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Chapter 1 of Ph.D. Dissertation (Brown University)

Chapter 1

Child Labor and Access to the Financial System: Cross-Country Evidence

Joint with André Switala

1.1 Introduction

While child labor has largely vanished from developed countries, it is still prevelant in the developing world. The International Labor Organization (ILO) (2006) reports that there are an estimated 191 million children between the ages of 5 and 14 working in the world. This corresponds to about 16% of children in that age group. Most of these working children live in Asia and the Pacific, and in Sub-Saharan Africa, where the shares of children who are working are 20% and 26% respectively.[1]

Empirical studies have shown the negative impacts of child labor on children's human capital. This is true for both the education and health components of human capital. For example, Heady (2003) shows that children who attend school and are also working have lower test scores in both, reading and math, than children who do not work. Beegle, Dehejia and Gatti (2005), using a panel data from Vietnam, find that children who attend school and work are more likely to drop out of school than children who attend school but do not work. Forastieri (2002) and Bequele and Myers (1995) report that children have a higher risk of suffering from injury while working, compared to adults. Children are also more vulnerable when exposed to hazardous chemicals and are hindered in their physical development due to being forced to perform repetitive tasks in confined spaces. Beyond these directly observable effects, we also have to consider the psychological consequences

[1]See ILO Convention No. 138 and ILO (2002) for definitions of child labor. Edmonds (2004) offers an interesting discussion about the terminology on child labor and how it is used by both producers and consumers of data on child labor.

on children, especially if they are involved in abusive or exploitative work. Evidence shows that these children display signs of withdrawal and depression, and generally suffer from low self-esteem. Some may exhibit violent and self-destructive behaviors. The negative consequences of child labor, ranging from low schooling and bad health outcomes, to psychological and socialization problems, not only affect the current welfare of working children but also their prospects for adulthood.

It is believed that poverty is the main cause of child labor. According to this view, parents prefer that their children do not work, but due to economic hardships they need the additional income children can bring home. In this formulation, child labor is the result of market imperfections that prevents families from smoothing consumption through borrowing. Moreover, since parents cannot borrow against future income of their children, they cannot invest in their education if income is not sufficiently high.[2] An increased use of the financial system by the poor may affect child labor through two channels: an intertemporal income transfer and a contemporaneous change in the opportunity cost of children's time. In the first case, a relaxation of credit constraints facilitates the transfer of income from the future to the present, reducing child labor. It also allows families to mitigate the effect of transitory income shocks without resorting to child labor. However, when there are imperfections in the labor market (e.g. moral hazard, or if children can only find work on the family enterprise), credit that is used for starting or expanding a family business might raise the opportunity cost of children's time, increasing child labor. This change in relative prices will reduce the beneficial effects that an increase in the use of the financial system by the poor has on child labor prevalence.

This paper empirically evaluates in a cross-country setting the net effect on the prevalence of child labor of an increase in the use of the financial system by the poor. This paper improves on the existing literature by using a data set that better reflects the use that the poor make of the financial system. The source of this increased access is financial institutions outside of the commercial banking system; that is, alternative financial institutions. This category includes microfinance and microcredit institutions, postal banks, credit unions, development banks, etc. These financial institutions are well suited to studying the effect of availability of financial services on child labor because many of their clients and members are poor households. This segment of the population is more prone to have to resort to child labor and also less likely to be served by traditional commercial banks. This paper thus contributes to the growing literature that tries to dissintangle the relevance of credit constraints on the decision of households to send their children to work.

We are interested in a measure of the extent to which poor households make use of financial

[2] See Basu (1999), Basu and Tzannatos (2003) and Edmonds 2007 for reviews of the literature on child labor.

services. We do not argue, though, that the traditional commercial banking system cannot service the needs of poor households.Since there is no indicator of the percentage of clients by income group in the traditional banking system, we suspect that the number of accounts in alternative financial institutions better reflect the differences between countries in the access to financial services by poor households.

The literature has studied the issue by looking at variables that measure financial development. In a cross-country study, Dehejia and Gatti (2005) (from now on referred to as DG) use the ratio of private credit to GDP as a measure of aggregate access to credit. They find that there is a significant and negative relationship between bank credit and child labor. Although this result suggests that the credit market imperfection is important in the context of child labor, it is less clear whether the bank credit variable used in their study is the appropriate one to measure the access to credit by families that need to resort to child labor. Improvements in bank credit might indicate that more access is given to middle income or low high income household, but it does not necessarily imply that poor families are having access to that credit. In fact, we reproduce the calculations made by DG using updated data on private credit and we find that their results are not robust to this change.

Our results indicate that countries with mechanisms that facilitate the access to the financial system by the poor reduce the prevalence of child labor compared to countries where that access is limited. Measures of general access to credit in the country, not necessarily by the poor, have no statistically significant impact on child labor.

The rest of the paper progresses as follows: section 1.2 reviews some of the related literature with regard to the effects of credit market imperfections on child labor. Section 1.3 describes the data used in this study, with an emphasis on the microfinance data that, to the best of our knowledge, hasn't been used in previous studies on child labor. Section 1.4 presents the empirical results when using the data on alternative financial institutions. Additionally, it is shown that the results from DG do not hold when updated data is used. Section 1.5 concludes.

1.2 Literature Review

Theoretical models on the determinants of child labor emphasize the role played by poverty. Basu and Van (1998) introduce the luxury axiom, which states that parents prefer if their children do not work. Only when adult income is below the minimum subsistance level for the family is child labor used as a necessary additional income source. Their model is a static one and therefore does not have a role for credit markets. Baland and Robinson (2000) have a dynamic model in which there is a trade off between child labor and accumulation of human capital. When there are imperfections in the capital and credit markets so that the non-negativity constraints on bequest or savings are binding, child labor will be inefficently high. In other words, child labor acts as a substitute of negative bequests or savings. In their model credit would be used as a way of transfering income from the future to the present and increase consumption in the first period. That is, credit takes the specific form of consumption credit. In this case, the unambiguous result of increases in the access to credit is a reduction in child labor.

Wydick (1999) considers a different type of credit. In his model, credit is used for the family enterprise rather than consumption and is either spent on working capital or for the purchase of physical capital. If the purpose of credit is to finance working capital, there may be a reduction in child labor as hired labor could be employed as a substitute. This is valid for types of businesses in which moral hazard by hired labor is not an issue. The opposite effect, that is an increase in child labor is expected if credit is used for purchase of physical capital. In this case, the productivity of children in the family enterprise increases, the opportunity cost of school or leisure is higher, and therefore child labor is more likely to occur.

From the theory on credit access and child labor we expect the empirical results to depend on the type of credit that is issued and the structure of the family business. The empirical microeconomic evidence is indeed mixed. Wydick (1999) using data from Guatemala, finds that in general, households with better access to credit tend to increase children's school attendance. However, the effect is smaller if it is harder to substitute hired labor for child labor. He also finds that the probability of a child being withdrawn from school to work in a family enterprise is greater in cases in which borrowers use funds for the purchase of capital equipment instead of strictly for working capital purposes.

Ersado (2005) finds that having a commercial bank branch in the area of residence, which is an indicator of access to credit, increases school attendance and reduces child labor in Nepal and Zimbabwe. In Peru however, Ersado observes that the same indicator increases child labor, although there is no evidence of decreasing school attendance. Hazarika and Sarangi (2008) explores the effect of household's access to microcredit on children's work in rural Malawi. During peak labor demand, households with access to microcredit have a higher propensity to increase their children's labor. They observe that the increase in child labor occurs in household domestic work. This indicates that while adults work in the household enterprise, children replace them in domestic chores. In their study, there is no significant effect of household's access to credit on children's school attendance.

In a macro approach, DG (2005) study the relation between child labor and financial development in a cross-country setting for the period 1960-1995. Their indicator of financial development is the amount of credit given to the private sector by deposit money banks as a proportion of GDP (from Beck et al. (2000)). They find that child labor is negatively and significantly associated with their measure of financial development. We show that the result is sensitive to updates of the bank credit measure.

1.3 Data

To measure the access to credit by poor households, we would ideally like country-level information on the distribution of credit by income level of the client, or on the number of clients of the financial system by their income level. An alternative indicator would be information on the minimum value of collateral required to obtain credit in a financial institution, as well as information on the costs and fees for application and approval. To the best of our knowledge, no such measures are available for a large number of countries. [3] A commonly used measure of financial development (the value of credit by financial intermediaries to the private sector as a proportion of GDP) does not provide information on how much of that credit goes to poor families. As a result, that measure does not answer the question of who is getting credit in each country.

To measure the access to the financial system by the poor we take advantage of data collected by the Consultative Group to Assist the Poor (CGAP) on what they call alternative financial institutions (AFIs).[4] What is common among the institutions included in this study is that they serve at least to some extent poor and near-poor individuals and that they pursue not only financial but also social objectives. Many of their clients are thus not the typical customers of commercial banks. The sample consists of microfinance institutions (MFIs), financial cooperatives/mutuals, state agricultural and development banks, postal savings banks and low-capital rural or local banks. To the best of our knowledge, this data set has not been previously used in studies of child labor.

Our main variable of interest, which we call Max_CGAP, is derived from the maximum of each institution's number of members, loan accounts and savings accounts.[5] This variable serves as a reference for the number of clients that each institution has. We use this approach for two main reasons. First, not all institutions report on all three variables, that is on the number of members, loan accounts and savings accounts. Table 1.1 shows the number of institutions that report each variable by region. By using the maximum value, we can include as many institutions as possible

[3] The Microfinance Information Exchange (MIX) collects some data on the number of clients below the poverty line. However, this data is only available for a small fraction of the institutions covered in their reports.

[4] For a more detailed description refer to the background paper of Christen et al. .

[5] This measure is called 'Big Numbers' in the CGAP data set.

for each country. More importantly, this approach allows us to control for the fact that some individuals may have both a savings and a loan account in the same institution. This way we avoid some double-counting within institutions. However, our measure does not properly address the fact that some individuals may have more than one account per institution or have accounts in different institutions that are reporting to CGAP. Similarly, we might be under-reporting the number of clients if the overlapping between those with savings accounts and those with loan accounts is not very big. Given the imperfections in the data, considering the maximum of the number of members, loan accounts and saving accounts provides the best available approximation to the number of clients of each institution. The total number for a country is calculated as the sum of the maximum over all institutions that report for that country.[6]

A drawback of the dataset is that it does not include data for the same institution over many years, but is also not limited to the same year for all AFIs. In fact, the reported data is the latest available figure at the time the report was written. Table 1.2 shows the distribution of the source year across regions. The highest concentration of source years is in 2000, which accounts for about 37% of all observations, followed by 2001 with 21% and 2002 with 16%. There are also regional differences: The year 2000 is more common as a source year for Africa and South Asia, while 2001 is more common among Europe and Central Asia as well as Latin America and the Carribean. We choose to use all observations as if they had occured in the year 2000, due to this being the most common year.[7]

We use this information as an indicator of the access to credit by poor individuals. We think that this is suitable data for this purpose because of the nature of the institutions reporting. However, we do not have direct measures of the composition of clients regarding their position in the income distribution. In data from the Microfinance Information Exchange (MIX)[8], which is one of the sources used by CGAP, there is scattered data on the percentage of clients that are below the poverty line. We don't use this data because the institutions represented in the MIX data set is only a subset of all institutions of interest and, additionally, the number of institutions reporting on this variable is small.

As mentioned in section 1.2 of this paper, DG use the amount of private credit by deposit money banks as a percentage of GDP as an indicator of financial development. We use the same variable for

[6]Honohan points out that a few institutions appear twice in the CGAP data set. The data we use has been corrected for this.

[7]Assuming that all accounts were held in 2000 has some problems. For example, we do not know if institutions that last reported prior to 2000 still existed in 2000 or had been replaced by other institutions. Similarly, there is no information on the growth in the number of accounts from year to year. As a result, we cannot assess whether our estimate is an overstatement or understatement of the true number of accounts in 2000.

[8]http://www.themix.org

the year 2000, which was not included in DG, to compare our results to the existing literature. The data on private credit has since been updated and we use the latest available version from November 2008. This version differs from previous ones in that it has been recalculated for the entire time period to ensure consistency over time. As a result, some of the observations available in earlier versions are no longer included. In the empirical section, we show that some of DG's results change once the latest version is used.

Child labor is measure of the labor force participation of children ages 10 to 14 estimated by ILO (1997).

Other controls included in the regressions are the logarithm of GDP per capita at PPP prices, from the Penn World Tables 6.2 ; the percentage of population that lives in rural areas and the share of agriculture in GDP, both from the World Development Indicators .

Table 1.3 reports summary statistics for the main variables.

1.4 Empirical Results

1.4.1 Alternative Financial Institutions

We begin our empirical exercise by looking at a regression of child labor on the access to alternative financial institutions as measured by the number of accounts in these institutions per 1,000 population. The analysis is a cross-country regression for the year 2000. Columns 1 through 4 of Table 1.4 report the results of this regression, controlling for different variables. Throughout all columns we control for the level of child labor in 1950 to account for the high persistence in the prevalence of child labor within a country. We also include regional dummies in all the regressions.

The regression results in Table 1.4 show that countries with a greater proportion of poor families using the financial system have experienced a lower rate of prevalence of child labor. In our baseline regression, in column 1, we simply control for the rate of child labor in 1950 and regional dummies. The coefficient of Max_CGAP is negative and significant.

The negative relationship between Max_CGAP and child labor is robust to a number of sensitivity tests. In columns 2 and 3 we include other controls to find out if CGAP is picking up the effect on child labor coming from omitted variables. For example, richer countries have a lower prevelance of child labor. If those countries also have a higher number of accounts in AFIs, our CGAP measure could be picking up the effect of GDP per capita. Column 2 includes the logarithm of GDP per capita allowing for non-linear effects. The negative relationship between Max_CGAP and child labor holds when conditioning on this factor, although the size of the coefficient is reduced by a third. In column 3 we control also for the percentage of the population living in rural areas and agricultural production as a share of GDP. These variables account for the fact that child labor is more prominent in rural areas and children are more likely to be employed in agricultural activities. As shown, the coefficient on Max_CGAP is still negative and significant and of similar magnitude. Finally, in column 4 we exclude outliers as determined by Hadi's (1992) criteria and find that CGAP is still significantly negative.[9] The coefficient on CGAP in column 4 suggests that an increase of the number of accounts by one standard deviation is associated with a one percentage point lower child labor.

The CGAP data measures specifically the access to the financial system by poor and near-poor individuals. This is important because that is the sector of the population that experiences child labor. To compare our results qualitatively to previously used measures, we run the same regressions using the ratio of private credit by deposit money banks to GDP. This variable has been used in the context of child labor by Dehejia and Gatti (2005) . Bank credit represents the financial depth of a country and thus describes a different aspect of the financial system than the CGAP data. The results are shown in columns 5 to 8 of Table 1.4. For this exercise, we use a sample that is consistent with the sample used when working with CGAP data. While the coefficient on bank credit is negative throughout, it is not significant once controlling for the level of GDP per capita. These results are not in line with those recorded by DG.

To check if the change in the results is due to sample selection, Table 1.5 reports the results of the impact of the financial variables on child labor using all the data available for 2000. The results of these regressions are in line with those using a consistent sample, indicating our findings are not due to sample selection. Controlling for both financial variables, bank credit and Max_CGAP, confirms the results (Table 1.6): Max_CGAP has a negative and significant effect on child labor, while Bank Credit is not significant. These results indicate that what is important for reductions in child labor is increasing the access to the financial system by the poor.

Our results on the effect of bank credit on child labor are opposite to the results from DG (2005) . It is important to point out that our measure of financial access by the poor limits our analysis to the year 2000, unlike Dehejia and Gatti (2005) who use data ranging from 1960 to 1995.[10] To make sure that our results are not based on the year 2000, in the next section we replicate the regression of Dehejia and Gatti (2005) using updated data.

[9]The outlier is Sri Lanka.

[10]The data correspond to the years 1960, 1970, 1980, 1990 and 1995

1.4.2 Bank credit revisited

In this section we show some results that indicate that the lack of significance of the Bank Credit variable in explaining child labor prevalence is not unique to the year 2000. Instead, we show that the result of DG on the significant and negative relation between Bank Credit and child labor is not robust to updates in the variable Bank Credit.

We start by reproducing the results of DG's Table 2, column 2 in our Table 1.7, column 1, using the same data set employed by DG. The data corresponds to the period 1960-1995. The regression includes regional dummies and the standard errors are clustered by country. Their results indicate that there is a negative and significant effect of Bank Credit on child labor, even when controlling for income, the proportion of population living in rural areas and the proportion of GDP that corresponds to agriculture. In Table 1.7, column 2, we replicate DG's exercise using updated information for all variables included in the regression. The results show that the measure of financial development is no longer significant. This result is consistent with our finding for the year 2000.

The number of observations with the updated data is smaller than the ones used originally by DG. Table 1.8 shows how the original and the updated set differ by listing all country-year observations and the missing variables. There are 312 common observations. DG's data set contains 75 observations that are not in the updated data set. There are 38 observations that appear only in the updated data set.

Table 1.9 reports summary statistics for the updated data set classified in three groups: 1) all available observations, 2) observations that are common to DG and SV data sets, and 3) observations that are unique to our updated data set. The observations that are unique have, on average, lower child labor prevalence and a higher proportion of private credit with respect to GDP than the observations common to both data sets. The same pattern is observed when comparing the averages of unique observations in the updated data set with those of the unique observations in DG's data set. Descriptive statistics for DG's data set classified in three equivalent groups are found in Table 1.10.

We repeat the regression using only common observations to check if there is some sample selection problem, but the results are consistent with those using the complete data sets. Table 1.7, column 3 shows the results of the regression using only common observations and the original DG data set. Column 4 of the same table uses common observations and the updated data set.

In order to determine whether a particular variable is responsible for the change in the results, we run the regressions with the data used by DG, replacing only one variable at a time with an updated series. The coefficient for Bank Credit is always significant, consistent with DG's results, except when Bank Credit itself or the proportion of agriculture in GDP are updated. Table 1.7, column 5, show the result of the regression when all data comes from DG's data set except Bank Credit, which has been updated. The coefficient for Bank Credit is no longer significant.

The results in this section show that the negative and significant relationship between child labor and the proportion of private credit as percentage of GDP that was found by DG is not robust to consistency updates made to the series on private credit. The non-significance found with updated data for the period 1960-1995 is consistent with the results found for the regression using only data for the year 2000 as presented in the previous section.

1.4.3 Other Measures

The two indicator we have used so far in this paper are not directly comparable, because they measure financial development in two different dimensions. Our CGAP variable represents the number of accounts (per 1,000 population) in AFIs, while bank credit measures the volume of private credit as proportion of GDP. To compare our results against another indicator of general access to financial intermediaries that is comparable to the CGAP variable, we use a variable constructed by Honohan (2008) .

Honohan's Composite Measure (HCM) represents the percentages of the adult population with access to financial intermediaries for each country. It is derived from household surveys when available, or constructed as a function of the number of accounts in banks and the average size of those accounts. Figure ... shows the relation between this composite measure and volume of credit by deposit money banks as proportion of GDP (bank credit). The correlation between these two series is 0.46. The dispersion of HCM for a given Bank Credit is higher than the dispersion of Bank Credit for a given HCM. It indicates that Bank credit does not reflect the access that individuals have to the financial system. HCM might do a better job in representing that. The correlation between CGAP and HCM is 0.42. CGAP is one of the data sets used by Honohan (2008) to estimate his composite measure when information from household surveys was not available. Table 1.11 reports the results of the cross-country regressions of the HCM variable on child labor, using the same controls as Table 1.4. Once we include GDP as a control, the coefficient on HCM is positive but not significantly different from zero.

HCM is comparable to CGAP in that both of them intend to capture the proportion of the population with access to the financial system. HCM measures this access for the whole population, while CGAP represents better the access by poor and near-poor individuals. The regression results indicate that measures of access by the whole population are not significantly correlated with child labor. These results are consistent with those found when using the proportion of credit with respect to GDP. Only the use of the financial system by poor individuals is significantly correlated with the prevalence of child labor in the country. The higher the proportion of poor individuals with access to the financial system, the lower is the proportion of children ages 10 to 14 who are working.

1.5 Conclusions

A previous study by Dehejia and Gatti (2005) finds a negative and significant relationship between the prevelance of child labor and financial development as measured by private credit as a percentage of GDP. In this paper we argue that their measure of financial development does not reflect the access to credit by the poor and thus by households which are affected by child labor. We propose the use of an alternative measure, which was compiled by CGAP (2004) and represents the number of clients of alternative financial institutions. Our results indicate that countries with mechanisms that facilitate the access to the financial system by the poor exhibit lower prevalence of child labor compared to countries where that access is limited. We also show that more general measures of access to credit, which includes access by rich and middle income individuals, do not have a statistically significant impact on child labor. Furthermore, we find that the results of Dehejia and Gatti (2005) are not robust once updated data is used. Our results suggest that it is important to refine our measures of access to the financial system by income groups, in order to better understand its effects on the dynamics of economic growth and development.

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Table 1.1: Number of Observations for Variables in the CGAP Dataset

	LA	SA	M	Max
Sub-Saharan Africa	801	754	741	828
East Asia and Pacific	244	198	168	254
Europe and Central Asia	169	52	45	180
Latin America and Caribbean	439	384	377	447
Middle East and North Africa	64	43	43	73
South Asia	776	569	673	782
Sum	2493	2000	2047	2564

LA = Loan Accounts, SA = Savings Accounts

M = Members, Max = Maximum of LA, SA and M

Table 1.2: Distribution of Source Years in the CGAP Database

Year	SSA	EAP	ECA	LAC	MENA	SA	Total
No Year	13	8	0	19	1	5	46
1995 and before	4	1	0	2	0	3	10
1996	12	2	1	5	0	2	22
1997	125	9	0	16	4	4	158
1998	45	26	2	26	14	74	187
1999	98	8	0	11	2	65	184
2000	349	80	8	75	8	422	942
2001	84	36	125	211	22	68	546
2002	88	75	29	64	15	133	404
2003	13	10	15	20	7	7	72
Sum	831	255	180	449	73	783	2571

SSA = Sub-Saharan Africa, EAP = East Asia and Pacific

ECA = Europe and Central Asia, LAC = Latin America and Carribean

MENA = Middle East and North Africa, SA = South Asia

Table 1.3: 2000 Data - Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Child Labor	123	12.748	14.580	0	51.200
Max_CGAP	135	94.105	141.467	0.112	988.804
Bank Credit	112	0.287	0.274	0.011	1.506
Log GDP	133	8.202	0.998	6.158	10.435
Rural Pop	131	51.750	22.002	0	91.700
AgrGDP	126	18.814	14.254	0.074	72.009
Child Labor 1950	123	26.632	18.942	0	80.700

Table 1.4: CGAP vs. Bank Credit on Child Labor, year 2000, consistent

	Dependent Variable: Child Labor (ILO) 2000							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max_CGAP	-0.013***	-0.005*	-0.008***	-0.008**				
	[0.004]	[0.003]	[0.003]	[0.003]				
Bank Credit					-4.466**	-0.310	-0.174	-3.080
					[2.248]	[1.836]	[1.848]	[2.866]
LogGDP		-39.103***	-44.104***	-47.308***		-41.614***	-45.859***	-46.595***
		[11.514]	[11.120]	[10.340]		[12.062]	[11.908]	[12.477]
LogGDP_sq		2.117***	2.442***	2.649***		2.260***	2.524***	2.587***
		[0.684]	[0.670]	[0.615]		[0.728]	[0.728]	[0.763]
AgrGDP			-0.064	-0.067			-0.048	-0.063
			[0.092]	[0.093]			[0.093]	[0.096]
Rural Pop			0.078**	0.079**			0.055*	0.068*
			[0.033]	[0.033]			[0.032]	[0.036]
ChildLabor1950	0.558***	0.459***	0.445***	0.443***	0.561***	0.460***	0.451***	0.448***
	[0.046]	[0.044]	[0.044]	[0.047]	[0.048]	[0.046]	[0.047]	[0.049]
RegDummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	107	107	105	104	107	107	105	101
Adjusted R^2	0.844	0.891	0.893	0.893	0.838	0.889	0.889	0.889

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 1.5: CGAP vs. Bank Credit on Child Labor, year 2000, full samples

	Dependent Variable: Child Labor (ILO) 2000							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Max_CGAP	-0.015***	-0.006**	-0.010***	-0.007**				
	[0.004]	[0.003]	[0.003]	[0.003]				
Bank Credit					-3.000*	-0.794	-0.957	-1.383
					[1.552]	[1.313]	[1.344]	[1.432]
LogGDP		-21.974	-33.636***	-42.864***		-39.582***	-41.834***	-48.352***
		[13.357]	[10.952]	[8.928]		[9.762]	[9.783]	[9.395]
LogGDP_sq		1.086	1.835***	2.423***		2.106***	2.264***	2.678***
		[0.799]	[0.675]	[0.546]		[0.581]	[0.582]	[0.530]
AgrGDP			-0.069	0.018			-0.027	-0.044
			[0.088]	[0.080]			[0.081]	[0.085]
Rural Pop			0.094**	0.062**			0.037	0.047*
			[0.039]	[0.031]			[0.027]	[0.027]
ChildLabor1950	0.526***	0.453***	0.431***	0.402***	0.544***	0.449***	0.444***	0.415***
	[0.045]	[0.041]	[0.042]	[0.046]	[0.049]	[0.049]	[0.049]	[0.053]
RegDummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	125	125	119	115	143	142	135	132
Adjusted R^2	0.830	0.870	0.875	0.883	0.836	0.891	0.892	0.883

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 1.6: Bank Credit and CGAP on Child Labor, year 2000

	Dependent Variable Child Labor (ILO) 2000
Max_CGAP	-0.008*
	[0.004]
Bank Credit	-2.579
	[3.007]
LogGDP	-46.340***
	[12.588]
LogGDP_sq	2.596***
	[0.771]
AgrGDP	-0.076
	[0.098]
Rural Pop	0.090**
	[0.041]
ChildLabor1950	0.438***
	[0.050]
Regional Dummies	YES
Observations	99
Adjusted R^2	0.889

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 1.7: Bank Credit Revisited

	Dependent Variable: Child Labor (ILO)				
	Original DG	All Upd.	Original DG com.	Upd. com.	Bank Credit Upd.
	(1)	(2)	(3)	(4)	(5)
Bank Credit	-3.979*	-0.867	-1.390	-0.338	-0.964
	[2.159]	[1.463]	[1.689]	[1.126]	[1.076]
LogGDP	-41.921***	-39.925***	-38.597***	-37.568***	-42.269***
	[5.376]	[5.838]	[6.383]	[6.439]	[5.319]
LogGDP_sq	2.510***	2.246***	2.303***	2.126***	2.504***
	[0.336]	[0.332]	[0.391]	[0.370]	[0.324]
AgrGDP	0.057	0.032	0.063	0.072	0.059
	[0.036]	[0.048]	[0.042]	[0.051]	[0.038]
Rural Pop	0.017	0.018	0.023	0.016	0.029
	[0.023]	[0.025]	[0.267]	[0.026]	[0.024]
ChildLabor1950	0.624***	0.650***	0.637***	0.645***	0.612***
	[0.044]	[0.044]	[0.048]	[0.046]	[0.049]
Year	-0.201***	-0.224***	-0.222***	-0.213***	-0.199***
	[0.026]	[0.032]	[0.032]	[0.032]	[0.029]
Regional Dummies	YES	YES	YES	YES	YES
Observations	384	344	312	312	347
Adjusted R^2	0.911	0.919	0.916	0.915	0.917

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 1.8: Data Differences for Bank Credit Regression between DG and SV

Observations used by SV only			Observations used by DG only		
WBCode	Years	Missing Data	WBCode	Years	Missing Data
ALB	1995	B	ARG	1970, 80	B
AUS	1980	A	BEL	1970	A
BFA	1970, 80	B	BGD	1980, 90, 95	B
CHE	1990, 95	A	BLR	1995	B
CPV	1990, 95	B	BRA	1980, 90	B
CZE	1995	G	CAN	1970	A
DEU	1980	A	CHL	1970	B
ESP	1980, 90	A	CHN	1990, 95	B
GBR	1980	A	COG	1970, 80, 90	B
GMB	1995	B	DNK	1970	A
GNQ	1995	B	FIN	1960, 70	A
IRL	1980	A	GRC	1960, 70	A
IRN	1970	A	GUY	1960, 70, 80, 90	B, G
ISL	1980	A	HTI	1990	A
KAZ	1995	G	IDN	1970, 80	B
KWT	1980, 95	B	ITA	1970	A
LTU	1995	G	JAM	1960, 70, 80, 90	A
LUX	1980	A	JPN	1960, 70	A
MAC	1995	B, A	LBR	1970, 80	B
MKD	1995	B	MAR	1970	A
NZL	1980	A	MMR	1960, 80, 90, 95	G
OMN	1995	B, A	MUS	1970	A
PNG	1995	B	NAM	1995	B
PRT	1980	A	NGA	1970, 80, 90, 95	A
SLB	1990	A	NIC	1980	B, A
SLB	1995	B, A	NIC	1990	A
SUR	1995	B	PER	1960, 70	B
SYR	1995	A	PER	1980	B, A
TZA	1990, 95	B	SDN	1960	B, G
USA	1980, 90, 95	A	SDN	1970	B
			SGP	1970	A
			SLV	1960, 70, 80	A
			SOM	1970, 80	B
			SYR	1970, 80	A
			TTO	1960, 70, 80	A
			TUR	1990, 95	A
			UKR	1995	B
			URY	1960, 70	B, A
			URY	1980	A
			ZAR	1970, 80, 90	B

A = Agricultural Share of GDP, B = Bank Credit, G = GDP

Table 1.9: Summary Statistics - updated data set

All observations, using updated data					
Variable	Obs	Mean	StdDev	Min	Max
Child Labor	350	14.690	16.697	0	75
Child Labor 1950	132	22.931	18.849	0	80.700
Bank Credit	350	0.313	0.304	0.004	1.954
LogGDP	350	8.388	1.134	6.097	10.499
Rural Pop	350	51.403	24.866	0	97.600
AgrGDP	350	19.826	15.904	0	70.632

Common observations, using updated data					
Variable	Obs	Mean	StdDev	Min	Max
Child Labor	312	15.057	16.274	0	63.100
Child Labor 1950	115	23.666	18.162	0	72.300
Bank Credit	312	0.304	0.290	0.004	1.954
LogGDP	312	8.339	1.104	6.097	10.499
Rural Pop	312	52.576	24.384	0	97.600
AgrGDP	312	20.173	15.796	0.137	70.632

Observations exclusively in the updated data set					
Variable	Obs	Mean	StdDev	Min	Max
Child Labor ILO	38	11.674	19.822	0	75
Child Labor 1950	17	17.959	22.990	0	80.700
Bank Credit	38	0.390	0.397	0.028	1.632
LogGDP	38	8.796	1.298	6.186	10.327
Rural Pop	38	41.776	26.975	0.100	94.300
AgrGDP	38	16.977	16.707	0	55.812

Table 1.10: Summary Statistics - DG data set

All observations, using DG data					
Variable	Obs	Mean	StdDev	Min	Max
Child Labor	387	15.079	15.576	0	63.100
ChildLabor1950	130	24.747	19.011	0	80.640
Bank Credit	387	0.264	0.235	0.000	1.486
LogGDP	387	7.834	1.016	5.413	9.848
Rural Pop	387	52.433	24.085	0	97.600
AgrGDP	387	20.876	15.899	0.143	70.632
Common observations, using DG data					
Variable	Obs	Mean	StdDev	Min	Max
Child Labor	312	15.051	16.270	0	63.100
ChildLabor1950	108	24.284	19.430	0	80.640
Bank Credit	312	0.283	0.243	0.000	1.486
LogGDP	312	7.882	1.052	5.413	9.848
Rural Pop	312	52.012	24.629	0	97.600
AgrGDP	312	20.435	16.032	0.143	70.632
Observations exclusively in the DG data set					
Variable	Obs	Mean	StdDev	Min	Max
Child Labor	75	15.197	12.365	0	39.880
ChildLabor1950	22	27.020	17.033	0	53.370
Bank Credit	75	0.184	0.177	0.009	0.864
LogGDP	75	7.637	0.828	5.756	9.329
Rural Pop	75	54.185	21.741	0	89.700
Agr GDP	75	22.708	15.299	2.253	68.419

Table 1.11: Using Honahan's Composite Measure

	(1)	(2)	(3)	(4)	(5)
HCM	-0.064***	0.009	0.002	0.018	0.018
	[0.024]	[0.017]	[0.020]	[0.019]	[0.019]
LogGDP		-34.038***	-40.502***	-40.881***	-40.881***
		[10.836]	[7.374]	[9.850]	[9.850]
LogGDP_sq		1.808***	2.206***	2.238***	2.238***
		[0.631]	[0.440]	[0.560]	[0.560]
Rural Pop			0.061*	0.037	0.037
			[0.036]	[0.030]	[0.030]
AgrGDP			-0.076	0.0260	0.0260
			[0.095]	[0.098]	[0.098]
ChildLabor1950	0.494***	0.420***	0.411***	0.370***	0.370***
	[0.048]	[0.043]	[0.044]	[0.046]	[0.046]
Regional Dummies	YES	YES	YES	YES	YES
Observations	150	148	141	131	131
Adjusted R^2	0.828	0.878	0.878	0.885	0.885

Robust standard errors in brackets

*** $p<0.01$, ** $p<0.05$, * $p<0.1$