogGDPpcCoV* is somewhat reduced, and that *HighTechExp* acquires explanatory power and appears with a positive sign. Such type of trade composition effect is supported by Parteka (2011). Nonetheless, despite acquiring significance, the magnitude of this variable's coefficient suggests that in practice the GDP share of high-tech exports has very limited influence on the wage ratio, in the sample considered.

[*Table 4 about here*]

In Table 4, column (1) reports once again the benchmark specification to facilitate comparison. In column (2) and (3), two additional variables are added to the instability vector. The first is a measure of ethno-religious fragmentation and the second is a measure of cultural fragmentation. For the purpose of this analysis, they are two conceptually similar variables,[7] which are included to

6 For a technical description of the reasons why both the mean and the median are tested, refer to Appendix B.
7 The exact definition of both is reported in Appendix A.

control for the instability that may come from social fragmentation which does not culminate in open armed confrontation - and is therefore not captured by *Conflict*. While the impact of ethno-religious fragmentation appears to be insignificantly different from zero; a 10% increase in cultural fragmentation leads to a decrease of about 2% points in the skill premium in this sample. This finding is in line with the results of Aisen and Vega (2011); and with the results of Alesina (1996b) who shows that social instability and social discontent caused by inequality lead to uncertainty, which hinders investment and growth. Once again most results for the other covariates carry over from the benchmark regression. The only variations which are worth mentioning are found in column (3), where the impact magnitude of worker rights protection, political fragmentation and armed conflict has slightly declined; while the impact magnitude of output volatility has increased.

Coming now to column (4) of Table 4, some interesting changes are brought about by the inclusion of *EduCompleted25*. To construct this variable, I use Barro and Lee (2011)'s data on the percentage of primary, secondary and tertiary schooling attained in the 25 and over population. Specifically, I build a ratio of the percentage of 25 and over population who has completed primary and secondary education, over the percentage that has completed tertiary education. While *AvgTertiary25* aims to control for the level and/or quality of educational attainment in a given country, *EduCompleted25* controls for supply side effects. Namely, its coefficient reveals the impact that the population composition with respect to education qualifications has on the wage differential. On one hand, *EduCompleted25*'s specific impact on the wage ratio is in practice very small. On the other hand, while part of the benchmark results carries over to this specification, other covariates adjusts to the inclusion of this labour force supply side variable. To be specific, the average years of tertiary education lose explanatory power; *HighTechExp* turns significant, suggesting that the skill premium is positively related to a trade composition which favours high-tech exports. Further to this, the sign of *Democracy* turns positive, indicating that the wage ratio increases in favour of unskilled wages in democratic settings. Such outcome suggests that the effect democracy was previously found to have on the skill premium is mediated through workforce supply side effects. In other words, it may be the case that there is a higher supply of skilled people in democracies; however, once this element is modelled explicitly, the residual impact of *Democracy* is a positive one, which implies higher wages for unskilled occupations. This finding is in line with Rodrik (1999)'s results. Finally, the most interesting effect is that on *BrainDrain*. Specifically, in all previous regressions *BrainDrain* appeared with a negative sign, indicating that, as skilled people in the economy emigrate and the ones who stay become scarcer, the skill premium for the latter increases. However, once the supply level of unskilled to skilled workforce is modelled explicitly, the 'net' effect of brain drain is that of decreasing skilled wages (Docquier et al., 2010). This could take place for a number of reasons. It could be due to a network effect, that is, skilled workers are weaker once their number in the economy decreases. Or it could be due to production side dynamics: notably, as innovative investment laga behind as a result of brain drain, it follows that demand for skilled work-force declines, something which leads, ultimately, to a lower skill premium. Along the same lines, Acemoglu (1998) shows that if more workers with the same level of skills coexist, in the short run this may depress individual returns, but in the medium run as skill-complementary innovative investment is fostered; returns will actually increase as demand for skills outstrips supply. Such dynamics picture quite well the so called 'standing on shoulders' effect (see Agenor and Canuto, 2012, for a similar point).

[*Table 5 about here*]

Variables representing institutional indicators can have multiple measurement specifications, but nonetheless capture the same underlying fundamental, such as democracy or instability. Thus, it is recommended that more than one variable specification is used, to avoid bias or *ad hoc* results when estimating the impact of institutional covariates (De Haan, 2007). This is why, in Table 5, the entire set of instability indicators is replaced. Once again, the new variables are estimated on their own first, in column (2), (3) and (4), and then jointly in column (5). Column (1) reports the benchmark regression to facilitate comparison. The results remain fairly stable, across this estimation set, with regards to impact direction and sign. Coefficients' magnitude, however, changes in a few instances. The impact of the level of development on the wage ratio fluctuates in magnitude across the various specifications, while the impact of the interaction term between GDP and the HI dummy increases.

On the other hand, the impact of *BrainDrain* drops, and so does that of *AvgTertiary25*. The magnitude of *WorkerRights'* coefficient also drops, albeit only marginally. *HighTechExp*, instead, gains explanatory power at the 10% level in column (2) and (4), and at the 5% level in column (3) and (5). *Democracy* has been dropped from this set of results because *GovernmFract* - the political fragmentation variable which now substitutes *PoliticalFract* - refers to the probability that two deputies in the government cabinet pertain to different parties. While the sample Spearman correlation between *PoliticalFract* and *GovernmFract* is of about 0.72, the first variable takes into account the whole parliament, while the second refers to the government cabinet only. Since a majority government may be formed by one party only, the remarks relative to dictatorial regimes biasing the coefficient interpretation no longer apply.

GovernmFract is estimated on its own in column (2), where it appears with a positive sign, indicating that the higher the fractionalisation at the government level, the lower the skill premium. Similar considerations to the ones made with respect to parliamentary fractionalisation apply in this case, too. Furthermore, a high degree of fractionalisation within the government cabinet may result in lacking long-term policy planning due to repeated turn-over. In this respect, Aisen and Vega (2011) show that political instability, as proxied by the number of government cabinet changes in a year, negatively affects growth by reducing the productivity of human and physical capital. The coefficient of *GovernmFract* suggests that, in the sample considered, a 10% increase in the probability that two deputies in the government cabinet pertain to different parties leads to a decrease of about 0.4% points in the skill premium. This value goes down to 0.027% points in column (5), where all the new instability indicators are estimated jointly. *Conflict* is substituted in column (3) by a measure of battle related deaths per 10,000 inhabitants (*BattleDeaths*). The sample Spearman correlation coefficient between these two variables is of around 0.98, and the coefficient of *BattleDeaths* indicates that 10 more deaths per 10,000 inhabitants leads to a decrease in the skill premium of between 4% (column 3) and 3% points (column 5). Finally, the volatility of output is measured in column (4) with the standard deviation of GDP per capita instead of its coefficient of variation. The coefficient magnitude of *LogGDPpcStDev* is higher when the instability indicator enters the regression on its own, indicating that one more standard deviation in GDP per capita leads to a 13% point decrease in the skill premium, a very sizable impact. This value, however, goes down to about 2% points when all instability measures are estimated jointly, in column (5). Lastly, column (6) and (7) of Table 5 re-estimate this specification to test its sensitivity to different lag structures. In particular, while the benchmark instrumentation set includes lags 2 to 7, column (6) uses lags 2 to 6, and column (7) uses lags 2 to 8. All results carry over and remain intact, with the following exceptions: *AvgTertiary25* loses explanatory power and so does *HighTechExp*; the magnitude of both *GovernmFract* and *LogGDPpcStDev* increases when the regression is estimated using lags 2 to 6.

5. CONCLUSIONS

To summarise, this study has sought to uncover the channels through which instability of the macroeconomic and institutional environment is detrimental to the formation of the skill premium. It has been shown that output volatility as well as political fragmentation and social unrest unrest hinder skilled premia formation In particular, it has been argued that the unskilled to skilled wage ratio increases when aggregate demand is more volatile, when internal armed conflict arises or when parliamentary and governmental fractionalisation hinders the pace of economic reforms. A number of mechanisms have been suggested as potentially underlying such negative relationship. Specifically, it has been argued that because instability lowers the incentive to engage in costly and risky innovation projects, the demand and retribution of skilled labour falls as a consequence. In addition, instability lowers the productivity of human capital both directly and indirectly. Productivity is directly affected when the quality of education and work performance of skilled individuals is hampered by unstable environments. It is indirectly affected when the productivity of the tangible and intangible capital skilled labour works with is disrupted. Because demand for and productivity of skilled workforce are two main determinants of skilled wages, decreasing levels of either will result in a reduction of the skill premium. The results have been shown to be robust to a number of sensitivity tests conducted to verify the validity of both methodological specification and underlying economic theory. In sum, the findings of this study reveal the importance of stable environments, especially in light of the fact that the existence of a skill premium is fundamental to human capital accumulation incentives. Human capital accumulation is, in turn, crucial to foster an innovation-led and self-sustainable growth path.

APPENDIX A

I. DATA SOURCES

WAGE RATIO	Mean value of unskilled (pimary + secondary education occupations) wages over skilled (tertiary education occupations) wages	Author's own calculation. Raw data is from OWW (Freeman & Oostendorp, 2012) http://www.nber.org/oww/ and ILO October Inquiry (2004) http://laborsta.ilo.org/STP/guest
GDP PER CAPITA	GDP/midyear population. Data are in constant 2000 US$	World Development Indicators (2012)
BRAIN DRAIN	Ratio of number of skilled (i.e. post-secondary certificate) emigrants aged 25+ to the six major receiving countries over number of skilled natives (residents + emigrants) aged 25+	Defoort (2006) http://perso.uclouvain.be/frederic.docquier/oxlight.htm
AVGTERTIARY25	Average years of tertiary schooling attained in the 25+ population	Author's own calculation. Raw data is from the Barro & Lee Dataset (2011) http://www.barrolee.com/
EDUCOMPLETED25	% of primary + secondary schooling attained in the 25+ population divided by % of tertiary schooling attained in the 25+ population	Author's own calculation. Raw data is from the Barro & Lee Dataset (2011) http://www.barrolee.com/
HIGHTECHEXP	Share of High-Tech exports (%GDP)	Own calculation. HighTech Exports as a % of tot manufacturing exports is from World Bank-WDI (2010)
WORKERRIGHTS	Worker's rights are: (0) Severely restricted (1) Somewhat restricted (2) Fully protected	Cingranelli & Richards – Human Rights Dataset (2010) http://www.humanrightsdata.org
DEMOCRACY	Index of Political plurality which measures the degree to which checks and balances are imposed on institutional decision-making , 0 indicates low levels of checks, and 18 indicates high levels	Database of Political Institutions (Beck et al., 2010) http://go.worldbank.org/2EAGGLRZ40
POLITICALFRACT	Probability that two randomly chosen deputies in the parliament belong to different parties.	Database of Political Institutions (Beck et al. 2010) http://go.worldbank.org/2EAGGLRZ40

CONFLICT	Conflicts between government and internal opposition groups (no intervention from abroad): (0)No internal conflict (1)Internal minor armed conflict (2)Internal intermediate armed conflict (3)Internal war	UCDP/PRIO Armed Conflict Dataset (version 3-2005) http://www.prio.no/cwp/armedconflict
GOVERNMFRACT	Probability that two randomly chosen deputies in the government will be from different parties	Database of Political Institutions (Beck et al., 2010) http://go.worldbank.org/2EAGGLRZ40
BATTLEDEATHS	All military and civilian deaths (per 10,000 inhabitants) happened during battlefield fighting, guerrilla, bombardments, etc.	World Development Indicators (2012)
ETHNORELIGFRACT	Probability that two randomly selected people from a given country will belong to different ethno-religious groups. The variable ranges from 0 (perfectly homogeneous) to 1 (highly fragmented)	Fearon (2003) http://www.stanford.edu/~jfearon
CULTURALFRAC	Structural distance between the languages spoken by different groups in a country. If the groups speak unrelated languages, their cultural diversity index will be the same as the level of *EthnoReligFract*. The more similar the languages they speak the more the index is reduced below the level of ethno-religious fractionalization. The variable ranges from 0 (homogeneous) to 1 (highly fragmented)	Fearon (2003) http://www.stanford.edu/~jfearon
LOGGDPPCCOV	Coefficient of Variation of (Log)GDPper capita	Author's own calculation. Raw data is from WDI (2012)
LOGGDPPCSTDEV	Standard Deviation of (Log)GDPper capita	Author's own calculation. Raw data is from WDI (2012)

II. COUNTRY LIST

Algeria	Cameroon	Denmark**	Italy **	Netherlands**	Russia	Trinidad&Tobago
Argentina	Canada**	Estonia**	Japan**	New Zealand**	Singapore	Tunisia
Australia**	Centr African Rep	Finland **	Kyrgizstan	Nicaragua	Slovak Rep**	Turkey
Austria**	China	Gabon	Latvia**	Norway**	Slovenia**	Uganda
Bangladesh	Colombia	Germany**	Lithuania	Papua New Guinea	S. Korea**	UK**
Belgium**	Costa Rica	Guyana	Malawi	Peru	Sri Lanka	USA**
Belize	Cote d'Ivoire	Honduras	Mauritius	Philippines	Sudan	Uruguay
Bolivia	Croatia	Hungary**	Mexico	Poland**	Sweden**	Venezuela
Brazil	Cyprus**	Iceland**	Moldova	Portugal**	Thailand	Zambia
Cambodia	Czech Rep**	India	Mongolia	Romania	Togo	

**High-Income countries (ATLAS classification)

APPENDIX B

Dependent Variable - I use the 'OWW' dataset by Freeman and Oostendorp (2004) to generate a mean ratio of unskilled to skilled wages. To do so, all occupations recorded in the 'OWW' dataset have been re-coded according to the average level of education needed to enter a determined profession. Occupations associated with primary, or secondary qualifications at most, are coded as unskilled, while those that need a tertiary qualification are coded as skilled occupations. Occupational observations in the OWW dataset are recorded as a micro-dataset, where occupational wage data appears every year on a country by country basis. To transform this panel into a macro-dataset, I construct two aggregated averages: one is calculated across all occupations coded as unskilled, the other across all occupations coded as skilled. The aggregated averages are calculated in this way for each year from 1983 to 2002, on a country by country basis. In short, the 'OWW' dataset is transformed twice, as follows:

$$\frac{\frac{1}{N}\sum_{t=1}^{N}(\gamma_{i,\,t} \;+\; \delta_{i,\,t})}{\frac{1}{N}\sum_{t=1}^{N}\mu_{i,\,t}}$$

The first time it is collapsed into a panel that every year has two observations only per country: one for the mean average of unskilled occupations and one for the mean average of skilled occupations. The second transformation creates the ratio of the two and results in an aggregated macro-dataset where every country has a wage differential time series from 1983 to 2002. This procedure has been repeated, in the sensitivity analysis, with the median average of both sets of occupations instead of the mean. This is done for robustness reasons: in fact, the raw data presents multiple and repeated gaps throughout the cross-sectional time series. Country-specific factors that affect the wage of a specific occupation (or groups of occupations) could bias the mean averages. This would happen if the occupation/s for which the biased data is recorded appeared in some countries only, and were missing in others. The resulting average calculated across the set of existing occupational data could thus inflate/misrepresent the true skill premium in country A when compared to country B. While we acknowledge the fact that it is impossible to entirely correct for this source of bias, we try to minimise the latter, by estimating the benchmark regression on the mean ratio first and then on the median ratio.

Coefficient of Variation - The Coefficient of Variation (C.o.V.) is calculated across a two year rolling window. This measure is defined as the ratio of the standard deviation to the mean of the rolling window. A backward looking strategy is used, this is done in order to reflect the type of knowledge agents might have of volatility at time *t*. Such type of knowledge is typically attained by comparing the volatility levels which prevailed at time *t-1* with those existing at time *t.* The standard deviation is calculated according to the following formula:

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \qquad (2)$$

whereas the C.o.V. is obtained as:

$$v = {}^{\sigma}/_{\mu}$$

where σ is the standard deviation as defined in (2) and μ is the mean calculated across a two-year rolling window.

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Table 1.

VARIABLE	OBS.	MEAN	STD. DEV.	MIN	MAX
WAGERATIO	449	0.568	0.206	0.164	1.74
GDPPC	449	11274	11056	142.4	38390
BRAINDRAIN	449	0.114	0.149	0.001	0.888
AVGTERTIARY25	449	0.493	.364	0.005	1.68
WORKERRIGHT	449	1.38	0.654	0	2
HIGHTECHEXP	449	0.074	0.093	0	0.635
POLITICALFRACT	449	0.611	0.213	0	0.921
DEMOCRACY	449	3.85	1.84	1	18
CONFLICT	449	0.298	0.831	0	3
GDPPCCOV	449	0.235	0.164	0	0.088

Table 2.

	SYSTEM GMM				
WAGE RATIO	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
LOGGDPPC	0.089*** (0.009)	0.08*** (0.001)	0.08*** (0.001)	0.08*** (0.002)	**0.07***** (0.003)
LOGGDPPCHI	-0.029*** (0.009)	-0.026*** (0.001)	-0.024*** (0.001)	-0.025*** (0.001)	**-0.018***** (0.001)
BRAINDRAIN	-0.98*** (0.019)	-0.124*** (0.013)	-0.8*** (0.01)	-0.61*** (0.024)	**-1.2***** (0.046)
AVGTERTIARY25	-0.043*** (0.002)	-0.0123*** (0.006)	-0.063*** (0.003)	-0.034*** (0.007)	**-0.11***** (0.017)
WORKERRIGHTS	0.062*** (0.004)	0.01*** (0.001)	0.087*** (0.001)	0.01*** (0.004)	**0.11***** (0.005)
HIGHTECHEXP	-0.002 (0.009)	-0.054*** (0.01)	-0.004 (0.015)	0.016 (0.015)	**-0.02** (0.04)
DEMOCRACY		-0.005*** (0.000)			**-0.001*** (0.001)
POLITICALFRACT		0.021*** (0.002)			**0.215***** (0.01)
CONFLICT			0.037*** (0.002)		**0.08***** (0.004)
LOGGDPPCCOV				0.012*** (0.000)	**0.01***** (0.000)
N. OBS.	475	449	472	472	449
N. GROUPS	72	69	72	72	69
AR (2) PR>Z	0.22	0.16	0.18	0.16	0.13
HANSEN TEST X^2	0.64	0.4	0.65	0.55	0.35

**** 1% significance level ** 5 % significance level * 10% significance level. Column (1) uses lags 2 to 12, column (2) uses lags 2 to 8, column (3) and (4) use lags lags 2 to 10, column (5) in bold uses lags 2 to 6 and it is the benchmark regression specification.*

Table 3.

	System GMM			
Wage Ratio	**(1)**	**(2)**	**(3)**	**(4)**
LogGDPpc	**0.07*** **	0.07***	0.063***	0.08***
	(0.003)	(0.006)	(0.003)	(0.003)
LogGDPpcHI	**-0.018*** **	-0.015***	-0.016***	-0.021***
	(0.001)	(0.003)	(0.001)	(0.001)
BrainDrain	**-1.2*** **	-1.32***	-1.08***	-1.13***
	(0.046)	(0.26)	(0.02)	(0.046)
AvgTertiary25	**-0.11*** **	-0.056	-0.14***	-0.19***
	(0.017)	(0.044)	(0.014)	(0.017)
WorkerRights	**0.11*** **	0.117***	0.127***	0.126***
	(0.005)	(0.009)	(0.002)	(0.003)
HighTechExp	**-0.02**	-0.16	-0.018	-0.016***
	(0.04)	(0.11)	(0.02)	(0.033)
Democracy	**-0.001***	0.001	0.0005	-0.004***
	(0.001)	(0.003)	(0.000)	(0.000)
PoliticalFract	**0.215*** **	0.16***	0.19***	0.14***
	(0.01)	(0.035)	(0.005)	(0.012)
Conflict	**0.08*** **	0.08***	0.073***	0.08***
	(0.004)	(0.01)	(0.001)	(0.006)
LogGDPpcCoV	**0.01*** **	0.013***	0.001***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
N. Obs.	449	449	449	446
N. Groups	69	69	69	68
AR (2) Pr>z	0.13	0.12	0.13	0.08

HANSEN TEST X^2	0.35	0.35	0.77	0.45

**** 1% significance level ** 5 % significance level * 10% significance level. Column (1) is the benchmark regression specification. Column (2) uses lags 2 to 5, column (3) uses lags 2 to 7, column (4) use lags lags 2 to 6 and it substitutes the median wage ratio to the mean*

Table 4.

	SYSTEM GMM			
WAGE RATIO	**(1)**	**(2)**	**(3)**	**(4)**
LOGGDPPC	**0.07***** (0.003)	0.06*** (0.006)	0.068*** (0.003)	0.066*** (0.005)
LOGGDPPCHI	**-0.018***** (0.001)	-0.011** (0.005)	-0.013*** (0.002)	-0.018*** (0.003)
BRAINDRAIN	**-1.2***** (0.046)	-1.14*** (0.04)	-1.12*** (0.03)	1.03*** (0.27)
AVGTERTIARY25	**-0.11***** (0.017)	-0.12*** (0.022)	-0.14*** (0.014)	-0.06 (0.06)
WORKERRIGHTS	**0.11***** (0.005)	0.11*** (0.005)	0.01*** (0.003)	0.08*** (0.02)
HIGHTECHEXP	**-0.02** (0.04)	-0.015 (0.041)	-0.0003 (0.025)	-0.187** (0.072)
DEMOCRACY	**-0.001*** (0.001)	-0.001 (0.001)	-0.004*** (0.000)	0.003*** (0.000)
POLITICALFRACT	**0.215***** (0.01)	0.213*** (0.008)	0.187*** (0.004)	0.095*** (0.02)
CONFLICT	**0.08***** (0.004)	0.084*** (0.003)	0.069*** (0.007)	0.056*** (0.006)
LOGGDPPCCOV	**0.01***** (0.000)	0.008*** (0.000)	0.12*** (0.003)	0.018*** (0.000)

ETHNORELIGFRACT		0.13 (0.1)		
CULTURALFRACT			0.19*** (0.08)	
EDUCOMPLETED25				-0.024*** (0.03)
N. OBS.	**449**	445	449	329
N. GROUPS	**69**	66	69	51
AR (2) PR>Z	**0.13**	0.14	0.14	0.15
HANSEN TEST χ^2	**0.35**	0.45	0.45	0.64

**** 1%, ** 5 % , * 10% signif. level. Column (1) is the benchmark regression. Column (2) and (3) use lags 2 to 6, column (4) uses lags 2 to 4*

Table 5.

				SYSTEM GMM			
WAGE RATIO	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
LOGGDPPC	**0.07*** (0.003)**	0.086*** (0.001)	0.088*** (0.000)	0.069*** (0.001)	0.069*** (0.001)	0.062*** (0.003)	0.069*** (0.003)
LOGGDPPCHI	**-0.018*** (0.001)**	-0.028*** (0.001)	-0.028*** (0.000)	-0.026*** (0.000)	-0.027*** (0.001)	-0.026*** (0.002)	-0.026*** (0.002)
BRAINDRAIN	**-1.2*** (0.046)**	-0.99*** (0.01)	-0.98*** (0.007)	-0.64*** (0.023)	-0.855*** (0.02)	-0.775*** (0.05)	-0.836*** (0.028)
AVGTERTIARY25	**-0.11*** (0.017)**	-0.061*** (0.002)	-0.056*** (0.004)	-0.03*** (0.007)	-0.022*** (0.008)	-0.009 (0.015)	-0.005 (0.01)
WORKERRIGHTS	**0.11*** (0.005)**	0.086*** (0.001)	0.075*** (0.000)	0.1*** (0.003)	0.087*** (0.002)	0.092*** (0.007)	0.084*** (0.002)
HIGHTECHEXP	**-0.02 (0.04)**	-0.037* (0.02)	-0.019** (0.007)	-0.039* (0.02)	-0.042** (0.02)	-0.073 (0.1)	-0.1 (0.018)
DEMOCRACY	**-0.001* (0.001)**						
POLITICALFRAC T	**0.215*** (0.01)**						
CONFLICT	**0.08*** (0.004)**						
LOGGDPPCCOV	**0.01*** (0.000)**						
GOVERNMFRAC T		0.038*** (0.001)			0.027*** (0.004)	0.065*** (0.01)	0.03*** (0.002)
BATTLEDEATHS			0.004*** (0.000)		0.003*** (0.000)	0.004*** (0.000)	0.004*** (0.000)

LogGDPpcStDev				0.13*** (0.000)	0.02*** (0.000)	0.026*** (0.000)	0.018*** (0.000)
N. Obs.	449	469	475	475	469	469	469
N. Groups	69	71	72	72	71	71	71
AR (2) Pr>z	0.13	0.19	0.2	0.16	0.17	0.16	0.18
Hansen Test χ^2	0.35	0.75	0.58	0.51	0.68	0.71	0.86

Key findings:
*** 1% significance level ** 5 % significance level * 10% significance level. Column (1) is the benchmark regression specification. Column (2, (3) and (4) use lags 2 to 10, column (5) uses lags 2 to 7, column (6) uses lags 2 to 6 and column (7) uses lags 2 to 8.*