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Productive Stagnation and Unproductive Accumulation: An Econometric Analysis of the United States

Tomás N. Rotta
University of Greenwich
Department of International Business and Economics
Park Row, London, SE10 9LS, United Kingdom
t.rotta@greenwich.ac.uk

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Abstract:

In this paper I evaluate the dynamic interactions between productive and unproductive forms of capital accumulation in the United States economy from 1947 to 2011. I employ time series econometrics to formally assess two questions that other scholars have hitherto considered mostly through verbal or descriptive approaches. First, I check whether unproductive accumulation hinders or fosters productive accumulation. Second, I check whether or not productive stagnation leads to faster unproductive accumulation. I introduce different measures of productive and unproductive forms of capital accumulation using a new methodology to estimate Marxist categories from conventional input-output matrices, national income and product accounts, and fixed assets accounts. A core feature of my methodology is the notion that the production of knowledge and information is also a form of unproductive activity. Results indicate two-way positive effects between productive and unproductive activities in the short run but no self-correcting mechanism that would bring productive and unproductive forms of accumulation back to a stable equilibrium path over the long run.

Keywords: Unproductive Activity, Capital Accumulation, Stagnation, Time Series Econometrics, United States

JEL Codes: B51; C32; O47

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Corresponding Author:
Tomás N. Rotta. University of Greenwich, Department of International Business and Economics. Park Row, London, SE10 9LS, United Kingdom.
Email: t.rotta@greenwich.ac.uk

1. Introduction

In this paper I employ econometric techniques to evaluate the dynamic interactions between productive and unproductive forms of capital accumulation in the United States from 1947 to 2011. The objective is to answer two questions: Does unproductive accumulation hinder or foster productive accumulation, in terms of both short- and long-run effects? Conversely, does productive stagnation lead to faster unproductive accumulation? Predicated on a new methodology to estimate Marxist categories for the United States economy, I apply time series econometrics to these estimates in order to evaluate the coevolution of capital accumulation in its productive and unproductive dimensions. I provide a formal econometric assessment of a question that other scholars have hitherto considered mostly through verbal or descriptive approaches.

I define *unproductive accumulation* as the growth either in the flow of income or in the stock of capital of unproductive activities. *Unproductive activity* is any economic activity that does not produce surplus value. To be productive of surplus value an activity must have workers creating useful commodities with value for sale. Activities that create new use-values or recirculate existing use-values, but not new commodities with value, are considered to be unproductive. Unproductive activities do not directly add any new surplus value to the economy and therefore draw their incomes out of the value generated in productive activities. Productive activities create and also consume value, but unproductive activities only consume it.

The productive-unproductive differentiation relies on the concept of surplus value and, as such, derives from the classical Political Economy notion that value needs to come from somewhere. Unproductive means neither unnecessary nor less important, and it is not a derogatory term. Neither is there a direct connection between productive and tangible, given that services and intangible commodities can be the output of productive activities. Moreover, unproductive endeavors should be conceptualized as *activi-*

ties instead of *sectors* since most enterprises operate with a mix of productive and unproductive activities, with few firms actually being classified as purely productive or purely unproductive.

A key difference of the approach developed in this paper in relation to previous studies on unproductive accumulation is the treatment of knowledge and information production as unproductive activity. The production of knowledge and information per se does not produce new value and, even more, gives rise to *knowledge-rents* to the proprietors of monopolized knowledge.

Despite directly consuming the surplus from productive endeavors, unproductive accumulation can well enhance labor productivity or even boost aggregate demand in productive activities, indirectly improving the creation of surplus value. There is hence a double effect under consideration in my estimates: unproductive activity might *indirectly* increase labor productivity, increase aggregate demand, and boost productive accumulation while it still draws on the surplus value that it does not *directly* produce.

My econometric approach shows that the indirect boost to productive accumulation has been greater than the direct draw on the surplus, implying that unproductive accumulation has had a net positive impact on productive accumulation in the United States from 1947 to 2011. Unproductive accumulation only becomes an obstacle for productive accumulation when the unproductive capital stock grows faster than its productive counterpart.

To formally check for significant co-movements between estimates of productive and unproductive forms of accumulation I use cointegration analysis, vector auto-regressions (VAR), Granger and instantaneous causality tests, impulse-response functions, and forecast error variance decompositions. Cointegration analysis and vector error correction models answer questions about the long-run behavior of the variables while the VAR methodology answers questions about the short run. In this time series framework it is possible to treat every variable as endogenous while estimating the dynamic interactions within the system.

Specifically, I find evidence that when the unproductive capital stock grows it has a positive impact on the growth of the total flow of productive value. However, when the unproductive capital stock grows faster than the productive capital stock it then has a negative impact on the growth of the flow of total value from productive activities. Conversely, faster growth in the total value produced in productive activities leads to faster growth of the unproductive capital stock, but also to a slowdown in the share of the unproductive capital stock. The absolute level of the unproductive capital stock grows faster when the total value from productive activities also grows faster, but the share of the unproductive capital stock relative to the total capital stock only grows faster when the total value from productive activities slows down. Over the longer run, however, productive and unproductive forms of accumulation have no common trend. There is hence no self-correcting mechanism that brings these two forms of capital accumulation back into a stable long-run equilibrium path.

My econometric approach confronts at least two strands of the heterodox tradition concerned with capital accumulation. First, it confronts the tradition that has focused on the one-way causality running from unproductive accumulation to productive stagnation. Second, it confronts the opposite tradition that has focused on the reverse one-way causality that runs from productive stagnation to unproductive accumulation. My findings reveal instead a two-way reinforcing relationship between productive and unproductive forms of accumulation in the postwar United States economy, with no tendency to revert to a stable long-run equilibrium path.

2. Comparison with Previous Studies

Economists have been divided for a long time in regard to the implications of unproductive growth. Thomas Malthus (1820) and some of his modern followers understand that unproductive expenditures are a saving grace, for they generate demand and employment without necessarily generating supply. Unproductive expenditures, Malthusians claim, can pump up a system suffering from a chronic lack of effective demand. David Ricardo (1821) and his modern followers, on the contrary, argue that increases in unproductive expenditures diminish the share of the surplus available for productive investment and hence decrease the growth rate of productive capital.

For the United States economy the empirical studies of unproductive activity and of its impact on productive capital accumulation date back at the least to the 1960s. There has been, however, no final agreement on the net effects between productive and unproductive forms of accumulation. And besides being divided in terms of the effects between productive and unproductive forms of capital accumulation, the existing literature is also divided in terms of the directions of causality.

On one side of the literature we have the advocates of the hypothesis that faster unproductive accumulation is preceded by an earlier phase of productive stagnation. Examples of this branch of the literature are Baran and Sweezy (1968), Sweezy and Magdoff (1987), James Crotty (2003), and David Harvey (2003; 2005). These authors have suggested that investors experienced a slowdown in productive accumulation and profitability before shifting their investments towards unproductive activities such as marketing, advertisement, finance, and real estate. What explains the shift from productive to unproductive forms of investment, these authors claim, is a prior profit squeeze in productive activities.

Little effort, however, has been put on estimating these effects with more formal econometric procedures. In terms of empirical analysis, the existing studies in the Political Economy tradition that suggest that productive stagnation can explain the rise of unproductive activity remain largely descriptive or merely verbal. Secondly, it has been frequent to disregard the possibility of reverse causality.

On the other side of the literature we have the advocates of the opposite hypothesis, namely that productive growth stagnates because of a previous episode of faster unproductive accumulation. The rationale for this hypothesis is that unproductive activity draws from the productive surplus and hence leaves less of it to be reinvested in productive outlets. The key studies in this group are those of Shaikh and Tonak (1994), Edward Wolff (1987), Fred Moseley (1997; 1992; 1985), Simon Mohun (2014; 2006; 2005), Paitaridis and Tsoulfidis (2012), and Cockshott, Cottrell, and Michaelson (1995).

Shaikh and Tonak (1994), in particular, posit that the interaction between unproductive and productive activities is more nuanced and that the effects must be separated into the short and long runs. In a dynamic setting, a rise in unproductive expenditures may indeed stimulate effective demand and productive output in the short run (as Malthus had originally claimed), but in so far as it diminishes the share of surplus value that stays within productive activities it reduces the rate of productive accumulation over the longer run (as Ricardo had originally claimed).

As the former group, these latter scholars have made important contributions in terms of estimating Marxist categories, but they have not provided econometric evidence to their claims on the potential negative effects that unproductive activity might have on productive accumulation.

One important sub-type of unproductive growth is certainly that of ‘financialization’ or the rising share of financial claims, and as such it has received significant attention from recent scholarship. The most recent literature has in fact focused much more on the effects of financialization on productive stagnation, and most of the contributions come from the neo-Kaleckian and post-Keynesian branches of heterodox macroeconomics. Onaran, Stockhammer, and Grafl (2011), Orhangazi (2008), Van Treeck (2008), Palley (2012), Lazonick (2013), and Stockhammer (2004) used both macro and micro datasets for the post-1970 decades and found that greater financial revenues have decreased the rate of investment in fixed assets in the US and in Europe. They concluded that financialization has had a negative effect on productive growth.

The Political Economy concept of unproductive accumulation, however, is broader than that of financialization since it includes other types of unproductive activity such as trade, public administration, armed forces, real estate, legal services, and – as Rotta and Teixeira (2015) and Teixeira and Rotta (2012) now claim – it also includes all economic activities that produce knowledge and information. The production and ownership of knowledge and information are also forms of unproductive activity.

Intellectual property rights assure rent-like revenues to knowledge and information proprietors such as pharmaceutical companies, software companies, publishers and editorial houses, movie producers, and record music companies. Once produced, knowledge and information require no labor time to be *re*-produced and thus contain *no value* from a Political Economy perspective. Marx ([1894]1994, p.522) posited in the third volume of *Capital* that "the value of commodities is determined not by the labor-time originally taken by their production, but rather by the labor-time that their reproduction takes". In standard Economics language, knowledge and information have *zero marginal costs* and in general would be classified as *public goods* (non-rivalrous and non-excludable) if it were not for intellectual property rights. Despite potential indirect contributions to productive growth, knowledge creation and ownership per se produce no new value and should be classified as unproductive (Rotta and Teixeira, 2015; Teixeira and Rotta, 2012).

The key contribution of this paper is to offer a more comprehensive formal treatment of the dynamic effects between productive and unproductive activities. Hitherto, the Political Economy literature has either been restricted to non-econometric approaches or has focused its econometric tests on the effects of particular sub-types of unproductive activity such as finance. The methodology that I employ offers estimates of unproductive accumulation in a broader way compared to previous attempts that have focused on measuring financialization (as in Lapavitsas, 2013; Orhangazi, 2008; Krippner, 2005; Lazonick, 2013; and Epstein, 2005) and it also offers a formal treatment of the coevolution of productive and unproductive forms of accumulation in the United States.

3. Econometric Results

To estimate the empirical interactions between productive and unproductive activities I employ the vector auto-regression (VAR) model for the short-run dynamics and the vector error correction (VEC) model for the long-run dynamics. The VAR and VEC methodologies are suitable for investigating interactions among a group of time series variables. The difference between these two models is that the VEC framework includes the common trend or the self-correcting mechanism that brings the endogenous variables back into a long-run equilibrium path. Unlike a single equation regression model, in which the dependent variable is by assumption endogenous and some of the independent variables are exogenous, the VAR and VEC models treat multiple variables as jointly endogenous and allow for both contemporaneous and lagged effects. Every endogenous variable is explained both by current and past values of itself and of other endogenous variables in the system.

The stock and flow variables that could serve as estimates of productive and unproductive forms of accumulation are summarized in Table 1. I compute these Marxist measures using input-output matrices, national income and product accounts, and fixed assets accounts from the Bureau of Economic Analysis (BEA) for the US economy from 1947 to 2011. In general terms, my methodology follows the procedures set forth by Shaikh and Tonak (1994), Simon Mohun (2014; 2006; 2005), Edward Wolff (1987), Fred Moseley (1997; 1992; 1985), and Paitaridis and Tsoulfidis (2012). Despite some minor differences, the main innovation in my computations is the inclusion of knowledge and information production as unproductive activity. Estimation techniques for all these measures are explained in detail in Rotta (2015).

[Table 1 about here]

Since accumulation can be analyzed either from a flow or from a stock perspective, I estimate two-variable regression models with different proxies for the accumulation of capital. In each model, one endogenous variable is a proxy for unproductive accumulation while the other endogenous variable is a proxy for productive accumulation. In the next two sections I summarize the main econometric findings and leave the more technical details on estimation procedures for the Appendix. Unit root tests and diagnostic checks for each model are also left to the Appendix.

3.1 The Long Run: Cointegration Analysis

The first econometric estimations that I present are on the long-run relationships between different pairs of variables listed in Table 1. All these Marxist measures of productive and unproductive forms of accumulation contain unit roots and therefore are not stationary, hence they do not reverse to a mean value over time. When variables are not stationary it becomes necessary to check if they are cointegrated before estimating a VAR model.

Cointegration means that variables share a common trend over time. If variables are cointegrated it is then required to include their long-run relationships in the VAR model, meaning that we should in fact estimate a vector error correction (VEC) model. The VEC model includes both the cointegrating long-run relationship and the lags of the endogenous variables as regressors. If variables are cointegrated we must include the error correction vector as a regressor since failing to do so implies a misspecification error. When variables are not cointegrated we can simply estimate the system using a VAR model without the error correction term. To test for cointegration between pairs of nonstationary variables I employ both the Engle-Granger and the Johansen methodologies.

The first step in the Engle-Granger procedure is to estimate the long-run equilibrium relationship between endogenous variables using ordinary least squares. If the estimated residuals from this long-run relationship are stationary it is then possible to conclude that there is a cointegration vector between variables. The second step, in case of cointegration, is to include the stationary residuals from the long-run equilibrium equation as the error correction term in the VAR model.

In Table 2 I summarize the results from 25 bivariate regressions, in which one endogenous variable is a proxy for productive accumulation while the other endogenous variable is a proxy for unproductive accumulation. In no case is there strong evidence of cointegration. The main entries on the table indicate t-statistics from Augmented Dickey-Fuller (ADF) tests without intercept or trend on the residuals from the long-run equilibrium relationship. The results indicate that for any of the 25 cases examined it is not possible to reject the null hypothesis of unit-root in the residuals either at the 5% or 1% significance levels.

[Table 2 about here]

To further investigate whether or not the pairs of nonstationary variables share a common trend I also perform cointegration tests using the Johansen methodology. The Johansen procedure avoids the two-step estimation present in the Engle-Granger methodology by implementing a multivariate generalization of the ADF test. The Johansen procedure is also more general and allows us to include deterministic elements inside and outside of the cointegration space.

In Table 3 I summarize the results for the same 25 cases as in Table 2 but now employing the Johansen methodology. Since it is possible to include different deterministic elements, the total number of estimated regression models becomes 75. The first column indicates the two endogenous variables used; the second column indicates the deterministic elements inside of the cointegration space; the third column indicates the deterministic element in the regression but outside of the cointegration space; the fourth column indicates the number of lags used. Lag lengths were chosen so as to remove serial correlation from the estimated residuals. For some of the models the number of lags is very high, which indicates that with less lags it is not possible to remove serial correlation. The fifth and sixth columns show the estimated λ_{max} and λ_{trace} test-statistics, together with their levels of significance under the null hypothesis that there are zero cointegration vectors ($r = 0$). Column seven finally concludes with the estimated rank of the Π matrix, which indicates the number of cointegrating vectors. Regression results are for the entire postwar period (1947-2011).

[Table 3 about here]

In none of the 75 regressions using the Johansen procedure I found evidence of cointegration, a result that confirms the conclusions drawn previously from the 25 regressions using the Engle-Granger methodology. In total, in none of the 100 cases analyzed is there evidence of a shared common trend between productive and unproductive forms of accumulation over the long run.

Cointegration analysis therefore indicates that productive and unproductive forms of accumulation do not have a stable long-run relationship. The absence of cointegration provides evidence that there is no self-correcting mechanism that would bring productive and unproductive forms of accumulation back into a stable long-run equilibrium. This econometric result is consistent with previous findings that unproductive accumulation has systematically occurred at a faster pace than productive accumulation both in terms of flows of income and stocks of fixed assets in the postwar United States (Rotta, 2015; Paitaridis and Tsoulfidis, 2012; Mohun 2006; Moseley, 1997; Shaikh and Tonak, 1994; Wolff, 1987). The fact that unproductive accumulation has been more rapid than productive accumulation is also consistent with the finding that the NUB, GUB, UCC, and K_{UA}/K_{PA} measures from Table 1 are all nonstationary with upward trends.

To the best of my knowledge I have conducted the most comprehensive cointegration test on the long-run interactions between productive and unproductive forms of capital accumulation using Marxist categories for the postwar US economy. Besides the lack of a self-correcting mechanism, the econometric results in this paper do not offer further evidence on the long-run effects between unproductive and productive activities. Because of the lack of cointegration and the fact that the residuals are not well behaved it is not possible to know if, as Shaikh and Tonak (1994) suggested, a boost in unproductive activity also boosts productive growth in the short run while decreasing the growth rate of productive activity in the longer run. I estimated the Johansen models using the long-run coefficient matrices, but the estimates do not provide enough evidence on the long run impacts. If there were cointegration it would have been possible to also test whether it is productive or unproductive accumulation that is responsible for making the adjustment towards a stable equilibrium. The results indicate however that in the long run there is no such stable relationship between productive and unproductive forms of accumulation.

3.2 The Short Run: Two-Variable VAR Models

Given the absence of a cointegrating vector over the long run, we do not need to estimate a VEC model to capture the dynamics between productive and unproductive activities. We can focus instead on the short-run interactions using a structural VAR model. The structural VAR is a vector auto-regression in which the exogenous shocks are independent of each other so that the model can mimic the structure of the system.

Unfortunately, it is not possible to directly estimate a structural VAR model since the strucural shocks are not readily identified. The solution to this identification problem is to first estimate the VAR model in its reduced form and then use a Cholesky decomposition on the estimated residuals in order to recover the structural error terms. The Cholesky decomposition offers a way to make the estimated residuals orthogonal (independent) to each other, thus allowing for the identification of the independent shocks that directly affect the endogenous variables. Further details on this procedure are explained in the Appendix.

I estimate three models in reduced form using different endogenous variables as proxies for unproductive and productive activity. In Table 4 I summarize the regression results for the two-variable VARs. For each model, endogenous variable 1 is a proxy for unproductive accumulation while endogenous variable 2 is a proxy for productive accumulation, all as described in Table 1. VAR Model 1 employs as endogenous variables the growth rate of the K_{UA} / K_{PA} ratio and the real growth rate of Total Value (TV) from productive activities. VAR Model 2 employs as endogenous variables the real growth rate of K_{UA} and the real growth rate of Marxist Value Added (MVA). VAR Model 3 employs as endogenous variables the real growth rate of K_{UA} and the real growth rate of Total Value (TV). Each of the series is in stationary real growth rates. The reason for using these specific variables and not others as in the previous cointegration VEC models is that these are cases in which the residuals are indeed well behaved. For other combinations of variables the residuals are not normally distributed or present problems of heteroskedasticity and serial correlation.

[Table 4 about here]

In Table 4 I also report the VAR results for three different time periods: the whole postwar period (1948-2011); the Regulated period only (1948-1979); and the Neoliberal period only (1980-2011). I use the Akaike information criterion (AIC) to determine the optimal lag length *p* and incorporate a deterministic regressor when appropriate. For each equation I report the p-values from the joint F-tests on the estimated regression coefficients; p-values lower than 0.10 indicate that the regression coefficients are jointly meaningful at standard significance levels. Lastly, for each model I report the residual correlation coefficient.

The results indicate the presence of negative residual correlation coefficients for the first model and of positive residual coefficients for the second and third models. In a reduced-form VAR the estimated residual correlation reveals the correlation of contemporaneous movements in the endogenous variables. The signs suggest that the real growth rates of the total value and the value added of productive activities move contemporaneously in opposite directions only with respect to the growth rate of the *share* of the unproductive capital stock. With respect to the growth rate of the *absolute level* of the unproductive capital stock, the real growth rates of the total value and the value added of productive activities actually move contemporaneously in the same direction.

In order to check for the statistical significance of the interactions I perform two causality tests for each VAR model in its reduced form. The first is an instantaneous causality test that verifies if current realizations of one endogenous variable explain current realizations of another endogenous variable. It is a Wald-type test for nonzero correlation between the estimated residual processes of the cause and effect variables, given that in a reduced-form VAR the contemporaneous feedback appears through the estimated residuals. The second is the Granger causality test, which verifies whether or not lags of one variable explain current realizations of another variable. The Granger test can thus be thought of as a prediction test: a variable z Granger-causes variable w if past realizations of z explain current realizations of w.

In Table 5 I report the p-values from instantaneous and Granger causality tests for the three estimated VAR models under different time periods. All tests are implemented as non-causality tests, meaning that if the calculated p-value is lower than 0.10 we can reject the null of no causality at the 10% significance level. The results do indicate the presence of significant dynamic interactions between productive and unproductive activities.

[Table 5 about here]

For the first model the estimates suggest significant contemporaneous and lagged interactions in both directions. For the Regulated period the Granger causality running from unproductive accumulation to productive accumulation is stronger that the reverse case. In contrast, the Granger causality running from productive accumulation to unproductive accumulation becomes stronger during the Neoliberal period. When the whole 1948-2011 period is considered both the instantaneous and Granger causality tests show very significant two-way effects between productive and unproductive forms of accumulation.

For the second model the results once more indicate that there are significant interactions in both directions. Similarly to the first model, Granger causality is relatively weaker during the Regulated period but highly significant when the whole postwar period and Neoliberal periods are considered. Compared to the first, the second model exhibits stronger two-way Granger causality between productive and unproductive accumulation but weaker instantaneous causality for all periods under consideration.

For the third model the results indicate that there are no significant instantaneous effects for any of the three periods. Similarly to the first and second models, Granger causality is relatively weaker during the Regulated period but very significant when the Neoliberal period is considered. Granger tests additionally suggest that for the whole postwar period there is stronger causality running from productive accumulation to unproductive accumulation than the reverse case.

Causality tests can reveal the statistical significance of the contemporaneous and lagged interactions between productive and unproductive forms of capital accumulation. They do not, however, reveal the signs and magnitudes of these dynamic effects. But instead of reporting coefficient estimates, in a VAR framework it is more meaningful to graph the impulse response functions (IRFs) to evaluate the shapes of the feedback patterns between endogenous variables. Impulse response functions allow us to check how endogenous variables in a multi-variable system coevolve over time when impacted by an unexpected change in any of the variables, holding everything else constant. These shocks are simulated as one-unit impulses imparted to the structural error terms.

To compute the IRFs it is first required to identify the structural system by imposing restrictions on the estimated residuals of the reduced-form VAR. The restrictions amount to forcing the structural shocks to be orthogonal to each other, assuring that shocks to one error term are not correlated with shocks to another error. With these restrictions it becomes possible to distinguish the effects of changes in one endogenous variable from the other endogenous variables.

Since the estimated VAR models in this study have only two endogenous variables it is enough to impose only one restriction. The restrictions can be applied using the Cholesky decomposition to orthogonalize the estimated residual vector by cancelling some of the contemporaneous cross effects. By limiting the contemporaneous feedback, each possible orthogonalization of the residuals imposes a specific ordering of the endogenous variables in the structural VAR.

With two endogenous variables there are only two possible orderings. In one ordering the variable associated with unproductive accumulation is posited as prior to the variable associated with productive accumulation. In the other ordering the exact opposite occurs. Positing an endogenous variable as causally prior to another in a structural VAR means that the first variable is not contemporaneously affected by the second, while the second is contemporaneously affected by the first. Changing the ordering in a two-variable structural VAR implies simply inverting this causal priority. The Cholesky decomposition therefore introduces a potentially important asymmetry in the system, but as long as the shapes of the IRFs are similar under the two orderings it is safe to state that the structural VAR is well identified.

In what follows I apply both possible orderings to plot the IRFs corresponding to the three models for the three time periods under consideration. The results indicate that the shapes of the impulse responses are similar under both decompositions, and hence that the estimated VARs are not sensitive to a specific ordering of the variables. Additionally, since each series is in stationary real growth rates, the lack of unit root implies that the IRFs decay to zero. Non-decaying IRFs would be evidence of unit root in the series.

In Figure 1 I graph the orthogonalized IRFs from the first model. Panel (a) uses the ordering "*Growth rate of* $\frac{K_{UA}}{K_{PA}}$ → *Real* $\widehat{TV}$" while panel (b) uses the opposite ordering "*Growth rate of* $\frac{K_{UA}}{K_{PA}}$ ← *Real* $\widehat{TV}$". Carets (^) indicate real growth rates. Plots in the left column are IRFs for the whole 1948-2011 period; plots in the center column are for the Regulated 1948-1979 period only; and plots in the right column are for the Neoliberal 1980-2011 period only. In each panel the first row contains IRFs with shocks from unproductive accumulation (endogenous variable 1) to productive accumulation (endogenous variable 2), while the second row contains IRFs with shocks from productive accumulation to unproductive accumulation. Each IRF is shown for 20 lags and the dashed lines indicate bootstrapped 90% confidence intervals with 100 runs.

The IRFs for VAR model 1 are similar under both orderings. Except for the Neoliberal period, an unproductive shock has a predominantly negative impact on productive accumulation. When the $\frac{K_{UA}}{K_{PA}}$ ratio grows faster it has a negative effect on the growth of Total Value (TV). Conversely, a productive shock also has a negative impact on unproductive accumulation, except during the Neoliberal period. Faster growth in productive Total Value (TV) has a negative impact on the growth of the $\frac{K_{UA}}{K_{PA}}$ ratio. These results imply that faster productive accumulation (measured through the annual real growth rate of the flow of Total Value) has a negative impact on the growth rate of the *share* of the unproductive capital stock. The converse is also true: when the stock of unproductive capital grows faster than its productive counterpart (so that the *share* of the unproductive capital rises) it imparts a negative effect on the growth rate of the productive Total Value. The opposite result holds for the Neoliberal period given that the IRFs between $\frac{K_{UA}}{K_{PA}}$ and TV are predominantly positive from 1980 to 2011.

In Figure 2 I plot the IRFs for the second model, displaying the impulses and responses in the same way as was done for the first model. Panel (a) displays the results for the "*Real* $\widehat{K_{UA}}$ $\rightarrow$ *Real* $\widehat{MVA}$" ordering, while panel (b) displays the results for the opposite "*Real* $\widehat{K_{UA}}$ $\leftarrow$ *Real* $\widehat{MVA}$" ordering.

The estimates from model 2 suggest that productive and unproductive forms of accumulation tend in fact to reinforce each other. Higher real growth rates of Marxist Value Added (MVA) impart positive effects on the real growth rates of the unproductive capital stock (K_{UA}). Conversely, faster growth of the unproductive capital stock produces greater growth in Marxist VA. These results imply that when measured in *absolute terms*, productive accumulation and unproductive accumulation are *mutually reinforcing*. The finding is consistent for both orderings, in both directions of causality, and for all periods under consideration.

In Figure 3 I plot the IRFs calculated from the third VAR model. Panel (a) displays the IRF for the "*Real* $\widehat{K_{UA}}$ $\rightarrow$ *Real* $\widehat{TV}$" ordering, while panel (b) displays the IRFs for the opposite "*Real* $\widehat{K_{UA}}$ $\leftarrow$ *Real* $\widehat{TV}$" ordering. The findings are similar under the two alternative decompositions. Similarly to model 2, the results further indicate that when measured in absolute terms productive accumulation and unproductive accumulation are mutually reinforcing. The finding is consistent for both orderings, in both directions of causality, and for all periods under consideration.

[Figure 1 about here]

[Figure 2 about here]

[Figure 3 about here]

The econometric results offer evidence that when the unproductive capital stock grows it has a *positive* impact on the growth of the total flow of productive value. However, when the unproductive capital stock grows faster than the productive capital stock (so that the *share* of unproductive capital rises), it then has a *negative* impact on the growth of the total flow of productive value. The slowdown in the total flow of productive value, similarly to the slowdown in the flow of productive value added, occurs not because the unproductive capital stock grows but because the unproductive capital stock grows *faster than* the productive capital stock. The annual flows of total productive value and productive value added are both boosted when the unproductive capital stock grows faster, but are adversely affected when the *share* of the unproductive capital stock increases. Conversely, once there is a slowdown in the annual flows of total productive value or in the productive value added then the growth of the unproductive capital stock also slows down, even though the share of the unproductive capital stock grows more rapidly.

Without further investigation, however, it is not possible to know with certainty through which channels productive accumulation and unproductive accumulation affect one another. Potential explanations would be that unproductive activity offers a source of aggregate demand and also provides ways to enhance labor productivity in productive activities. The production of useful knowledge, innovations, cheaper credit, and government expenditures, for example, could well induce faster productive growth and higher labor productivity. Likewise, more rapid productive growth could provide further aggregate demand and extra surplus value for unproductive accumulation.

The three estimated models indicate the existence of a dynamic interaction between productive and unproductive forms of accumulation. To offer more evidence on the presence of feedback between the endogenous variables it is convenient to decompose the variance of forecast errors into a portion attributable to productive accumulation and another portion attributable to unproductive accumulation. As is the case with IRFs, the decomposition of the forecast error variances also necessitates the identification of the structural shocks. In what follows I apply the same Cholesky decompositions as before and present the results under both possible orderings of the endogenous variables.

In Figure 4 I present the forecast error variance decomposition from the first VAR model in percentage terms for a horizon of 20 years. Panel (a) displays the variance decompositions under the "*Growth rate of* $\frac{K_{UA}}{K_{PA}}$ → *Real* $\widehat{TV}$" ordering, while panel (b) displays the variance decomposition under the opposite "*Growth rate of* $\frac{K_{UA}}{K_{PA}}$ ← *Real* $\widehat{TV}$" ordering. In Figure 5 I present the forecast error variance decomposition from the second VAR model. Panel (a) displays the variance decompositions under the "*Real* $\widehat{K_{UA}}$ → *Real* $\widehat{MVA}$" ordering, while panel (b) displays the variance decomposition under the opposite "*Real* $\widehat{K_{UA}}$ ← *Real* $\widehat{MVA}$" ordering. In Figure 6 I present the forecast error variance decomposition from the third VAR model. Panel (a) displays the variance decompositions under the "*Real* $\widehat{K_{UA}}$ → *Real* $\widehat{TV}$" ordering, while panel (b) displays the variance decomposition under the opposite "*Real* $\widehat{K_{UA}}$ ← *Real* $\widehat{TV}$" ordering.

[Figure 4 about here]

[Figure 5 about here]

[Figure 6 about here]

Plots in the left columns are for the whole 1948-2011 period; in the center columns for the Regulated 1948-1979 period only; and in the right columns for the Neoliberal 1980-2011 period only. In each panel the first row contains the plots for the decomposition of the variable representing the unproductive accumulation of capital, while the second row contains the plots for the decomposition of the variable representing the productive accumulation of capital. Grey areas indicate the share of the forecast error variance attributable to productive accumulation, and black areas indicate the complementary share of the forecast error variance attributable to unproductive accumulation.

The results from the forecast error variance decompositions for all three models provide further evidence of the coevolution between productive and unproductive forms of capital accumulation. There are significant interactions within the system and no variable can therefore be deemed exogenous. In any of the cases under consideration, each variable's forecast error variance is jointly explained by its own realizations as well as realizations of the other variable. Shares do not change substantially across time periods and the results are sensitive to the ordering of the variables only for the third model.

4. Conclusion and Implications

In this paper I provided an econometric assessment of the dynamic effects between productive and unproductive forms of accumulation using Marxist categories for the Unites States from 1947 to 2011. I conducted a formal evaluation of a question that other scholars have dealt with only through verbal or descriptive analyses. I employed time series techniques using Marxist categories estimated with a new methodology for the postwar United States economy. A core feature of the methodology that I introduced is the classification of knowledge and information production as an unproductive activity whose expansion is predicated on knowledge-rents. In this way, my measures of unproductive accumulation are broader than the more common measures of financialization that have featured in the existing scholarship. The Marxist notion of unproductive accumulation incorporates the idea of financialization and further acknowledges that many other unproductive activities also draw on the surplus value that productive workers generate.

The main empirical results are as follows. First, productive and unproductive forms of accumulation share no common trend or no stable long-run equilibrium relationship. In the postwar period, unproductive accumulation has occurred systematically at a faster pace than productive accumulation. There is, hence, no self-correcting mechanism that brings these two forms of capital accumulation back into a stable long-run equilibrium. Second, productive and unproductive forms of accumulation tend to be mutually reinforcing in the short run. Despite consuming the surplus from productive endeavors, unproductive accumulation still has a net positive effect on productive accumulation. Third, I find evidence that the total value and the value added produced in productive activities grow faster when the unproductive capital grows, but are negatively affected when the unproductive capital stock grows faster than the productive capital stock. Fourth, I find evidence of reverse causality indicating that when there is a slowdown in the total value and value added produced in productive activities, the growth in the unproductive capital stock is negatively affected even though the growth of its share is positively impacted.

This paper is the first to use econometric techniques and Marxist categories to estimate the interactions between productive and unproductive activities in the postwar US economy. There are, however, two issues that still need further investigation. The first is on the actual channels through which productive and unproductive activities affect one another, whether it is through boosts to aggregate demand or via improvements in labor productivity. The second is on the differential effects of each sub-type of unproductive accumulation such as knowledge-rents, finance and insurance, trade, unproductive services, and public administration. In this paper I employed aggregate measures of unproductive activity and hence more research is required so as to unveil the different impacts from each particular sub-component of unproductive activity.

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Tables and Figures for the Main Text

Table 1: Description of Variables

Proxies for Productive Accumulation		
Real TV	Real Total Value produced in productive activities, in 2005 dollars	flow
Real MVA	Real Marxist Value Added produced in productive activities, in 2005 dollars	flow
Real K_{PA}	Real stock of fixed capital in productive activities, in 2005 dollars	stock
K_{PA} / K_{UA}	Stock of fixed capital in productive activities relative to the stock of fixed capital in unproductive activities	stock over stock
Proxies for Unproductive Accumulation		
Real GI_{UA}	Real Gross Income of unproductive activities, in 2005 dollars	flow
Real NI_{UA}	Real Net Income of unproductive activities, in 2005 dollars	flow
Real K_{UA}	Real stock of fixed capital in unproductive activities, in 2005 dollars	stock
K_{UA} / K_{PA}	Stock of fixed capital in unproductive activities relative to the stock of fixed capital in productive activities	stock over stock
NUB	Net Unproductive Burden: ratio of Net Income of unproductive activities to the Surplus Value created in productive activities	flow over flow
GUB	Gross Unproductive Burden: ratio of Gross Income of unproductive activities to the Total Value produced in productive activities	flow over flow
UCC	Unproductive Composition of Capital: ratio of the stock of fixed capital in unproductive activities to the value of labor power employed in productive activities (or variable capital)	stock over flow

Notes: All measures computed from the BEA's input-output matrices, national income and product accounts, and fixed assets accounts for the US from 1947 to 2011. Estimation techniques from Rotta (2015).

Table 2: Cointegration Tests — Engle-Granger Methodology

Left-hand-side Variables	Right-hand-side Variables: GUB	NUB	UCC	Real GI_{UA}	Real NI_{UA}	Real K_{UA}	K_{UA} / K_{PA}
Real TV	t = -2.58	t = -3.18	t = -2.27	t = -1.66	t = -1.72	t = -2.68	t = -2.08
Real MVA	t = -2.82	t = -2.97	t = -2.24	t = -1.55	t = -1.79	t = -3.39(.)	t = -2.13
Real K_{PA}	t = -1.55	t = -2.84	t = -1.81	t = -0.87	t = -1.15	t = -1.27	
K_{PA} / K_{UA}	t = -3.44(.)	t = -2.72	t = -2.60	t = -3.11	t = -2.99		
Total obs.	65	65	65	65	65	65	65

Notes: Main entries indicate the estimated t-stats for the ADF test on the residuals from the long-run relationship using pairs of endogenous variables. Regression results are over the entire postwar period (1947-2011). ADF implemented with the optimal number of lags chosen with the Bayesian Information Criterion (BIC). Null hypothesis for the ADF t-tests (with no intercept or trend) on the estimated residuals is of nonstationarity. Null hypothesis can be rejected at the following significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Since the residuals being tested for nonstationarity derive from a regression, we cannot use the usual ADF critical values. In this case the appropriate critical values are taken from Hamilton (1994, Table B7) and Enders (2010, Table C).

Table 3: Cointegration Tests — Johansen Methodology

Endogenous Variables	Deterministic element in the cointegration space	Deterministic element in the regression	Lags	λ_{max} (r = 0)	λ_{trace} (r = 0)	rank(Π)
Real TV and Real GI_{UA}	none	trend	9	6.21	6.74	0
	constant	none	9	13.91(.)	17.99	1(d)
	trend	none	9	15.49	18.22	0
Real TV and Real NI_{UA}	none	trend	9	6.62	7.25	0
	constant	none	9	11.32	15.37	0
	trend	none	9	14.01	18.71	0
Real TV and GUB	none	trend	any	-	-	0
	constant	none	any	-	-	0
	trend	none	any	-	-	0
Real TV and NUB	none	trend	any	-	-	0
	constant	none	any	-	-	0
	trend	none	any	-	-	0
Real TV and UCC	none	trend	4	7.77	7.80	0
	constant	none	9	12.06	15.17	0
	trend	none	9	13.85	20.85	0
Real TV and Real K_{UA}	none	trend	4	5.17	5.48	0
	constant	none	4	10.22	14.40	0
	trend	none	4	9.98	14.70	0
Real TV and K_{UA} / K_{PA}	none	trend	any	-	-	0
	constant	none	any	-	-	0
	trend	none	any	-	-	0
Real MVA and Real GI_{UA}	none	trend	9	12.72	13.38	0
	constant	none	9	22.04(**)	26.30(**)	1(a)
	trend	none	9	21.44(*)	29.55 (**)	1(a)
Real MVA and Real NI_{UA}	none	trend	12	10.74	11.85	0
	constant	none	12	12.86	19.06(.)	1(b)
	trend	none	12	11.16	21.12	0
Real MVA and GUB	none	trend	10	4.52	7.60	0
	constant	none	10	9.24	12.48	0
	trend	none	any	-	-	0
Real MVA and NUB	none	trend	3	12.21	12.80	0
	constant	none	6	8.77	15.01	0
	trend	none	8	12.54	19.62	0
Real MVA and UCC	none	trend	3	10.32	10.33	0
	constant	none	3	21.79(**)	24.47(*)	1(a)
	trend	none	3	10.33	16.01	0
Real MVA and Real K_{UA}	none	trend	3	10.42	10.51	0
	constant	none	3	13.94 (.)	18.65 (.)	1(c)
	trend	none	3	12.80	17.51	0
Real MVA and K_{UA} / K_{PA}	none	trend	3	4.00	4.87	0
	constant	none	7	11.52	15.52	0
	trend	none	7	-	-	0

Real K_{PA} and GUB	none	trend	any	-	-	0
	constant	none	any	-	-	0
	trend	none	any	-	-	0
Real K_{PA} and NUB	none	trend	any	-	-	0
	constant	none	any	-	-	0
	trend	none	any	-	-	0
Real K_{PA} and UCC	none	trend	3	20.44(**)	21.37(*)	1(a)
	constant	none	4	17.71(*)	20.43(*)	1(c)
	trend	none	4	11.99	21.6	0
Real K_{PA} and Real GI_{UA}	none	trend	8	7.20	7.28	0
	constant	none	any	-	-	0
	trend	none	8	14.13	20.97	0
Real K_{PA} and Real NI_{UA}	none	trend	10	14.47(.)	16.71(.)	1(b)
	constant	none	10	26.59(**)	30.12 (**)	1(d)
	trend	none	10	16.29	27.05 (*)	1(d)
Real K_{PA} and Real K_{UA}	none	trend	10	7.03	7.18	0
	constant	none	10	8.86	13.85	0
	trend	none	10	15.88	22.90(.)	0
K_{PA} / K_{UA} and GUB	none	trend	3	5.35	5.83	0
	constant	none	4	10.25	13.55	0
	trend	none	4	7.49	9.13	0
K_{PA} / K_{UA} and NUB	none	trend	3	3.83	4.71	0
	constant	none	6	13.42	18.39(.)	0
	trend	none	6	11.63	19.41	0
K_{PA} / K_{UA} and UCC	none	trend	4	5.67	7.68	0
	constant	none	6	9.99	14.00	0
	trend	none	6	10.73	15.48	0
K_{PA} / K_{UA} and Real GI_{UA}	none	trend	11	11.58	16.19(.)	0
	constant	none	11	14.67(.)	19.29(.)	1(c)
	trend	none	11	20.13 (*)	27.83 (*)	1(d)
K_{PA} / K_{UA} and Real NI_{UA}	none	trend	10	10.81	12.33	0
	constant	none	10	11.23	14.28	0
	trend	none	10	23.24 (*)	32.56 (**)	1(b)

Note 1: Regression results are for the entire postwar period (1947-2011). Lag lengths chosen so as to remove serial correlation from the estimated residuals. A dash (-) indicates that the system is computationally singular and that Π is either rank-deficient or indefinite. Critical values are taken from Osterwald-Lenum (1992). Null hypotheses can be rejected at the following significance levels: 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Note 2: (a) Residuals are not normal; (b) Residuals are not normal and are still serially correlated; (c) Residuals are not normal and are heteroskedastic; (d) Residuals are not normal, still serially correlated, and heteroskedastic.

Table 4: Estimated Reduced-Form VAR Models

	Whole period (1948-2011)	**Regulated period** (1948-1979)	**Neoliberal period** (1980-2011)
Reduced-form VAR Model 1			
Endogenous variable 1: *Growth rate of* $\frac{K_{UA}}{K_{PA}}$	0.00	0.34	0.00
Endogenous variable 2: *Real* $\widehat{TV}$	0.01	0.02	0.00
Deterministic regressors	constant	none	none
Optimal lag length (using AIC)	2	3	1
Residual correlation coefficient	-0.31	-0.50	-0.08
Reduced-form VAR Model 2			
Endogenous variable 1: *Real* $\widehat{K_{UA}}$	0.00	0.00	0.00
Endogenous variable 2: *Real* $\widehat{MVA}$	0.00	0.02	0.00
Deterministic regressors	none	none	none
Optimal lag length (using AIC)	2	2	2
Residual correlation coefficient	+0.13	+0.33	+0.09
Reduced-form VAR Model 3			
Endogenous variable 1: *Real* $\widehat{K_{UA}}$	0.00	0.00	0.00
Endogenous variable 2: *Real* $\widehat{TV}$	0.00	0.02	0.00
Deterministic regressors	none	none	none
Optimal lag length (using AIC)	3	3	2
Residual correlation coefficient	-0.01	+0.14	+0.01

Notes: Each estimated VAR model in reduced form has two endogenous variables and no exogenous variables. For each regression equation I report the p-values from the joint F-tests that the estimated coefficients equal zero. Optimal lag length chosen through the Akaike Information Criterion (AIC). Carets (^) indicate real growth rates.

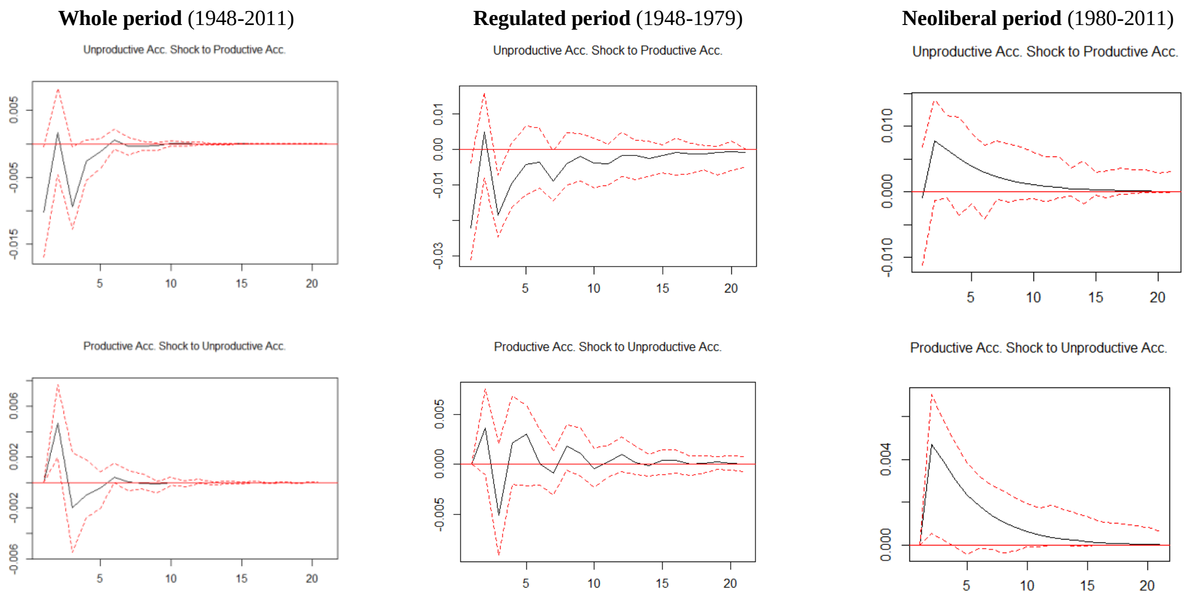
Table 5: Instantaneous and Granger Non-Causality Tests (p-values)

	Whole period (1948-2011)	**Regulated period** (1948-1979)	**Neoliberal period** (1980-2011)
Reduced-form VAR Model 1			
Instantaneous non-causality:			
Growth rate of $\frac{K_{UA}}{K_{PA}} \leftrightarrow$ *Real* $\widehat{TV}$	0.02	0.01	0.85
Granger non-causality:			
Growth rate of $\frac{K_{UA}}{K_{PA}} \rightarrow$ *Real* $\widehat{TV}$	0.00	0.06	0.04
Growth rate of $\frac{K_{UA}}{K_{PA}} \leftarrow$ *Real* $\widehat{TV}$	0.01	0.08	0.01
Reduced-form VAR Model 2			
Instantaneous non-causality:			
Real $\widehat{K_{UA}} \leftrightarrow$ *Real* $\widehat{MVA}$	0.23	0.06	0.58
Granger non-causality:			
Real $\widehat{K_{UA}} \rightarrow$ *Real* $\widehat{MVA}$	0.01	0.06	0.00
Real $\widehat{K_{UA}} \leftarrow$ *Real* $\widehat{MVA}$	0.00	0.07	0.00
Reduced-form VAR Model 3			
Instantaneous non-causality:			
Real $\widehat{K_{UA}} \leftrightarrow$ *Real* $\widehat{TV}$	0.98	0.47	0.94
Granger non-causality:			
Real $\widehat{K_{UA}} \rightarrow$ *Real* $\widehat{TV}$	0.09	0.08	0.01
Real $\widehat{K_{UA}} \leftarrow$ *Real* $\widehat{TV}$	0.00	0.08	0.00

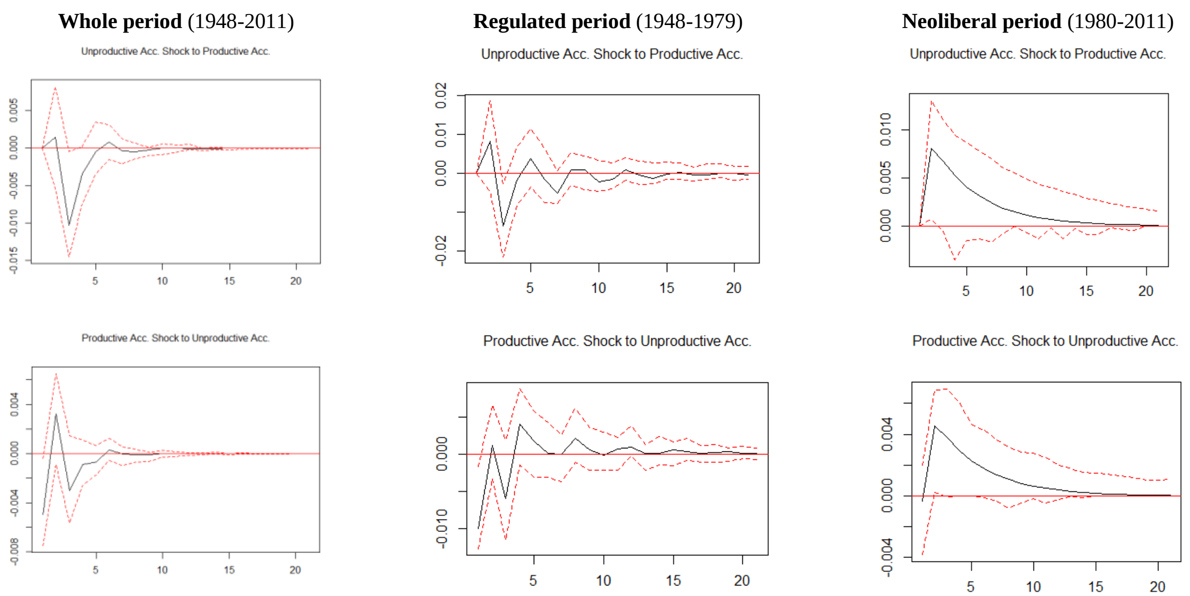
Notes: p-values reported for the instantaneous and Granger non-causality tests. Granger non-causality Ho: x does not Granger-cause y. Instantaneous non-causality Ho: x does not instantaneously cause y.

Figure 1: Impulse Response Functions from VAR Model 1

(a) Ordering: *Growth rate of* $\frac{K_{UA}}{K_{PA}} \rightarrow$ *Real* $\widehat{TV}$



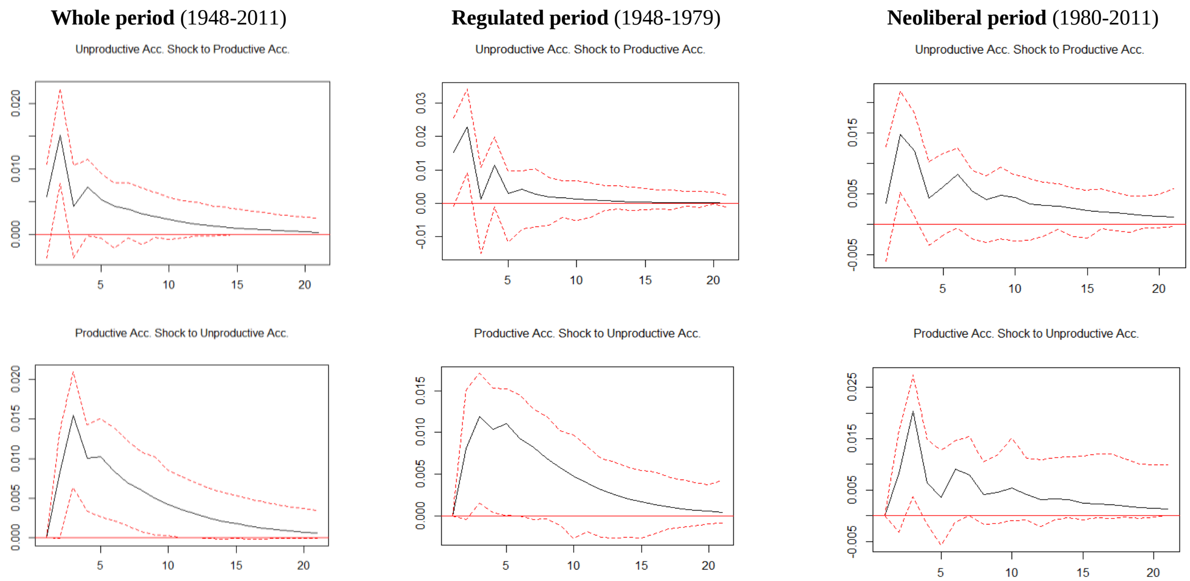
(b) Ordering: *Growth rate of* $\frac{K_{UA}}{K_{PA}} \leftarrow$ *Real* $\widehat{TV}$



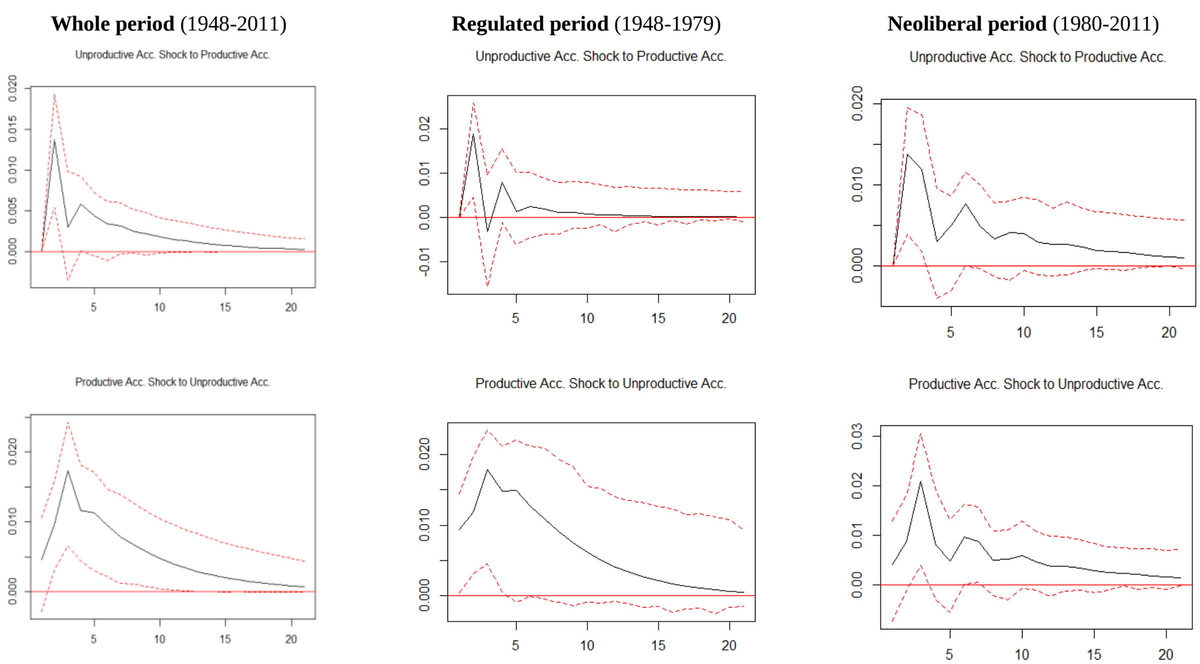
Notes: Dashed lines indicate bootstrapped 90% confidence intervals with 100 runs. IRFs shown for 20 lags.

Figure 2: Impulse Response Functions from VAR Model 2

(a) Ordering: *Real* $\widehat{K_{UA}} \rightarrow$ *Real* $\widehat{MVA}$



(b) Ordering: *Real* $\widehat{K_{UA}} \leftarrow$ *Real* $\widehat{MVA}$

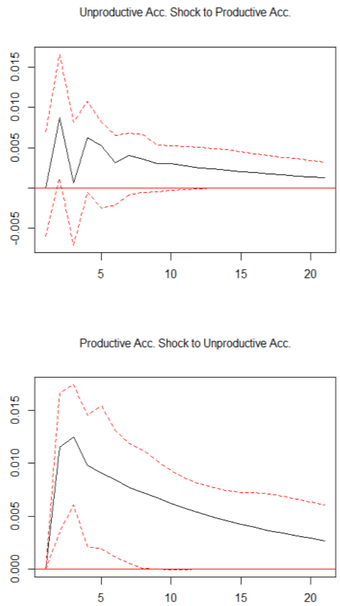


Notes: Dashed lines indicate bootstrapped 90% confidence intervals with 100 runs. IRFs shown for 20 lags.

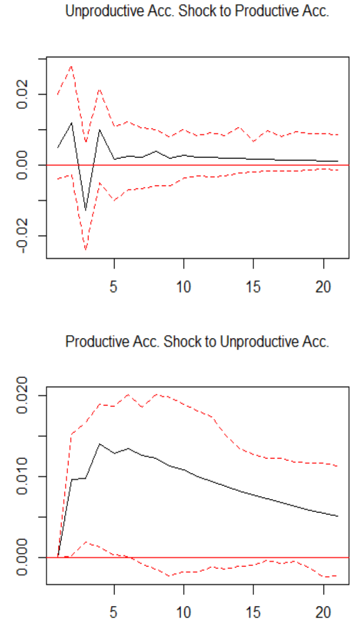
Figure 3: Impulse Response Functions from VAR Model 3

(a) Ordering: *Real* $\widehat{K_{UA}} \rightarrow$ *Real* $\widehat{TV}$

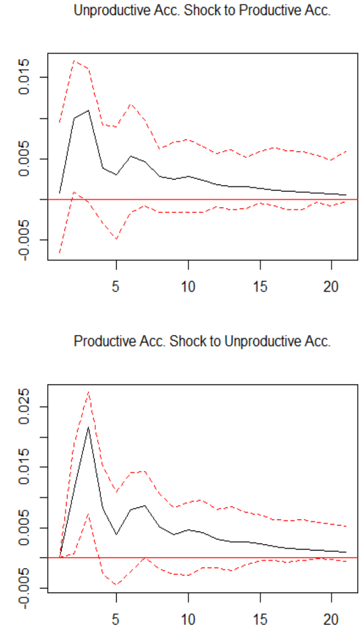
Whole period (1948-2011)



Regulated period (1948-1979)

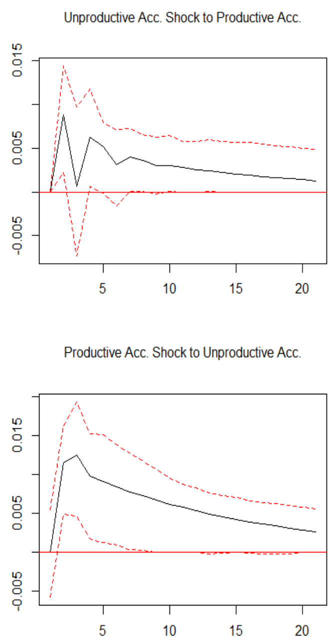


Neoliberal period (1980-2011)

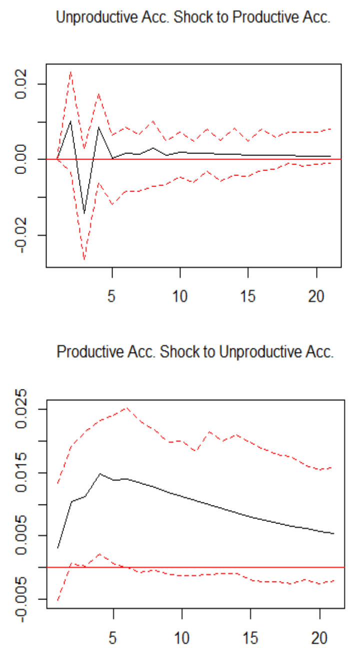


(b) Ordering: *Real* $\widehat{K_{UA}} \leftarrow$ *Real* $\widehat{TV}$

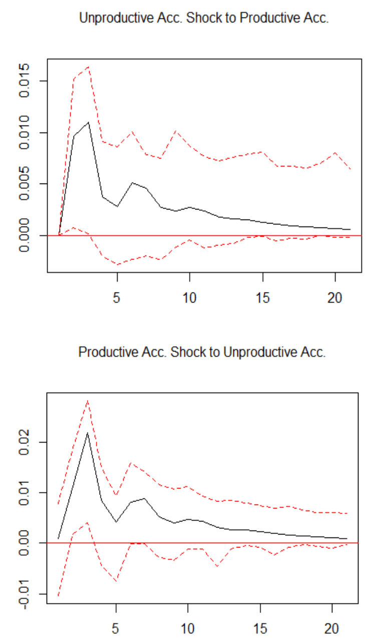
Whole period (1948-2011)



Regulated period (1948-1979)



Neoliberal period (1980-2011)

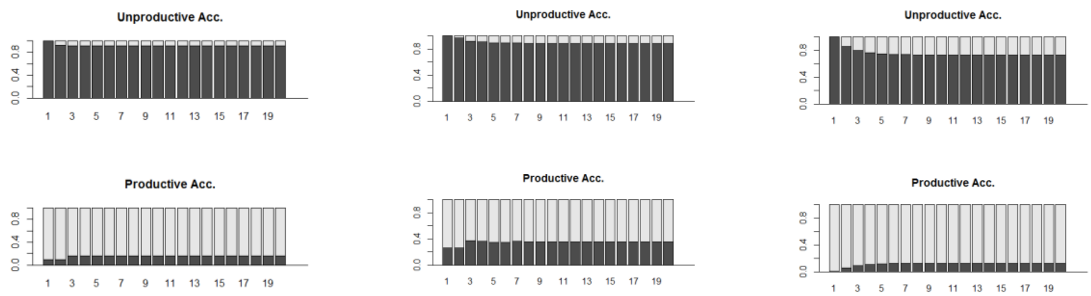


Notes: Dashed lines indicate bootstrapped 90% confidence intervals with 100 runs. IRFs shown for 20 lags.

Figure 4: Forecast Error Variance Decompositions from VAR Model 1

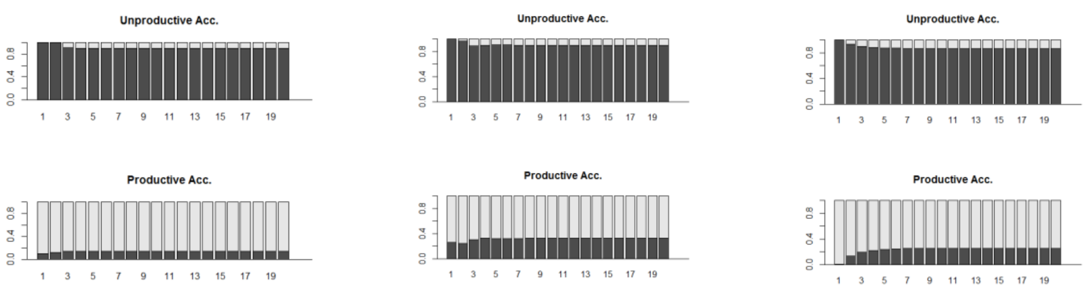
(a) Ordering: *Growth rate of* $\frac{K_{UA}}{K_{PA}} \rightarrow$ *Real* $\widehat{TV}$

Whole period (1948-2011) | **Regulated period** (1948-1979) | **Neoliberal period** (1980-2011)



(b) Ordering: *Growth rate of* $\frac{K_{UA}}{K_{PA}} \leftarrow$ *Real* $\widehat{TV}$

Whole period (1948-2011) | **Regulated period** (1948-1979) | **Neoliberal period** (1980-2011)

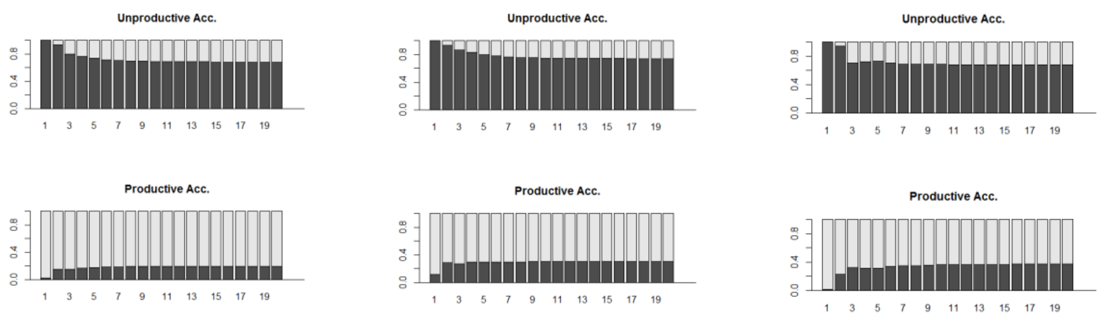


Notes: Forecast error variance decomposition in percentage for a horizon of 20 years. Grey area = share of the respective forecast error variance attributable to productive accumulation; Black area = share of the respective forecast error variance attributable to unproductive accumulation.

Figure 5: Forecast Error Variance Decompositions from VAR Model 2

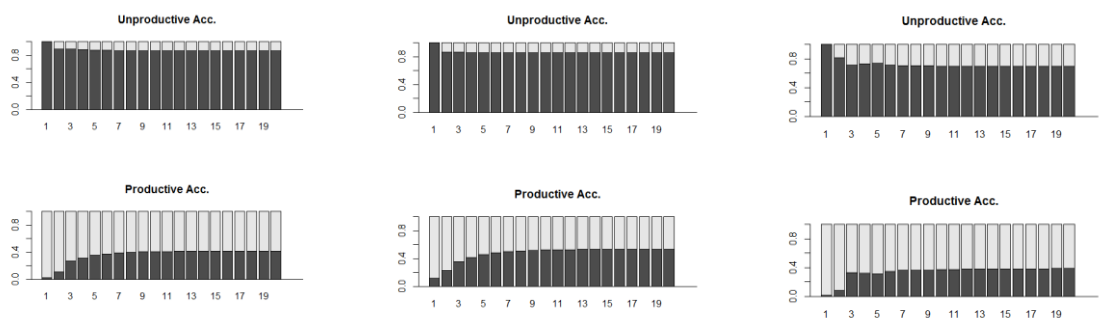
(a) Ordering: *Real* $\widehat{K_{UA}} \rightarrow$ *Real* $\widehat{MVA}$

Whole period (1948-2011) **Regulated period** (1948-1979) **Neoliberal period** (1980-2011)



(b) Ordering: *Real* $\widehat{K_{UA}} \leftarrow$ *Real* $\widehat{MVA}$

Whole period (1948-2011) **Regulated period** (1948-1979) **Neoliberal period** (1980-2011)

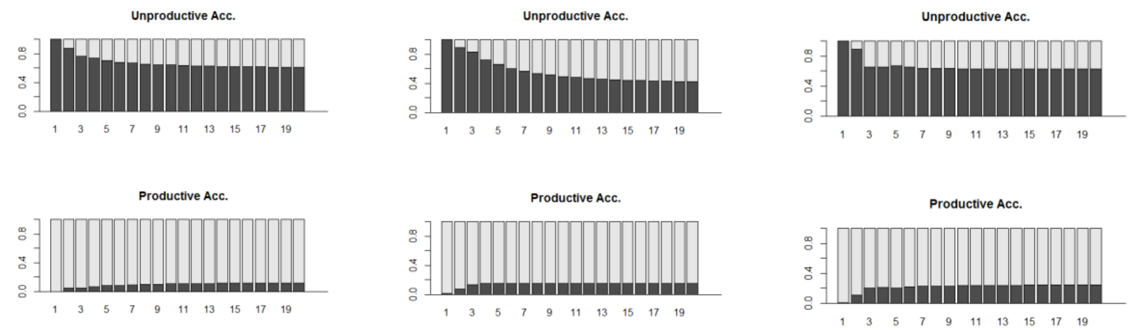


Notes: Forecast error variance decomposition in percentage for a horizon of 20 years. Grey area = share of the respective forecast error variance attributable to productive accumulation; Black area = share of the respective forecast error variance attributable to unproductive accumulation.

Figure 6: Forecast Error Variance Decompositions from VAR Model 3

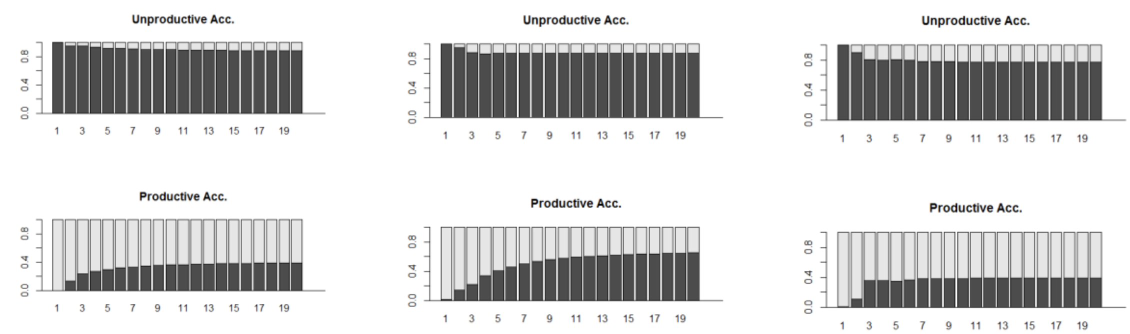
(a) Ordering: *Real* $\widehat{K_{UA}} \rightarrow$ *Real* $\widehat{TV}$

Whole period (1948-2011) | **Regulated period** (1948-1979) | **Neoliberal period** (1980-2011)



(b) Ordering: *Real* $\widehat{K_{UA}} \leftarrow$ *Real* $\widehat{TV}$

Whole period (1948-2011) | **Regulated period** (1948-1979) | **Neoliberal period** (1980-2011)



Notes: Forecast error variance decomposition in percentage for a horizon of 20 years. Grey area = share of the respective forecast error variance attributable to productive accumulation; Black area = share of the respective forecast error variance attributable to unproductive accumulation.

Appendix

In this appendix I provide the technical details on estimation procedures.

A.1 The Vector Auto-Regression (VAR) Model

The structural-form VAR(p) model with *p* lags for *k* endogenous variables is:

$$Bx_t = \sum_{i=1}^{p} B_i x_{t-i} + B_0 d_t + \varepsilon_t \qquad \text{(A.1)}$$

in which x_t is the (*k* x 1) vector of *k* endogenous variables, *B* is the (*k* x *k*) matrix containing the coefficients for the contemporaneous interactions between the endogenous variables, B_i are the (*p* x *k*) matrices containing the coefficients for the lagged interactions, B_0 is the coefficient matrix of potentially deterministic regressors, d_t the (*k* x 1) vector holding the appropriate deterministic regressors, and ε_t the (*k* x 1) vector of structural errors. Though the elements of ε_t must be uncorrelated white noise in the structural-form VAR there may be systematic variations caused by contemporaneous feedback across endogenous variables, which would appear as non-zero non-diagonal elements in matrix B. In this case, structural shocks to one endogenous variable have immediate effects on the other endogenous variables.

A.2 Nonstationarity and De-Trending

Prior to estimating the VAR model it is necessary to check for the presence of nonstationary variables. Nonstationarity can invalidate coefficient estimates and Granger causality tests. The Granger causality test statistic does not have the usual asymptotic distribution if some of the variables are nonstationary. To formally check for nonstationarity I perform unit root tests on the levels of all variables described in Table 1. I perform Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests and compile the calculated test statistics in Tables A.1 and A.2. I employ the

Bayesian information criterion (BIC) to determine the optimal lag length in the ADF tests, noting that the Akaike information criterion (AIC) gives the exact same results. While the ADF procedure uses parametric autoregressive lags to correct for serial correlation in the residuals, the Phillips and Perron (1988) procedure checks for unit roots by implementing a nonparametric correction for serial correlation and heteroskedasticity in the regression residuals. The PP procedure employs the Newey-West heteroskedasticity- and autocorrelation-consistent covariance matrix estimator. The ADF and PP tests are asymptotically equivalent but the PP performs better with smaller samples. Since both the ADF and PP tests are estimated under the null hypothesis of nonstationarity, I also crosscheck the results by employing KPSS tests under the opposite null hypothesis of stationarity.

[Table A.1 about here]

[Table A.2 about here]

Results are consistent across different methods and suggest that all variables in Table 1 are not stationary. It is not possible to reject the null hypothesis of nonstationarity for any of the series using the ADF and PP models. Likewise, we can reject the null hypothesis of stationarity for all series using the KPSS procedure. Since it is not recommended to estimate VAR models with nonstationary variables I address the unit root problem by instead using real growth rates of the variables listed in Table 1. As expected, a shortcoming of working with stationary growth rates upon de-trending nonstationary series is the partial loss of information.

A.3 Cointegration Analysis

The one-step Johansen methodology consists of computing a vector error correction (VEC) model of the form:

$$\Delta x_t = \Gamma_1 \Delta x_{t-1} + \cdots + \Gamma_{p-1} \Delta x_{t-p+1} + \Pi x_{t-p} + B_0 d_t + \varepsilon_t \qquad \text{(A.2)}$$

in which $\Gamma_i = -(I - B_1 - \cdots - B_i)$ with $i = 1, \ldots, p-1$; and $\Pi = -\left(\mathrm{I} - B_1 - \cdots - B_p\right)$, and the B_i matrices are from the VAR(p) model in equation A.1. The Γ_i matrices therefore contain the cumulative long-run impacts. It is also possible to decompose Π as the product of the speed of adjustment coefficients (α) times the cointegration space (β): $\Pi = \alpha\beta'$, in which vector β can be augmented so as to include an intercept and a linear trend within the cointegration space. Vector B_0 can also be modified so as include deterministic elements outside of the cointegration space.

A.4 Reduced-Form VAR Model

Multiplying both sides of the structural-form VAR(p) model in equation A.1 by B^{-1} leads to the reduced-form VAR(p) model with *p* lags for *k* endogenous variables in equation A.3:

$$x_t = \sum_{i=1}^{p} A_i x_{t-i} + A_0 d_t + e_t \tag{A.3}$$

in which A_i is the (*p* x *k*) coefficient matrix on the lagged endogenous variables x_{t-i}, A_0 is the coefficient matrix of potentially deterministic regressors, and e_t is the (*k* x 1) estimated residual vector with time invariant positive definite covariance matrix $\sum_e = E[e_t e_t']$.

A.5 Impulse Response Functions

The key procedure in calculating the IRFs is to transform the vector auto-regressions into vector moving averages. Every stationary auto-regressive (AR) process has a convergent infinite moving average (MA) representation. When dealing with multiple variables it is then possible to represent a vector auto-regressive (VAR) system of order *p* as an infinite vector moving average (VMA) process:

$$x_t = \mu + \sum_{i=0}^{\infty} \phi_i \varepsilon_{t-i} \tag{A.4}$$

in which μ is the vector with the unconditional means of the endogenous variables in x_t, and $\phi_i = \frac{A_1^i}{\det(B)} B^{-1}$ are the impact multiplier matrices, which in turn rely on the A_i and B matrices as previously defined in equations A.1 and A.3.

Using equation A.4 it becomes possible to visualize the IRFs directly from the ϕ_i matrices by graphing its coefficients against *i*. The coefficients of ϕ_i generate the effects of the structural shocks in ε_t on the entire time path of the x_t sequence. Given that the impact multipliers are associated with the structural errors it is necessary to recover ε_t from the estimated residual vector e_t. The orthogonal Cholesky decomposition is applied to the B matrix in equations A.1 and A.4 and the structural errors are then recovered using $\varepsilon_t = Be_t$.

A.6 Variance Decomposition

From the vector moving average (VMA) representation and the associated coefficients in ϕ_i it is possible to iterate equation A.4 forward so as to obtain the forcast errors of each model. From the forecast errors it is then easy to compute the associated variances and to further decompose them into the proportion of movements in one varaible due to its own shocks versus shocks to the other variables.

A.7 Diagnostic Tests

I perform seven diagnostic tests for the three estimated VAR models across all time periods analyzed. I summarize the results in Table A.3, indicating under each diagnostic test the respective null hypothesis and calculated p-values. P-values lower than 0.10 suggest that the null can be rejected at standard significance levels. The general conclusion is that the three regression models are well specified.

[Table A.3 about here]

The first diagnostic check is the multivariate Portmanteau test for serial correlation in the estimated residuals, in which the null is of no serial correlation. I apply the adjusted version of the test for smaller samples. In a static system the autocorrelation in the residuals reduce the efficiency of the OLS coefficient estimators even though they remain unbiased. In a dynamic VAR the auto-correlation in the residuals makes OLS estimates inconsistent, hence invalidating t- and F-tests. The results show no problems for any version of the three models.

The second is the Edgerton-Shukur test for serial correlation in the estimated residuals. This test is based on the asymptotic Breusch-Godfrey procedure but corrected for smaller samples. The null is also of no serially correlated errors. The results show no problems for any version of the three models, except for a slight evidence of serial correlation at the 9% confidence level for the first model under the whole 1948-2011 period.

The third is the multivariate Jarque-Bera test for normality in the residuals. The multivariate version of this test is computed using a Cholesky decomposition of the variance-covariance matrix for the standardized residuals. The null is of jointly normal residuals. Non-normal distributions distort estimates and confidence intervals. I perform the Jarque-Bera test together with the multivariate tests for skewness and kurtosis, checking if the multivariate skewness and kurtosis match a normal distribution. These fourth and fifth diagnostic checks test the null hypothesis of joint zero skewness and zero excess kurtosis. Since test results are dependent upon the ordering of the variables, I report p-values for the Jarque-Bera normality test, skewness, and kurtosis tests under the two possible orderings for each model. The computed statistics suggest no problems for any version of the three models.

The sixth is the parameter stability test. It computes an empirical fluctuation process according to a specified method from the generalized fluctuation test framework. This is a visual test for structural change and there is no associated p-value. I apply the recursive cumulative summation criterion. The results point to no stability problems in any of the models. The seventh and last diagnostic check is the test for autoregressive conditional heteroskedasticity in the estimated residuals. It computes a multivariate ARCH-LM test for a VAR system. The results indicate no problems in any of the models.

Tables for the Appendix

Table A.1: Unit Root Tests

	Real TV	Real MVA	Real GI_{UA}	Real NI_{UA}	K_{UA} / K_{PA}
Augmented Dickey-Fuller: Ho = series has a unit root (nonstationarity)					
Optimal lag length	1 lag	1 lag	1 lag	1 lag	1 lag
No drift, no trend: τ	3.30(**)	3.61(**)	3.88(**)	3.90(**)	0.64
Drift, no trend: τ_μ	0.39	0.93	2.38	2.21	-1.07
Drift, no trend: ϕ_1	6.48(*)	7.47(**)	8.57(**)	9.31(**)	0.84
Drift and trend: τ_τ	-2.76	-2.07	-0.65	-1.10	-2.29
Drift and trend: ϕ_2	7.56(**)	7.14(**)	7.27(**)	8.01(**)	2.18
Drift and trend: ϕ_3	4.16	3.16	4.89	4.76	2.99
Phillips-Perron: Ho = series has a unit root (nonstationarity)					
Optimal lag length	1 lag	1 lag	1 lag	1 lag	1 lag
Drift, no trend: Z_α	0.33	0.66	1.77	1.43	-8.89(.)
Drift, no trend: Z_τ	0.55	1.17	3.03(*)	2.83(.)	-2.14
Drift and trend: Z_α	-9.25	-5.04	-0.87	-1.56	-18.69(.)
Drift and trend: Z_τ	-2.35	-1.87	-0.61	-1.09	-4.13(**)
KPSS: Ho = series does not have a unit root (stationarity)					
Lag length	3 lags	3 lags	3 lags	3 lags	3 lags
Drift, no trend	1.69(**)	1.66(**)	1.51(**)	1.57(**)	0.82(**)
Drift and trend	0.32(**)	0.38(**)	0.40(**)	0.41(**)	0.30(**)
Total observations	65	65	65	65	65
Conclusion	I(1)	I(1)	I(1)	I(1)	I(1)

Notes: ADF implemented with the number of lags chosen with the Bayesian Information Criterion (BIC). Critical values from Hamilton (1994, Appendix B). Null can be rejected at the following significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table A.2: Unit Root Tests (continued)

	NUB	GUB	UCC	Real K_{UA}	Real K_{PA}
Augmented Dickey-Fuller: Ho = series has a unit root (nonstationarity)					
Optimal lag length	1 lag	1 lag	1 lag	1 lag	1 lag
No drift, no trend: τ	1.84(.)	2.90(**)	2.12(*)	3.99(**)	3.85(**)
Drift, no trend: τ_μ	-0.98	0.65	1.07	1.32	0.44
Drift, no trend: ϕ_1	2.85	4.35 (.)	2.52	9.60(**)	11.31(**)
Drift and trend: τ_τ	-3.09	-1.29	-1.10	-1.66	-2.20
Drift and trend: ϕ_2	5.00(*)	3.90	2.84	8.26(**)	9.83(**)
Drift and trend: ϕ_3	4.82	1.60	2.23	3.16	2.73
Phillips-Perron: Ho = series has a unit root (nonstationarity)					
Optimal lag length	1 lag	1 lag	1 lag	1 lag	1 lag
Drift, no trend: Z_α	-1.08	1.04	2.97	0.84	0.25
Drift, no trend: Z_τ	-0.71	1.14	1.78	1.42	0.53
Drift and trend: Z_α	-21.28(*)	-3.53	-5.87	-4.2	-7.46
Drift and trend: Z_τ	-3.43(.)	-1.35	-1.56	-1.87	-2.30
KPSS: Ho = series does not have a unit root (stationarity)					
Lag length	3 lags	3 lags	3 lags	3 lags	3 lags
Drift, no trend	1.61(**)	1.52(**)	1.41(**)	1.61(**)	1.68(**)
Drift and trend	0.10	0.36(**)	0.23(**)	0.38(**)	0.32(**)
Total observations	65	65	65	65	65
Conclusion	I(1)	I(1)	I(1)	I(1)	I(1)

Notes: ADF implemented with the number of lags chosen with the Bayesian Information Criterion (BIC). Critical values from Hamilton (1994, Appendix B). Null can be rejected at the following significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table A.3: Diagnostic Tests of VAR Residuals (p-values)

	Serial Correlation	Serial Correlation	Normality	Skewness	Kurtosis	Stability	ARCH
Test Type	Adjusted Portmanteau	Edgerton-Shukur	Jarque-Bera			Recursive CUSUM	Autoregressive conditional heteroskedasticity
Null hypothesis (Ho)	No serial correlation	No serial correlation	Normal residuals	Zero skewness	Zero excess kurtosis		No heteroskedasticity
VAR Model 1							
1948-2011	0.30	0.09(.)	0.54/0.49	0.77/0.94	0.27/0.19	no break	0.40
1948-1979	0.22	0.49	0.77/0.82	0.88/0.90	0.45/0.52	no break	0.51
1980-2011	0.81	0.69	0.79/0.92	0.54/0.63	0.79/0.98	no break	0.73
VAR Model 2							
1948-2011	0.91	0.15	0.58/0.38	0.26/0.13	0.91/0.95	no break	0.23
1948-1979	0.92	0.61	0.68/0.67	0.47/0.35	0.68/0.87	no break	0.33
1980-2011	0.68	0.83	0.91/0.76	0.72/0.46	0.84/0.84	no break	0.54
VAR Model 3							
1948-2011	0.71	0.56	0.67/0.68	0.50/0.50	0.63/0.63	no break	0.12
1948-1979	0.72	0.37	0.71/0.72	0.73/0.75	0.47/0.48	no break	0.16
1980-2011	0.78	0.85	0.97/0.97	0.88/0.88	0.89/0.89	no break	0.26

Notes: For each test I report p-values, except for the stability test using the recursive CUSUM for which I report the conclusion from visual inspection. For the Jarque-Bera normality test and the skewness and kurtosis tests I report p-values under the two possible orderings for each model. Null hypotheses can be rejected at the following significance levels: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.