POLITICAL INSTABILITY AND VOLATILITY OF INVESTMENT GROWTH: EVIDENCE FROM TURKEY[*]

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Abstract

This paper offers an econometric model that provides an evidence of the positive relationship between political instability and volatility of private investment growth in Turkey during 1984-2015. A politically stable government structure is necessary for stable investment patterns, and hence stable accumulation. Using political instability index (calculated as propensity of an imminent government change) and an economic control variable, regression results on the base model suggest a significant positive relationship between political instability and investment growth volatility. This result is then shown to be robust to introduction of a structural break. A structural break test on the base model suggests dividing the time period into two sub-periods as pre- and post-2000, which is highly consistent with historical facts, as Turkey experienced rapidly changing government during 1990s. It turns out that effect of political instability on volatility of investment growth is positively significant for pre-2000 period, but not significant for the later period. Finally, it is shown that the result is also robust to estimation method of political instability index, as positive relationship during pre-2000 period is preserved even if the political instability index is estimated with a different method.

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1. Introduction

Annual GDP growth rate of Turkey during the neoliberal period (post-1980) shows high volatility. When GDP is decomposed into its aggregate demand components, it is seen that volatility in private gross fixed capital formation (GFCF) growth is a major source of volatility in GDP growth. This paper argues that political instability, due to rapidly changing governments especially during 90s, can be considered as an important reason of this phenomenon. From a theoretical perspective, a politically stable government structure is necessary for stable investment patterns, and hence stable accumulation. As government changed every year on average, it is expected that private GFCF growth exhibits frequent ups and downs. The underlying institutional structure remains stable, but each change in government leads capitalists to pause in their accumulation behavior. Once the change has been completed and the institutional structure is still in place, they resume high investment. Data presented in the table below on volatility of private GFCF growth (reflected by standard deviations of annual growth rates in the corresponding time period) and number of new governments per year offers a *clear correlation* between these two. As correlation does not necessarily imply causation, an econometric test can provide an evidence for causality relationship, which is the aim of this paper.

Table 1: Private GFCF growth volatility vs. number of new governments

Period	Standard deviation of private GFCF growth rate	# Governments per year
1984-1990	12.1	0.4
1991-2002	19.5	1.0
2003-2015	17.2	0.6

The periodization in the above table is not random. Both the first (1984-1990), and the third (2003-2015) periods were periods of single party government. The government changed several times during those periods, but it was always run by a *single* political party. However, the second period (1991-2002) is called *coalition* governments period, as the government was always shared by at least two political parties. There was a new government every year on average during the second period, and standard deviation of private GFCF growth rate was higher in the very same period than it was during the other two periods[2].

Although there are many studies on how political instability affects *level* of investment growth[3], there are only a few studies in the literature that focuses on effect of political instability on *volatility* of investment growth. By using annual data for thirteen emerging and frontier market economies in sub-Saharan Africa (for a period of 35 years), Brafu-Insaidoo and Biekpe (2011) find that political instability increases investment volatility. On the other hand, Denizer et. al. (2000) find no affect of political instability

[2] A note for the time scope of this study: The neoliberal period in Turkey started by declaration of a new set of economic policies on January 24th 1980 to overcome the economic crisis that had lasted since 1976. These policies are known as 'January 24th Decisions' (J24D) and include many neoliberal elements, such as liberalization of foreign trade, financial liberalization, and privatization. Then a coup d'état took place in September of the same year. Since there is no civil government in Turkey during 1980-1983 period, as Turkish army ruled the country until the general elections in November 1983, this paper does not cover the first three years of the neoliberal period. Also, some statistics (such as workdays lost in strike, which will be used in estimation of political instability index) is not available for 1980-1983 period.

[3] For instance, see Feng (2001) and Alesina and Perotti (1996). Both of these studies find a significant negative relationship between political instability and *level* of investment growth.

on investment volatility in their study with 70 countries. But they also state that this 'no affect' is due to the fact that the political instability variable does "not change much over time" for many countries in their sample. There is another group of studies that focuses on effect of political instability on (volatility or level of) economic growth[4], which can also be considered as similar to this paper.

The contribution of this paper to the literature will be from two aspects: content and technique. As to content, this paper contributes to small literature on relationship between political instability and investment growth volatility. While the two other studies mentioned previously used panel data sets that aggregate many countries, this paper uses data for a single country. In that sense, it also contributes to the literature on Turkish economy. In terms of its technique, this paper estimates political instability index by a tree-based classification method (random forest), which is a contribution to political instability literature. As will be discussed in the next section, application of machine learning algorithms is a very recent phenomenon in social sciences literature.

The next section includes a basic time-series model and details of the data used. Estimation of political instability index, along with a discussion of two different types of estimation techniques in the literature, can also be found in that section. Then, section 3 presents results of the first regression on the basic model. In section 4, the basic models will be tested for robustness with respect to structural break and to method of estimation

[4] On volatility of economic growth, see Klomp and Haan (2009) for instance. They state that government instability and regime instability have significant positive affects on economic growth volatility. As to level of growth, in a relatively recent and influential paper, Aisen and Vega (2013) find that "higher degrees of political instability are associated with lower growth rates of GDP per capita."

of political instability. Finally, section 5 offers a conclusion based on the results, and also includes a discussion of limitations of the model presented here.

2. Basic Model, Data, and Methodology

The basic model that will be tested is the following:

$$VOL.GFCF_T = B_1{*}POL_T + B_2{*}VOL.INT_T + e_T\ ,\ \ (T=1984, \ldots, 2015) \qquad (1)$$

where, VOL.GFCF is volatility of GFCF growth in *private* sector[5] and POL is political instability indicator. VOL.INT is volatility of real interest rate, which serves as an economic control variable. For data sources, see Appendix.

2.1 Calculation of volatilities

Most studies in the literature calculate volatility of investment or output growth as standard deviation of five (or ten) year windows for every country in panel data sets. However, if the data is for a single country, standard deviation is not applicable[6]. In order to overcome this difficulty, two volatility measures, VOL.GFCF and VOL.INT, are

[5] Most of the literature on relationship between investment and political (in)stability use private investment, not total investment. Investment decisions of capitalists, private investments, are directly affected by political situation, so it makes sense to exclude public part. Moreover, private GFCF forms the majority (around 70-90%) of total investment in Turkey during most of the period of interest.

[6] This is due to significant reduction in number of data points. For instance, this paper covers a period of 32 years. Standard deviation of 4-year window will decrease number of data points to 8, which makes it impossible to have a *reliable inference* by OLS.

calculated as absolute deviations from their corresponding trends[7]. The figure below shows how volatility of private GFCF growth and volatility of real interest rate change over time:

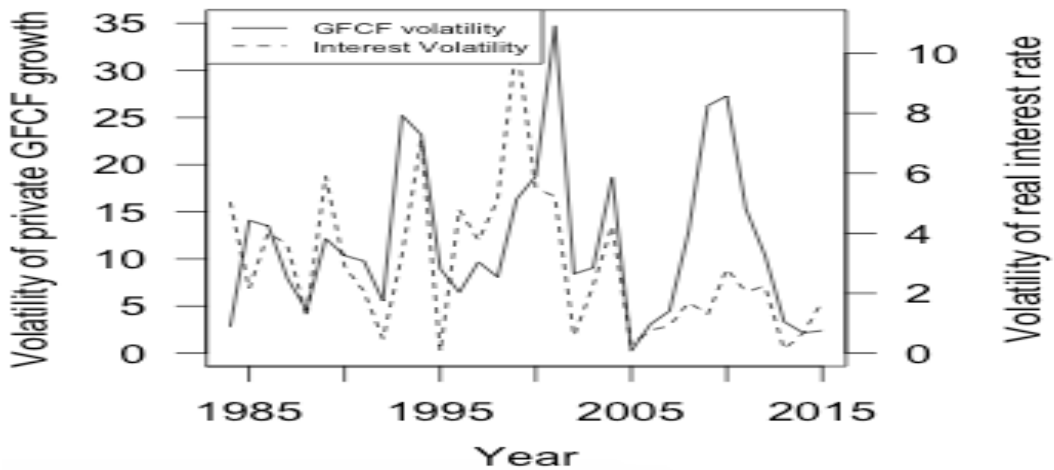

Figure 1: Volatility of private GFCF vs. volatility of real interest rate (1984-2015)

2.2 Political instability index

Literature Review of Estimation Methods and Data Properties

Since political instability is *not* a directly observable variable, there are different measures and techniques that have been used in the literature to come up with a meaningful instrument for political instability. Literature can be divided into two groups

[7] Trends are calculated by Hodrick–Prescott (HP) filter, the most common technique for detrending time series in macro-econometrics literature. Smoothing parameter (lambda) is 6.25, as the data is annual. Absolute deviation is just the absolute value of the cyclical component obtained from H-P filter. The reason why absolute value is used instead of actual value is that both positive and negative deviations from trend imply volatility.

in terms of approach to quantify political instability. The first group includes studies that combine several quantitative social and political indicators at different weights. This *sociopolitical indicators approach* seems to start with Venieris and Gupta (1986), who calculate sociopolitical instability index by applying discriminant analysis to three variables: protest demonstrations, death from domestic political violence, and regime type. Chauvet and Guillaumont (2004), in their study on developing countries, use weighted sum of the number of coups d'état, of the number of demonstrations and of a dummy variable for civil war breaks out. Annett (2001) uses nine different variables (including genocidal incidents, civil war, violent demonstrations), and then reduce the dimension by linear combination that assigns more weights to those with most information. Heintz (2002) performs a principal component analysis of three variables (average annual prison population, estimated number of persons held in detention without trial, and number of strikes) to come up with a political instability index for South Africa. Similarly, Jong-a-Pin (2009) uses explanatory factor analysis method with more than twenty different variables, including assassinations, riots, and strikes.

The second approach in calculating political instability is to predict the *probability of government change*. In their influential paper, Alesina et. al (1992) define political instability as "the propensity of an imminent government change." By using a simple probit specification (binary government change variable on the left and several economic/political control variables on the right), they calculate the probability of change in government, which then can be used as an index for political instability. Among other studies, Cukierman et. al. (1992) also use a probit model to estimate propensity of government change. Chen and Feng (1996) apply the same idea, but use a logit specification.

This study uses the second, propensity of government change, approach to estimate a political instability index for Turkey[8]. There are two important issues to discuss about the approach. First, the propensity of government change can be calculated by different methods. Since it is basically a classification problem, with factor "1" denoting government change and "0" denoting otherwise, several different classification techniques can be applied. In addition to logit/probit models, more other classification techniques have been developed in recent decades. Especially tree-based algorithms (basic classification tree, pruned tree, and random forest) are highly popular in machine

[8] Why not using the other (sociopolitical indicators) approach? There are two reasons. First is the lack of enough sociopolitical indicators for Turkey to use in sociopolitical indicators approach. For instance, annual prison population in TurkStat database starts from 1998, so not covering all the years of the period of interest. Second, Turkey experienced political instability during 1990s due to rapidly changing governments, *not* due another reason. A country may experience high political instability due to, say, civil war or social unrest, but a change in government does not necessarily take place. So, although Turkey's political instability can best be defined as "high propensity of an imminent government change", this definition may not fit to another country's experience. Actually, this is a defect that can be found in a part of the literature. Without taking history into account, which is specific to every country, some studies use very broad terms as if those terms apply to all countries. For instance, using 'civil war' indicator in a panel data study that includes European countries does not make any sense. On the other hand, in a panel data study on African countries, 'civil war', as an indicator for political instability, *must* be used. Similarly, a country that experiences civil war may not experience 'rapidly changing governments' at the same time, if its regime is a dictatorship.

learning literature. In this section, random forest method will be used to calculate propensity of government change. The method will be briefly explained below.

Second issue to consider is whether to include government changes that occur due to elections on regular election cycle. For instance, consider the following scenario: assume a country is expected to have parliamentary elections once in every five years. After an election in year T, a new government comes into power, and the next government change will *expected* to be at year T+5. Assume, for some reasons, current government resigned two years later, at year T+2, and a different government runs the country until the next general elections of T+5. The question is, shall we assign “1”s to years T, T+2, and T+5? Or, shall we assign “1” to only year T+2, as it is ‘unexpected’ government change? This study follows the second way, as it makes more sense. Since people form their expectations that a new government will be elected at year T+5, they don’t perceive that regular government change as ‘political instability’[9].

Random Forest

Random forest is a tree-based classification technique. In order to understand random forest, one should be familiar with construction of single classification trees. Classification trees take two sets of variables, target and input variables. Target is the variable that we want to predict, and it is either binomial (with two factor levels/classes) or multinomial (more than two factor levels/classes). Inputs are the variables that are used in prediction. What a classification tree does is basically creating partitions in the

[9] Actually, in case of Turkey, within the period of interest, there were only two (expected) government changes that took place on regular election cycle, in 2007 and 2011.

predictor space, and choosing the partition that minimizes the classification error rate (i.e. Gini Index). Difference, and also superiority, of random forest algorithm relative to single classification tree is that random forest grows so many classification trees based on random sampling of predictors at *each split* of a tree. Then, each resulting classification tree has a vote on the class of the target variable, and the algorithm chooses the class with the most votes. How does each tree vote on a class? After running the model, each tree determines a probability 'p' for class '0' and '1-p' for class "1". Unless otherwise stated[10], each tree votes for class '0' if p is smaller than 0.5, and votes for '1' otherwise. Changing the threshold from 0.5 to some other probability affects the predictive power (accuracy rate) of the model. On the other hand, since the aim in this study is not prediction, but coming up with an index for political instability, the threshold value is *not* important and hence will *not* be used. What is important is the probability for class "1" (unexpected government change), which is used as an index for political instability.

Although random forest is a common classification technique in statistics, and specifically in machine learning, its application to social science research is a recent phenomenon, and not as common as logit/probit regressions. Muchlinski et. al. (2015) compare random forest method with logistic regression for predicting civil war onset, and conclude that the former provides significantly more accurate predictions than the latter. In a recent World Bank research paper, Sohnesen and Stender (2016) state that random

[10] Cutoff probability is 0.5 by default, but it can be changed in order to achieve higher accuracy in prediction.

forest method is “largely absent in the economics literature.”[11]. They use random forest for poverty prediction, and conclude that it is often more accurate than common practices.

Estimation

The following model is used to estimate political instability index with random forest method:

$$GOV_T = INF_T + GPC_T + TT_T + WLS_T \ , (T=1984, \ldots, 2015) \tag{2}$$

where,

GOV: unexpected government change indicator (factor variable that takes value “1” for unexpected government change, and “0” otherwise), INF: inflation rate (percent change in consumer price index), GPC: growth rate of *per capita* GDP, TT: terms of trade, and WLS: workdays lost in strike in a year[12]. The following figure shows how dependent variable (volatility of private GFCF growth) and estimated index for political instability change over time:

[11] In terms of econometrics literature, discussion of machine learning techniques and their application to economic problems seem to be triggered by an interesting paper: Varian (2014).

[12] Although most studies in the literature use number of strikes as an index for this type of conflict, ‘workdays lost in strike’ is better for the case of Turkey. For instance, the effects of big strikes in 1995 and 2007 can better be reflected by workdays statistics, not by the number of strikes.

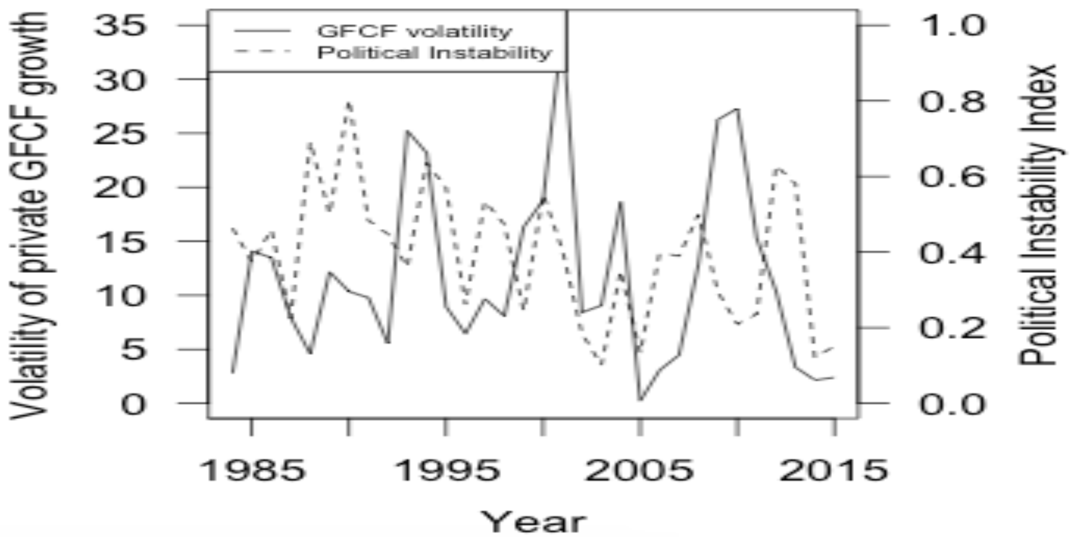

Figure 2: Volatility of private GFCF growth vs. political instability index (1984-2015)

3. Results

The table below summarizes the results of the OLS regression[13] on the base model, which is represented in equation (1):

[13] For all variables, unit root and stationarity tests were performed. As to VOL.GFCF, both Augmented Dicky-Fuller (ADF) and Philips-Perron (PP) tests suggest that there is no unit root. Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test for level and trend stationarity *fail to reject* that VOL.GFCF is level and trend stationary. In terms of the other two variables (POL and VOL.INT), ADF and PP tests provide conflicting result, as the former suggests a presence of unit root for both but the latter test does not. This conflicting result in two tests is most probably due to low sample size (n=32). However, KPSS tests on both POL and VOL.INT *fail to reject* that these two variables are level and trend stationary. Moreover, autocorrelation function (acf) plots for all three variables do *not* show any significant autocorrelation between the variables and their lags. It is, therefore, safe to use OLS regression. (All test results and acf plots are available upon request.)

Table 2: OLS estimation of equation (1)

Dependent Variable: *Volatility of private GFCF growth*	**OLS (1)** **Estimate**
Independent Variables:	
Political Instability	12.108 * (2.448)
Volatility of real interest rate	2.005** (3.458)
Adjusted R^2	0.675
Sample size	32
Note: t-statistics in parantheses. significance levels: 0.01 ** , 0.05 *	

According to results above, both political instability index and volatility of real interest rate are significant with expected (positive) signs at 0.05 and 0.01 levels, respectively. These results, therefore, suggest that volatility of private GFCF growth rate is positively affected by both political instability and volatility of real interest rate in Turkey during 1984-2015 period. The correlation between number of governments per year and volatility of private GFCF growth (presented previously in Table 1) can now be supported by this additional evidence, since high political instability (high propensity of unexpected government change) leads to high volatility of private GFCF growth.

4. Robustness of the evidence

In this section, two different modifications will be applied to the base model so as to check its robustness. First, the base model will be tested for possible structural breaks. Second, the political instability index will be estimated by a different method (logistic regression).

4.1 Testing for structural break(s)

The time scope of the model spans 32 years from 1984 to 2015. Before formally testing for possible structural break(s), it is better to discuss the following question: what is (are) the expected structural break(s), if there is any? As stated by Rao (2007), statistical methods are "tools to develop credible summaries of the observed facts." So, in order to evaluate the results of a formal test for structural break(s) in a time series regression, one should have an idea of the relevant historical facts of the period. As discussed in section 1, in terms of politics, post-1983 period of Turkey can best be understood if the whole period is divided into three sub-periods/phases (see Table 1 above and related discussion). So, if there is any structural break, it must be either late 1980s (between first and second phase) or early 2000s (between second and third phases), or at both. Here is the result of the structural break test on the base model that is provided by '*breakpoints*' function in R:

Table 3: Result of structural break test for the base model.

	Corresponding to break dates				
m=1		2000			
m=2		2000		2011	
m=3		2000	2007	2011	
m=4	1992	2000	2007	2011	
	Fit				
m	0	1	2	3	4
RSS	2020.5	1186.1	1073.1	872.7	799.9
BIC	233.9	227.2	234.4	238.2	245.8

'*breakpoints*' function determines the number of breakpoints (denoted by '*m'* in the table above) and corresponding break dates based on minimizing Bayesian Information Criterion (BIC). As BIC is minimized at m=1, this result suggests a single break date at 2000, which is consistent with our previous expectation based on historical facts. In order to incorporate this structural break into the base model, an indicator variable ('I') is created, which takes value "0" for T less than or equal to 2000, and "1" otherwise. In other words, the indicator variable takes account for post-2000 period. The following model in eq. (3) is estimated, and the result is presented in the table below:

$$VOL.GFCF_T = B_1{*}POL_T + B_2{*}\ POL_T{*}I + B_3{*}\ VOL.INT_T + B_4{*}VOL.INT_T{*}I + e_T \tag{3}$$

Table 4: OLS estimation of equation (3)

Dependent Variable: *Volatility of private GFCF growth*	**OLS (3)** **Estimate**
Independent Variables:	
Political Instability	11.965 * (2.459)
*Political Instability * I (T>2000)*	-7.828 (-0.928)
Volatility of real interest rate	1.415 * (2.717)
*Volatility of real interest rate * I (T>2000)*	4.386 ** (3.654)
Adjusted R^2	0.795
Sample size	32
Note: t-statistics in parentheses. significance levels: 0.01 ** , 0.05 *	

Two comments on these results: First, all coefficients in eq. (3) have expected signs, and all but one are significant at different levels. Why is it expected to have a negative sign in coefficient of POL_T*I(T>2000)? Political instability was more severe in Turkey during 1990s then it was during 2000s and later. It is, therefore, expected that the effect of political instability on volatility of investment growth would be higher for the former period. On the other hand, the coefficient is insignificant. Relation between political instability and private GFCF volatility does, therefore, *not* show a significant change between two periods separated by structural break. Were the coefficient significant, we would comment that the relation weakens during post-2000 period as the sign is negative[14]. Second, based on adjusted R^2 criteria, it can be concluded that OLS on eq. (3) gives a better fit than OLS on eq. (1) So, introducing structural break to the model increases the goodness of fit[15].

4.2 A different estimation method for political instability index

The political instability index used in regressions so far is estimated by random forest method. In this part, it will be tested whether the model in eq. (3) is robust to the estimation method of the political instability index. The point of interest is whether there is any change in the signs and significance levels of coefficients relative to previous results presented in Table 4 above.

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[14] Although the coefficient of POLT*I(T>2000) is negative, this would *not* mean that political instability affects volatility of investment negatively during the post-2000 period, even if it were significant. A true slope of the relationship during the later period, which can be found by adding two coefficients, would *still* be positive (11.965- 7.828).

[15] In a separate regression where insignificant variable, POL * I (T>2000), is removed, so structural break is applied only to VOL.INT, negligible increase in adjusted R^2 (from 0.795 to 0.796) can be obtained.

Table 5: OLS estimation for (3) with a different political instability index

Dependent Variable: *Volatility of private GFCF growth*	**OLS (3) Estimate**
Independent Variables:	
Political Instability (logit)	8.947 # (1.950)
*Political Instability (logit) * I(T>2000)*	-4.886 (-0.430)
Volatility of real interest rate	1.682 ** (3.331)
*Volatility of real interest rate * I(T>2000)*	4.228 ** (3.221)
Adjusted R^2	0.779
Sample size	32
Note: t-statistics in parantheses. significance levels: 0.01 ** , 0.05 * , 0.1 #	

The main difference between the results in Table 4 and Table 5 is in the coefficient of political instability[16]. Its level of significance increased from 0.05 to 0.1 (and hence it becomes *less* significant), and its size decreased from 11.96 to 8.95. On the other hand, it is still positively significant. We can, therefore, conclude the model represented by eq. (3) is robust to estimation method of political instability index. Moreover, it can also be said that when political instability is estimated by random forest algorithm, the model has slightly better fit than when the index is estimated by logit regression, as the adjusted R^2 in Table 4 is slightly higher than it is in Table 5.

5. Conclusion and Limitations

Turkey has experienced highly volatile growth pattern during the neoliberal period (post-1980). According to aggregate demand component analysis, volatility of

[16] Changes in the sizes and significance levels of coefficients of VOL.INT variables have secondary importance and can be neglected.

investment growth seems to be the main reason of GDP growth volatility. Furthermore, the political environment, especially during 1990s, was highly unstable. This paper attempts to find an evidence of a link between these two phenomena. By controlling only for volatility of real interest rate, which is an important determinant in investment decisions, the results suggests that there is a significant positive relationship between political instability and volatility of private GFCF growth. As political environment becomes more unstable, private GFCF growth becomes more volatile. This evidence is also shown to be robust to structural break in the underlying relation and also to estimation method of political instability index.

There are two limitations regarding to the results presented here. First, it may be argued that volatility in private GFCF may lead to political instability, in other words causality can also be reversed. Due to low number of data points, it is not reasonable/meaningful to run formal causality tests on the model. On the other hand, even the direction of causality is not tested, one can judge about the direction of causality based on historical facts. Investment decisions of capitalists are highly affected by political situation and political authority. This is especially true for less-developed countries such as Turkey, where good relations with government circles and close ties with state bureaucracy have always brought good opportunities for investment. Considering the fact that rapidly changing governments during late 1980s and 1990s created a highly unstable political environment, it is expected that political instability led to unstable investment patterns, not the other way around. The second limitation of the model is its very small set of economic control variables. The model tested here includes only one economic control variable, volatility of real interest rate, as interest rate is the major determinant in investment decisions. The model would, however, be more powerful if more economic control variable was introduced. On the other hand, low number of data points limits the number of control variables included. If the number of data points were big enough, effect of including more control variables on reducing degrees of freedom (and on increasing variance) would be negligible. However, in small data sets, like the one used here, increasing model complexity will severely distort estimation results. Because, as bias-variance trade-off suggests, introducing more variables will lead to higher variances in model, although bias of the model will decrease. Despite these two limitations, we believe that this paper provides clear evidence from a less-developed country on the underlying (positive) relationship between political instability and investment volatility.

Appendix – Data Sources

(in order as they appear in the text)

- *Gross Fixed Capital Formation (GFCF):* Ministry of Development (2015), and Turkish Statistical Institute (TurkStat) database.
- *Real Interest Rate*: Own calculation by using inflation rate data (as percent increase in consumer price index) from TurkStat database and nominal interest rate data from Ministry of Development (2015).
- *Per capita GDP growth*: Ministry of Development (2015) and TurkStat database.
- *Inflation Rate*: TurkStat database.
- *Terms of Trade*: OECD database.
- *Workdays Lost in Strike*: Ministry of Labour and Social Security database.

References

Aisen, A. and Veiga, F. J.. 2013. How does political instability affect economic growth? European Journal of Political Economy. 29: 151-167.

Alesina, A. and Perotti R.1996. Income distribution, political instability, and investment. European Economic Review, 40, 1203-1228.

Alesina, A., Ozler, S., Roubini, N., and Swagel P. 1992. Political instability and economic growth. NBER Working Paper Series. No: 4173.

Annett, A. 2001. Social Fractionalization, Political Instability, and the Size of Government. IMF Staff Papers. 48/3.

Brafu-Insaidoo W. and Biekpe N. 2011. International capital flows and investment volatility in selected sub-Saharan African countries. Review of Development Finance, 1, 223–228

Chauvet, L. and Guillaumont, P. 2004. Aid and growth revisited: Policy, economic vulnerability and political instability. in (B. Tungodden, N. Stern and I. Kolstad, eds.), Towards Pro-Poor Policies: Aid, Institutions, and Globalization. pp. 95–109, Oxford: Oxford University Press.

Chen, B. and Feng. Y. 1996. Some political determinants of economic growth: Theory and empirical implications. European Journal of Political Economy. 12: 609-627.

Cukierman A., Edwards S., and Tabellini G. 1989. Seignorage and political instability. NBER Working Paper Series. No: 3199.

Denizer, C., Iyigun, M., Owen, A., 2002. Finance and macroeconomic volatility. Contributions to Macroeconomics. 2, 1–30.

Feng, Y. 2001. Political freedom, political instability, and policy uncertainty: A study of political institutions and private investment in developing countries. International Studies Quarterly, Vol. 45, No. 2, 271-294.

Heintz, J. 2002. Political Conflict and the Social Structure of Accumulation, The Case of South African Apartheid. Review of Radical Political Economics. 34 (3): 319-26.

Jong-A-Pin, R. 2006. On the Measurement of Political Instability and its Impact on Economic Growth. European Journal of Political Economy. 25/1: 15-29.

Klomp J. and Haan, J. 2009. Political institutions and economic volatility. European Journal of Political Economy. 25: 311-326.

Ministry of Development. 2015. Economic and Social Indicators (1950-2014). Ankara: Ministry of Development.

Muchlinski, D., David Siroki, Jingrui He, Matthew Kocher. 2015. Comparing Random Forest with Logistic Regression for Predicting Class-Imbalanced Civil War Onset Data. Political Analysis, 24 (1), 87-103.

Rao, B. 2007. Estimating Short and Long Run Relationships: A Guide to the Applied Economist. Applied Economics, 39 (13), 1-13.

Sohnesen T.P. and Stender, N. 2016. Is random forest a superior methodology for predicting poverty? World Bank Policy Research Working Paper. No: 7612.

Varian, H. 2014. Machine learning: New tricks for econometrics. Journal of Economic Perspectives. 28/3.

Venieries, Y. and Gupta, D. K. 1986. Income Distribution and Sociopolitical Instability as Determinants of Savings: A Cross-Sectional Model. Journal of Political Economy. Vol. 94, No. 4: 873-883.