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(Dis)crediting the Swedish Economy

An empirical investigation of the relationship between Financial Sector Development and Economic Growth in Sweden during 1971-2020

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Abstract: This paper examines the finance-growth relationship in Sweden over the course of 1971 – 2020. We apply the Vector Error Correction framework (VECM) and utilize credit allocated by domestic banks and non-bank entities to the private non-financial sector as a percentage of GDP as main proxy for financial sector development. Our analysis reveals evidence of a negative long-term impact of finance on economic growth. Household lending activities appear to drive this negative relationship while credit allocated to the corporate sector impacts growth positively. The relationship is robust when using credit extended by domestic banks as a proxy for financial sector development, indicating that the negative finance-growth relationship is not solely driven by non-banking activities. In turn, we cannot reject the possibility of long-run bidirectional causality between finance and growth. In addition, the hypothesis of Corporate credit as a negative force on growth through innovation, proxied by patents, does not hold true for this period of time. Overall, we find no evidence that innovation has played a significant role in promoting Swedish growth during the period studied. Finally, we find no non-linear cointegrating finance-growth relationship. However, we cannot exclude the possibility of an inverted-u shaped finance-growth relationship in Sweden.

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Contents

1 Introduction

In the beginning of the 2000s, academia had reached an overall consensus that financial sector development generates economic growth, see e.g. Barro, 1991; Goldsmith, 1969; King & Levine, 1993; Levine & Zervos, 1998; Levine et al., 2000 McKinnon, 1973; Rajan & Zingales, 1996 and Shaw, 1973. The positive impact of finance on growth had become widely accepted and established, serving as a predisposition for research on the topic both within the academia and beyond.

After the global financial crisis the subject was revisited among economists. New evidence suggested, contrary to previous conventions, that the positive impact of financial sector development on economic growth may not necessarily be constant over time. An initial contribution in this area was made by Rousseau and Wachtel (2011), who found evidence that the impact of finance on growth appeared to be changing over time, from being positive to around zero and insignificant. In fact, it has been demonstrated that finance becomes a drag on growth after surpassing a certain threshold level. This threshold has been estimated to lie around 80 − 100% of GDP, measured as credit extended to the private sector (Arcand et al., 2015; Cecchetti & Kharroubi, 2012; Law & Singh, 2014). Researchers have particularly found an inverted-u shaped relationship between financial sector development and economic growth, using cross-country data (see e.g. Arcand et al., 2015; Cecchetti & Kharroubi, 2012; Law & Singh, 2014; Samargandi et al., 2015; Zhu et al., 2020). As the size and depth of the financial sector increases, the growth rate in GDP per capita increases up until a certain point, after which increases in the size and depth of the financial sector corresponds to a lower growth rate in GDP per capita.

This paper focuses on the finance-growth relationship in Sweden. As evidence shows that the finance-growth relationship varies across countries due to differences in regulation and institutional quality, there is reason to perform a country-specific analysis. To this end, a time series approach is adequate. To our knowledge, the finance-growth relationship in Sweden has not been visited since Hansson and Jonung (1997) performed a time series analysis using data up until 1991, as well as briefly in Rousseau and Wachtel (1998). Hansson and Jonung provide evidence of a positive impact of financial development on economic growth in Sweden, in particular during the pre-World War II period (1890 – 1939). The Swedish economic and financial landscape has changed considerably since 1991. Sweden has experienced two major economic and financial crises; the 1990s crisis and the 2008 crisis, both having severe impacts on the Swedish economy (especially the 1990s crisis). The crises were followed by stricter banking regulations (Englund, 1990), directly impacting the credit levels, and a change in the Swedish monetary policy in the case of the 1990s crisis. Simultaneously, the composition of the Swedish financial system has changed, with regulatory changes regarding e.g. international capital movements allowing non-bank financial institutions to emerge (Englund, 1990; Hansson & Jonung, 1997). Further, overall credit levels have increased dramatically; for example, credit allocated to non-financial corporations to GDP has tripled since 1980 (BIS, 2024b). In turn, Household credit have reached historically high levels during the 2000s, mainly explained by a significant compositional shift on the housing market with households choosing home-ownership over renting. These major changes in the size and composition of the financial sector, as well as the overall economy, provide reason to revisit the Swedish finance-growth relationship.

The purpose of this study is to investigate the nature of the finance-growth relationship in Sweden over the course of 1971 – 2020. Since credit provided to the private non-financial sector exceeds 100% of Sweden's GDP for our entire data sample, it is possible that the financial sector has indeed surpassed the threshold, implying that financial sector development may have a negative impact on Swedish growth. The main inquiries of this paper are threefold. First, what is the long-run relationship between financial development and economic growth in Sweden between 1971 – 2020? Second, is the direction of this relationship mainly driven by the firm or household channel? Thirdly, can a (potentially) negative Corporate credit-growth relationship be explained by a negative impact of credit growth on innovation?

Given previous research and empirical findings, four hypotheses will guide this paper. *First*, our main hypothesis is that there exists a negative long-run relationship between financial development and economic growth in Sweden from 1971 – 2020. This relationship may be driven by both the household and the corporate channel, generating three sub-hypotheses. *Second*, we hypothesize that there exists a negative long-run relationship between Household credit and economic growth. This can be explained by Household credit generally being used for unproductive activities and investments (e.g. real estate). However, a negative finance-growth relationship may also be driven by credit to non-financial corporations ('Corporate credit'). This leads to our *third* hypothesis: there exists a negative long-run relationship between Corporate credit and economic growth. The corporate channel may, in turn, be driven through the impact of finance on innovation; specifically, increased credit levels may lead to decreased funds allocated towards innovative projects, as supported by Zhu (2020) and Cecchetti and Kharroubi (2019). Hence, our *fourth* hypothesis is that growth in Corporate credit has a negative impact on growth in innovation.

We apply the Vector Error Correction (VEC) framework with the Johansen methodology and credit allocated by domestic banks and non-bank entities to the private sector as a percentage of GDP ('Private sector credit') as main proxy for financial sector development. The results provide evidence of a negative long-run relationship between finance and growth; in particular that financial sector development has negatively contributed to long-run Swedish growth for the period 1971 – 2020. Furthermore, our findings suggest that the household channel drives this negative relationship, as evidenced by a robust negative long-run relationship between Household credit and economic growth. In contrast, we find evidence of a positive relationship between Corporate credit and economic growth. Moreover, the negative finance-growth relationship is robust when using credit extended by domestic banks as a proxy for financial sector development, indicating that the relationship is not solely driven by non-banking activities. It also holds true when control variables are added to the model. Regarding the long-term causal relationship, we cannot dismiss the potential bidirectional influence between finance and growth, as the direction of causality varies based on which proxy we use. Additionally, we do not find support for the hypothesis that growth in Corporate credit negatively impacts growth through innovation, as expected from the positive Corporate credit-growth relationship. Further, we do not find an important role of innovation in promoting Swedish economic growth for the period studied. Finally, when allowing for a non-linear finance-growth relationship through the Engle-Granger methodology for cointegration, we do not find evidence of cointegration among our main variables. However, this does not allow us to preclude the possibility of a non-linear relationship and leaves room for further investigation.

2 Previous research and theory

2.1 Literature review

This topic, along with closely interrelated themes, has been rigorously addressed through various methods and angles. As mentioned, a wide array of studies have found a positive relationship between financial development and economic growth, where the former influences the latter positively, see e.g. Calderón and Liu (2003), Chang and Caudill (2005), King and Levine (1993), Levine et al. (2000), Levine and Zervos (1998), Rajan and Zingales (1996), Rousseau and Vuthipadadorn (2005), Rousseau and Wachtel (1998; 2000), Xu (2000), Qamruzzaman and Wei (2018). This empirical finding appears to be typical for studies carried out mainly in between 1990 and 2005. The positive relationship has also been confirmed by studies using time series techniques, which are naturally relevant for our study. For instance, Xu (2000) investigates the finance-growth relationship in a VAR-model using data from 41 countries between 1960 – 1993. They find strong evidence of an important relationship between financial development and economic growth, where financial development in particular impacts economic growth positively through domestic investment. In addition, Calderón and Liu (2003) apply a VAR-model with data for 109 countries between 1960 – 1994 to investigate the direction of causality in the relationship, confirming the positive relationship between finance and growth. Swedish data is included in several of these studies,[1] where in particular Rousseau and Wachtel (1998) provide a discussion of the Swedish case.

However, Sweden has not been subject to a case study on this topic since Hansson and Jonung (1997) carried out a time series analysis of the long-run relationship between finance and growth for the period 1834 – 1991, using the Vector Error Correction Model (VECM). The findings of Hansson and Jonung are of particular interest here. Hansson and Jonung find that total lending from the financial sector to the non-bank public has a positive long-run relationship with GDP per capita over the period 1834 – 1991; particularly during 1890 – 1939. Both finance and growth adjust to deviations from this long-run relationship; GDP per capita adjusts negatively and finance positively. This suggests that growth in total lending causes GDP per capita growth *and* vice versa. Further, during the period 1890 – 1939, finance seems to impact growth directly and positively through investment. For the period 1946 – 1991, they find that the relationship between growth and investment is particularly strong. However, the relationship between investment and finance no longer moves together; for this period, Hansson and Jonung find that both investment and finance are weakly exogenous, indicating that finance and investment causes growth, but not the other way around.

[1] Calderón and Liu (2003), Rajan and Zingales (1996) and Rousseau and Wachtel (2011; 2000) all include Swedish data in their cross-country investigations.

Overall, there is hence an abundance of studies confirming the positive impact of financial development and economic growth. It can be observed that this has indeed been a leading perspective in academia when investigating this relationship during this specific period of time. However, after the financial crisis in 2008, and mainly from 2010 and onwards, there are studies questioning whether the relationship between financial development and economic growth is necessarily positive.

In particular, several cross-country studies have found that there is a non-monotonic and concave relationship, or an inverted-u shaped relationship, between financial development and economic growth (see e.g. Arcand et al., 2015; Cecchetti & Kharroubi, 2012; Law & Singh, 2014; Samargandi et al., 2015; Zhu et al., 2020). This indicates that financial development has a positive effect on economic growth when the financial system is smaller, but after a certain threshold financial development becomes detrimental for economic growth. This threshold is mainly estimated to lie around $80 - 100\%$, representing intermediate levels of financial development. As an example, Cecchetti and Kharroubi (2012) investigate the impact on economic growth of both the size of the financial sector and speed of financial development, using data from 50 countries spanning over the years 1980-2009. They find an inverted-u shaped relationship between the size of the financial sector and growth in GDP per worker. Similarly, Arcand et al. (2015) find that the finance-growth relationship is concave and non-monotonic, confirming that there exists a threshold after which financial depth has a non-positive effect on economic growth. Further, Law and Singh (2014) confirms the existence of a threshold around $88 - 99\%$ of GDP in the finance-growth relationship, using more sophisticated techniques that allows for non-linearity in a non-symmetric way. However, Law and Singh find that the impact of growth in finance is either negative or non-significant after the threshold, depending on the choice of proxy. Notably, the impact of an increase in private credit to GDP is slightly larger in absolute terms if the economy is below the threshold (Law & Singh, 2014).

In addition, cross-country studies have found that the positive finance-growth relationship weakens over time and varies with the level of economic development in specific countries. For instance, Rousseau and Wachtel (2011) find that the impact of financial development on economic growth is weakening substantially over time in both developing and developed countries; results show a significant and positive relationship when using data from $1960 - 1989$, but an insignificant coefficient around zero for financial development when using data for $1990 - 2004$. In addition, Rousseau and Wachtel (2011) find that the impact of financial development on economic growth is larger for middle-income countries than for advanced countries. Hassan et al. (2011) similarly find that the impact of financial development on economic growth varies across countries depending on income level and institutional quality, with a positive finance-growth relationship in low- and middle-income countries and negative for high-income countries.

Another orientation of this topic explores the role of households versus firms in the finance-growth relationship. Cecchetti and Kharroubi (2019) investigate the relationship between the rate of growth in credit and the rate of growth in output per worker and find that the negative relationship between them is driven by credit to non-financial firms. Thus their perspective is supply-side, where productivity grows slower when credit to non-financial firms increases, which they interpret as credit going to less productivity-enhancing activities. In contrast, a number of studies find that Household credit drives the negative aspect of the finance-growth relationship, while credit allocated to firms appears to have a positive impact on growth, see e.g. Jappelli & Pagano (1994); Sassi & Gasmi (2014); Beck et al. (2012). Additionally, Greenwood & Scharfstein (2013) investigate how the securities and credit intermediation industries have driven financial sector development forward over time. The authors show that the growth of the credit intermediation industry accounts for approximately one-quarter of the overall growth in the financial sector during the period 1980 – 2007. In particular, this is driven by an expansion in Household credit in the form of mortgages, and the authors argue that this rapid increase in household indebtedness may have severe consequences for macroeconomic stability. This argument is repeated by Bezemer et. al. (2016) and Lorenzoni et. al. (2008), both finding increased overall macroeconomic instabilities along with substantial credit expansions.

Consequently, previous literature underscores the relevance of the purpose of this study. Given the rapid and considerable transformation of various aspects of Sweden's financial system during the past 30 years, it is time for a new closeup of the dynamics of the Swedish finance-growth relationship. This is of particular interest given that Sweden is an advanced economy with a highly developed financial sector, but low GDP per capita growth rate. It may be that further financial development does not contribute much to further growth. Investigating the driving forces behind the finance-growth relationship is of high relevance, which is why we incorporate an analysis of the role of Household credit and Corporate credit. Furthermore, since the role of innovation in the finance-growth relationship has been highlighted in theory and in the literature, we also investigate innovation as a possible driver. Innovation could significantly influence how well Corporate credit promotes, or does not promote, economic growth. Below we will discuss some findings from the literature concerning the role of innovation in the finance-growth relationship.

Hansson and Jonung (1997) incorporate the role of innovation in the long-run relationship between finance and growth in Sweden by using patent applications as proxy. For the period 1836 – 1991 they find evidence of cointegration among GDP per capita, total lending and patent applications, but no significant estimate for patent applications. Hansson and Jonung find this surprising, considering the important role of technological progress in conventional theories of economic growth. Further, the long-run relationship between patent applications and financial lending for the period 1890 – 1939 is positive, where patent applications responds fast and positively to deviations. For the post-World War II period, they instead find a positive cointegrating relationship between GDP per capita and total lending, and another positive relationship between GDP per capita and patent applications. The latter relationship is particularly strong, suggesting an important role of patent applications for Swedish growth during this period.

Additionally, studies have investigated the innovation channel in cross-country analyses. Similarly to Hansson and Jonung, Pradhan et al. (2016) employ a panel VECM-framework to investigate the relationship between financial development, innovation and economic growth using data from 18 Eurozone countries. They use up to five proxies for innovation, all regarding patents or R&D. Their overall findings demonstrate that both financial sector development and innovation significantly contribute to long-run economic growth. Notably, they find that GDP per capita and financial development Granger causes innovation in the long-run, and that innovation Granger causes GDP per capita in the long-run.

Furthermore, Zhu et al. (2020) extend the cross-country literature by demonstrating that a nonlinear finance-growth relationship may be driven through the innovation channel. Zhu et al. find that private credit growth has a positive impact on growth in patent applications in countries with lower levels of financial development, and a smaller positive but insignificant impact for high financial development countries. Moreover, they find that the impact of patent applications on economic growth is larger for countries with lower levels of financial development than for countries of higher levels of financial development, where the estimate is insignificant. Zhu et al. also perform an analysis investigating whether effect of innovation on growth varies with the level of financial development. In this analysis they find that the positive effect of growth in patent applications on growth in GDP per capita decreases as the level of financial development increases; after a certain level the impact might even become negative. Thus, these findings contradict those of Pradhan et al., as the data used by Pradhan et al. consists of advanced countries with highly developed financial sectors. Note that the findings of Zhu et al., together with the theory by Cecchetti and Kharroubi (2019) that will be explained below, motivates our hypotheses regarding how Corporate credit may have a negative impact on growth through the impact of Corporate credit on innovation in Sweden.

2.2 Contributions to the literature

In our understanding, studies finding a potentially negative impact of finance on growth when the financial sector is relatively advanced are primarily based on panel data. Our contribution to this literature involves re-examining the finance-growth relationship in a single advanced country. This approach allows for a better consideration of the country-specific dynamics impacting the finance-growth relationship. Further, we have aimed to use a relatively long dataset, which includes data from the post 2008 global financial crisis era. Almost all of the studies finding an inverted-u shaped or negative finance-growth relationship mentioned above are based on shorter sample sizes.[2] Moreover, using time series methods for a single country allows us to better investigate the direction of causality in the finance-growth relationship. In particular, none of the more recent studies studies finding a negative or nonlinear finance-growth relationship uses the VEC framework, and by using this we are able to investigate both short-run and long-run causality.

Furthermore, Sweden has not been the focus for an in-depth case study of the finance-growth relationship since Hansson and Jonung's study in 1997, based on data up until 1991. As mentioned, the Swedish financial and economic climate has changed dramatically since then, as well as the types of innovative activities shaping its landscape. By re-visiting the Swedish finance-growth relationship using additional 29 years of data, our investigation may provide important policy implications. Compared to the contributions made by Hansson and Jonung, our study also investigates the specific roles of Corporate credit and Household credit in promoting Swedish growth.

2.3 Theoretical background

As mentioned, if a negative finance-growth relationship indeed exists, it may be driven by two channels that we will investigate in this paper: Corporate credit or Household credit. As Household credit is mainly used for unproductive investments such as real estate, one can expect growth in Household credit to have a negative impact on economic growth. However, with Corporate credit it is more reasonable to expect that credit growth has a positive impact on economic growth; a larger credit supply promotes firm investment in activities that generates output, employment and overall growth-enhancing innovative activities. Therefore, if there indeed exists a negative finance-growth relationship that is at least partly driven by the corporate channel, we need a model that can explain this.

Cecchetti and Kharroubi (2019) created an overlapping generations model to explain how financial sector growth can be detrimental to real economic growth through the corporate channel. The model focuses on how credit growth impacts the incentive of entrepreneurs to invest in productive activities. In the model, entrepreneurs choose to invest in projects that vary in risk and return. The model assumes that entrepreneurs' borrowing ability grows over time, as the financial sector grows and better technologies for recovering debt are developed. As a result, lenders are willing to extend more credit. Cecchetti and Kharroubi show that when entrepreneurs' borrowing capacity is higher in the next time period, entrepreneurs choose projects with lower risk/return. This means that when credit grows at an increasing rate, entrepreneurs choose less risky projects. On the aggregate this

[2] Most studies are based on data from 1980-2008/2009/2010, although Arcand et al. 2015 use data from 1960-2010.

results in a lower productivity growth rate. This model is later confirmed in an empirical investigation, where they e.g. find that productivity grows faster (slower) during credit booms in industries where the R&D intensity is low (high).

The underlying intuition is that when future borrowing ability is larger, risky projects become costlier. If an entrepreneur undertakes a risky project at time t and the borrowing ability is higher at time t+1, the entrepreneur will borrow more in t+1. Consequently, the final period marginal utility of consumption becomes relatively larger, as entrepreneurs need to repay their loan and have less remaining money for consumption than if they had taken a smaller loan. If the risky investment leads to a bad outcome, the entrepreneur will have even less money left for consumption. Since entrepreneurs dislike volatile consumption, they prefer to invest in low-risk projects during periods of credit growth. On the other hand, if the future borrowing ability is not higher in t+1, the overall debt to repay becomes smaller. Hence, the consequences of a bad investment outcome is not as bad – the entrepreneur will have more money left for final period consumption. Thus entrepreneurs are more prone to invest in risky projects in time periods without credit growth.

3 Data

3.1 Data description

A total of ten data series are used in this study. These series are presented in table 1 and described thoroughly below. Note that some series have a longer range than others. This will be explained below. The full data set ranges from 1971Q1-2020Q3 consists of 198 observations. The shorter sample ranging from 1980Q4-2020Q3 consists of 160 observations.

Variable name	*Description*
1. GDP per capita	GDP per capita
2. Private sector credit	Credit to the non-financial sector, % of GDP
3. Private sector bank credit	Credit to the non-financial sector provided by domestic banks, % of GDP
4. Household credit	Credit to households and Non-Profit Institutions Serving Households, % of GDP
5. Corporate credit	Credit to non-financial corporations, % of GDP
6. Interest rate	Nominal interest rate (Call money/Interbank rate)
7. CPI	Consumer price index, Growth rate same period previous year
8. Unemployment	Total unemployment in percent, population 16-64 years
9. Prv_patstat	Number of patent applications, data from both patstat and PRV
10. Patstat	Number of patent applications, data from patstat

Table 1: Variables 1-5 and 9-10 are used in logarithms unless stated otherwise in the text. All variables are indexed at time 1995Q4 = 100.

First, in accordance with the majority of literature on this topic, we use quarterly GDP per capita between 1970-2022 measures in US dollars as proxy for economic growth. This is calculated by dividing quarterly seasonally adjusted GDP (OECD, 2024c) by a linearly interpolated yearly population variable (World Bank, 2024). Note that GDP values are based on estimations for all observations up to and including the final quarter of 1992.

In order to capture financial sector development, we use four proxies; Private sector credit to GDP ('Private sector credit'), Private sector bank credit to GDP ('Private sector bank credit'), Credit to households & NPISHs (Non-Profit Institutions Serving Households) to GDP ('Household credit') and Credit to non-financial corporations to GDP ('Corporate credit'). Private sector credit to GDP is defined as credit to the private non-financial sector as a percentage of GDP, and captures financing from all possible sources; credit from domestic banks as well as from other domestic financial corporations, non-financial corporations and non-residents (BIS, 2024c). In comparison, private sector bank credit to GDP only captures financing from domestic banks, defined as credit from domestic banks to private non-financial sector as a percentage of GDP (BIS, 2024d). These two variables are gathered quarterly at market value (in US dollars) and are adjusted for breaks. Both variables includes credit allocated to households, and to non-financial corporations. These two variables function as indicators of the overall size of the financial sector in the form of financing as a share of the size of the overall economy. They are advantageous as they exclude credit allocated to the public sector and credit to the private financial sector, making them good indicators of the ability of the financial sector in allocating funds to private actors. Since the Private sector credit to GDP variable captures a wider scope of the financial sector activities, it serves as our main proxy for financial sector development. However, we include the Private sector bank credit variable as a comparison in the robustness check to investigate whether the results are driven mainly by banking sector activities. Finally, note that these variables are not proxies of the total financial sphere as they do not capture equity market activities.[3]

In order to gain insight in which parts of the financial system are driving the relationship of interest, we also make use of two variables representing the credit allocated to the household and corporate sector, respectively. First, we use credit from all sectors to households and NPISHs (Non-Profit Institutions Serving Households) as a percentage of GDP (BIS, 2024a). To capture the corporate side of the relationship, we use the variable displaying credit from all sectors to non-financial corporations as a percentage of GDP (BIS, 2024b). These variables are gathered on a quarterly basis, are both adjusted for breaks, and are measured in market value US dollars. The data ranges back from the quarter 4 of year 1980 and onwards, and consequently provide a shorter time span than the financial development proxies mentioned earlier. However, they nevertheless provide interesting perspectives on the relationship of interest in this paper.

As control variables we use inflation, unemployment and interest rates. All control variables range from 1970-2022 and are estimated on a quarterly-basis, collected monthly and then converted. The inflation variable is based on seasonally unadjusted Consumer Price Index (CPI) OECD (2024d).[4] The index does not include food or energy prices. Taking the natural logarithm of CPI would have been adequate; however, we were unable to do so because it sometimes inhibits negative values. The unemployment variable (SCB, 2024) concerns the number of unemployed persons out of the total population ranging from 16-64 years of age. Further, the interest rate variable is based on total immediate interbank rates (OECD, 2024e).

To investigate the corporate channel of the finance-growth relationship more thoroughly, we include the role of innovation by using patent applications as proxy. The patent data is collected using the European Patent Office (EPO) data service PATSTAT 2023 and non-published data from the Swedish Patent Authority (Patent- och Registreringsverket, PRV) on monthly Patent Applications to the authority (2024). We were unable to use the PRV data directly, as patent application procedures have changed over time. Since the EPO was created by the European Patent Convention (EPC) in 1973 and came into effect on the 7th of October 1977, any inventor wanting to apply for patent in Sweden

[3]We were unable to find available proxies for the equity market that covered the entire time period.

[4]Note that it would be preferable to use data for Consumer Price Index excluding interest payments instead of Consumer Price Index as inflation variable, but this is not possible due to data availability limitations.

could apply either to PRV or to the EPO. By applying to the EPO, the inventor can obtain patent protections in multiple countries through one application process. Hence, data of patent applications to both PRV and the EPO had to be included.

We created two variables covering patent applications: one using PATSTAT data only which we refer to as *patstat*, and another using a combination of data from PATSTAT and PRV, denoted as *prv_patstat*. The *patstat* variable is created by counting the total number of unique patent application identifications in each quarter to PRV and to EPO, subitted by inventors listing Sweden as their origin. Note that the patent applications to PRV in this context refer to applications reported in the PATSTAT database. The *prv_patstat* variable counts the number of unique patent application identifications in each quarter to the EPO made by inventors reporting Sweden as their origin using the PATSTAT database, as well as the number of patent applications to PRV in each quarter according to the data directly from PRV.[5]

Upon comparing the patent variables, we observe that the *patsat* data for the first few years reports fewer patent applications to PRV than *prv_patstat*, indicating potential omissions in the *patstat* variable. Conversely, while *patstat* is based on data counting unique patent applications in each quarter, *prv_patstat* counts an application twice if it is sent both to PRV and to EPO during the same quarter. However, they exhibit a consistent pattern over time, except for the initial five years.

Henceforth, the variables will be referred to with the names in accordance with table 1. We provide a graphical representation of the series in appendix A.

3.2 Correlation among the variables

As a first overview of the relationships across our variables, we display the correlation across the detrended[6] series in table 2 and 3.

	Private sector credit	Private bank credit	Interest rate	CPI	Unemp
GDP per capita	**-0.57**	-0.22	0.73	0.07	0.07
Private sector credit	1.00	**0.87**	-0.22	0.16	-0.23
Private sector bank credit		1.00	0.17	0.30	-0.22
Interest rate			1.00	0.53	-0.20
CPI				1.00	-0.56
Unemp					1.00

Table 2: The table displays the correlation across the detrended series, with correlations of particular interest displayed in bold. The table uses the full data sample and hence displays the correlation across the variables that will be used forestimatio the entire sample period.

From table 2 we observe that the correlation between GDP per capita and Private sector

[5]Note that both variables may include applications to the EPO for products not marketed on Swedish markets.

[6]The series are detrended by first regressing each series with a time variable, and then generating the detrended series by calculating the *actual values − predicted values*.

credit is negative and relatively high. In comparison, the correlation between GDP per capita and Private sector bank credit is negative as well, but lower. This is expected given that the Private sector bank credit captures a smaller share of the financial activities in the economy. These negative correlations indicate that we *may* find negative long-run finance-growth relationships, in line with our main hypothesis. Further, the correlation between the two proxies for financial sector development is positive and very high. Moreover, we observe a positive and high correlation between GDP per capita and the interest rate, which may capture that the policy rate often is set to be high during periods of strong economic growth. In contrast, the correlation between GDP per capita and inflation as well as unemployment is low and positive, where the latter is less intuitive.

	Household credit	Corporate credit	Patstat	Prv_patstat
GDP per capita	**-0.22**	**0.32**	−0.17	−0.27
Household credit	1.00	0.09	NA	NA
Corporate credit	0.09	1.00	**-0.41**	**-0.48**
Private sector credit	**0.66**	**0.81**	NA	NA
Private sector bank credit	0.69	0.71	NA	NA

Table 3: The table displays the correlation for detrended Household credit and Corporate credit with GDP per capita, Private sector credit, Private sector bank credit, Patstat and *Prv_patstat*. Correlations of particular interest are displayed in bold. The correlations are based on data from the last quarter in 1980 and onwards.

From table 3, we observe a negative correlation between GDP per capita and Household credit, and a positive correlation between GDP per capita and Corporate credit. This indicates that the long-run relationship between GDP per capita and Household credit *may* be negative, in accordance with our hypothesis, but that the long-run relationship between GDP per capita and Corporate credit *may* be positive, which is not in line with the corresponding hypothesis. The size of these correlation estimates is smaller than that between GDP per capita and Private sector credit in table 2, which is expected. Further, we note that the correlation between Household credit and Private sector bank credit is higher than that with Private sector credit, which is reasonable given that households generally obtain credit from banking institutions. In comparison, the correlation between Corporate credit and Private sector credit is higher than that with Private sector bank credit – indicating that some firms obtain credit from e.g. other firms and non-banking institutions. Further, all correlations displayed between financial sector development proxies are positive and strong. Finally, we observe that the correlation between Corporate credit and the two patent variables is negative, which *may* capture a negative long-run relationship between Corporate credit and patent applications. This also holds for the correlation between GDP per capita and the patent proxies, which is slightly surprising.

3.3 Pretesting of variables

An initial step of time series analysis is to identify the character of each series in order to treat them correctly. This includes determining the order of integration, which identifies number of differencing operations needed to make the series stationary. This step is highly relevant for identifying the adequate model framework.

The main method used to identify the order of integration is the Augmented Dickey-Fuller test (ADF). The test is based on a transformation of the underlying Autoregressive (AR) process of each series x_t, which can have the following form:

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \cdots + \alpha_k x_{t-k} + \tau t + e_t \tag{1}$$

Where α_0 is a constant, t is a time trend variable, $\alpha_1, \ldots, \alpha_k$ and τ are coefficients and e_t is the error term. In order to determine whether a constant, constant and trend or neither should be included in the specification, we perform visual inspection of the variables. If $\alpha_1 \in (-1, 1)$, the series is either stationary around zero, a constant or follow a trend-stationary process, depending on whether α_0 and τ are included. If $\alpha_1 = 1$, the series is a unit root process; it is either a random walk without a drift in the case with no constant, or a random walk with a drift with or without a time trend.

The ADF-test transforms the underlying AR-process into the following model (Enders, 2014):

$$\Delta x_t = \alpha + \gamma x_{t-1} + \delta t + \beta_1 \Delta x_{t-1} + \beta_2 \Delta x_{t-2} + ... + \beta_k \Delta x_{t-k} + e_t \tag{2}$$

The added β_k augmentation terms are added to capture all serial correlation in the data. We denote the case when the series has neither a constant nor a trend ($\alpha = \delta = 0$) as case 1. When the series has a constant but no trend we denote this as case 2, and when the series has a constant and a trend we denote this as case 3. The null hypothesis of the test is that $\gamma = 0$, which is the same as testing that $\alpha_1 = 1$ in equation 1. If the null hypothesis is rejected, the series follow a stationary process. The number of lags used in each test is based on Akaike's information criterion, Schwarz's Bayesian information criterion and White noise testing.

The Augmented Dickey-Fuller test is generally a good method for identifying the order of integration. However, if there exists a structural break in the data the critical values of the ADF-test may lead one to draw the wrong conclusion (Perron, 1989). Hence, Perron (1989) developed another type of unit root test, which is more powerful when there exists a one-time structural break. We will use the Perron test if the visual representation suggests that there exists a structural break in the series.

In order to account for the structural break the Perron test includes a dummy variable, allowing for two distinct regimes in the series before and after the break. The series is then detrended and the test is performed on the residual series. The critical values of the test vary depending on the time period of the structural break. This is denoted by $\lambda = \frac{\tau}{T}$, where τ is the observation number for the time period with the structural break and T is the number of observations. The results from the Augmented Dickey-Fuller test and the Perron test are presented in Table 5 and 6 below.

	Level			1st diff		
Variable	Lags	Statistic	Critical value	Lags	Statistic	Critical value
GDP per capita	2	-2.450	-3.437	2	-5.063	-2.884
Private sector credit	5	-2.864	-3.438	5	-3.699	-1.950
Private sector bank credit	4	-2.844	-3.438	3	-3.304	-1.950
Household credit	4	-1.446	-3.443	3	-2.999	-1.950
Corporate credit	5	-2.671	-3.443	5	-3.803	-2.886
Patstat	9	-2.612	-2.887	7	-4.677	-1.950
Prv_patstat	7	-2.391	-3.443	6	-3.779	-1.950
Interest rate	6	-2.876	-3.438	6	-3.084	-1.950
CPI rate	5	-2.894	-3.438	6	-6.136	-1.950

Table 4: The table displays the Augmented Dickey-Fuller tests for each variable, with the null hypothesis for each test that the variable has a unit root. The table displays statistic and critical values at 5% significance level for the variables in levels and in first differences. The number of lags are chosen based on Akaike's information criterion, Schwarz's Bayesian information criterion as well as white noise testing of the error terms. Note that the critical value varies depending on the composition of the time series; when the Critical value is -3.437 or -3.438 or -3.443 (-2.884 or -2.886) (-1.950) the test is a case 3 (case 2) (case 1). Moreover, the critical values for the same case varies slightly across the variables. This is caused by two factors impacting the number of observations used in the test, and in turn the critical values. First, the tests for Household credit, Corporate credit, Patstat and Prv_patstat are all based on a smaller sample. Further, the number of lags used changes the number of observations in the test, explaining why e.g. the critical value for GDP per capita is not the same as for Private sector credit.

Table 5 presents the results from the Augmented Dickey-Fuller test, which includes all series except unemployment. By observing the test statistics and critical values for the level variables, the null hypothesis of a unit root cannot be rejected in any case. When taking the first difference of the variables, the null hypothesis of a unit root can be rejected at 5% significance level for all variables. Hence, they are I(1) processes.

Regarding unemployment, we perform the Perron test of the variable in levels as there seems to exist a structural break in the data around 1992-Q1-1993-Q2. This is expected given that the unemployment rate rose dramatically in Sweden during the 1990s crisis, and then persisted at a higher rate post crisis than during the pre-crisis period. We present the result of the test in Table 6 below. While the critical value generally depends on the time period of the structural break in the test, it remains the same for all possible time periods of structural break between 1992-Q1 and 1993-Q2. Note that the test of the unemployment variable in first differences is based on the critical values from the ADF-test.

	Level	1st diff
Test statistic	-3.540	-5.080
Critical value	-3.72	-1.950

Table 5: The table displays the unit root testing for the unemployment variable, executed using the Perron test. The critical value of the test in levels is based on Perron table IV.B, with $\lambda \approx 0.4$. The critical value of the test in first differences is based on the Augmented Dickey-Fuller test, case 1. The first test is estimated with 5 lags, the second with 6 lags. The decision rule is based on 5% significance level.

Based on the results in Table 6, we conclude that unemployment follows a (1) process.

4 Methodology

4.1 Methodological considerations

To comprehensively explore the causal and relational dynamics between economic performance and financial sector development over time, multivariate time series analysis is the proper choice for a number of reasons. First, to thoroughly understand the interaction between our variables a multivariate framework is a necessity, making the Vector Autoregressive (VAR) framework a suitable choice. The basic VAR framework takes into account the lagged effects of the variables on themselves and the associated variables. It consequently allows for multivariate analysis while also addressing endogeneity problems. This feature is particularly desirable when analyzing macroeconomic variables, where the direction of causality may be multidirectional – such as in the case of the relationship between Private sector credit and GDP per capita. However, since it is established that our series are integrated of order 1, the VAR framework in its basic form is not well suited if the series turn out to be cointegrated – a concept explained in detail further on. In this case, we turn to the Vector Error Correction (VEC) framework, an extension of the VAR model that have the additional feature of allowing for analysis of non-stationary variables with joint stochastic trends, as well as the analysis of both long- and short run dynamics of the relations in question (Enders, 2014).

In addition, our framework allows for the investigation of individual cases. Cross country analyses indeed provide useful insights in the relationship between economic performance and financial sector growth at large. However, the impact of financial sector development on economic growth and/or innovation may vary much across countries, due to the institutional quality, regulatory differences and compositional setup of the financial sector in individual states (see for example Levine et al., 2000; Neusser and Kugler, 1998; De Gregorio and Guidotti, 1995; Law and Singh, 2018; Peia and Roszbach, 2015; Levine et al., 2000; Demetriades and Hussein, 1996). When focusing on the finance-growth relationship in a single country, time series methods such as the VEC framework are more suitable as these country specific dynamics are taken into account in more detail.

4.2 Vector Autoregressive Models (VAR)

As mentioned, the VAR framework is useful in analyzing interactions between variables over time when the variables impact each other in multiple directions. The interactions are captured by the lagged effects of the variables on themselves and on each other. A reduced VAR(p) model in standard form with p lags is defined as follows;

$$\mathbf{y}_t = \mathbf{a} + \mathbf{A}_1\mathbf{y}_{t-1} + \cdots + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{e}_t, \tag{3}$$

where $\mathbf{y}_t = (y_{1t}, \ldots, y_{kt})'$ is a $(K \times 1)$ vector of values of K endogenous variables at time

t, $\mathbf{a} = (a_1, \ldots, a_k)'$ is a $(K \times 1)$ vector of intercept terms, and $\mathbf{A}_i =$ terms are $(K \times K)$ coefficient matrices. The inclusion of the intercept vector allows the variables to have a non-zero mean. Note that in our case, a time period t corresponds to a quarter. Further, $\mathbf{e}_t = (e_{1t}, \ldots, e_{Kt})'$ is a $(K \times 1)$ vector of error terms with the following properties; the expected values $E(\mathbf{e}_t) = 0$, the variance-covariance matrix $E(\mathbf{e}_t\mathbf{e}_t') = \Sigma_{\mathbf{e}}$, and the autocorrelations $E(\mathbf{e}_t\mathbf{e}_s') = 0$ for all $s \neq t$ (Lütkepohl, 2005). As the expected values of the error terms are zero, the constant variance and the autocovariances for the individual error terms being zero, the error terms follow a white-noise process. Note that the covariance between the error terms is constant and allowed to be non-zero, implying that shocks to the system can be correlated (Enders, 2014).

In the standard VAR-framework, the direction of causality among the variables is typically investigated using the Granger causality test. The Granger causality test examines whether one variable is useful in predicting another, that is, whether a certain variable contains information that helps forecast another variable (Granger, 1969). In particular, this test investigates whether the lags of one variable are present in the equation for another variable (Enders, 2014). We will investigate the direction of causality in a slightly different manner however, see section 4.3. Furthermore, VAR models are considered stable when the absolute values of all eigenvalues of A_1 are less than unity, that is, if $\det(\mathbf{I}_K - \mathbf{A}_1 z - \cdots - \mathbf{A}_p z^p) \neq 0$ for all $|z| \leq 1$. Similar to AR models, this suggests that in order for the series to be stable, the roots of the lag polynomial lie outside the unit circle, that is, that they are stationary (Enders, 2014).

It is important to note that the VAR model only captures short run effects of the variables on each other. In this study, we are especially interested in investigating the (possibility of) **long-run relationship(s)** across the variables; in particular across the financial sector development proxies and GDP per capita. In order to do this, we turn to an extended version of the VAR framework; the Vector Error Correction Model (VECM). The second reason for using a VEC model is that the series are unit roots in levels and if they are **cointegrated**, a VAR model in first differences will be biased due to an (or multiple) omitted cointegration matrix (Enders, 2014). In the following section, we will provide an overview of VEC models and the concept of cointegration.

4.3 Cointegration and the Vector Error Correction Model (VECM)

The processes examined in this study are established as non-stationary processes – meaning that they appear to have trends and/or changing variances, which is a common feature with many macroeconomic processes. Intuitively, many economic variables depend heavily on their previous values and will at times have their courses altered by stochastic shocks or major movements in the economy. Since this paper deals with non-stationary original series, and not their rates of change, we are required to apply models that can accommodate irregular features of the data. If one simply estimates a VAR in first differences when having non-stationary macroeconomic variables, the model ignores these features and consequently omits important components of the relationships across the variables. Therefore, it is desirable to develop a model that includes the series in their original form. Macroeconomic variables especially often have common stochastic trends such that there exists equilibrium relationships among the variables (Lütkepohl, 2005). By using the methodological framework of the Vector Error Correction (VEC) model, these equilibrium relationships can be used to estimate a balanced model – i.e where all components are integrated of the same order – and thus take these interesting features into account.

An important feature is that the VEC framework makes it possible to extend the VAR model and investigate the relationship across non-stationary variables in levels if they are **cointegrated**. This occurs if there exists a linear combination of the unit root variables which is stationary. If the variables are cointegrated, they have a **long-run relationship** with one another. This means that the VEC framework enables analysis of the long-run relationships as well as the short run dynamics between the variables simultaneously (Enders, 2014).

The definition of cointegration, first outlined by Engle and Granger (1987), is as follows. The components in a (n x 1) vector of economic variables $x_t = (x_{1t}, x_{2t}, \dots, x_{nt})$ are cointegrated of order d,b-or $x_t \sim CI(d, b)$-if they are integrated of order d and if a vector $(\beta_1, \beta_2, \dots, \beta_n)$ exists such that the linear combination $\beta_1 x_{1t} + \beta_2 x_{2t} + \dots + \beta_n x_{nt} = 0$ is integrated of order $(d - b)$, where $b > 0$. When any variable in the system deviates from the long-run equilibrium, an equilibrium error occurs; $e_t = \beta x_t$. In order for the variables to inhibit joint stochastic trends, these shocks must be temporary. This implies that the equilibrium errors $e_t \sim I(0)$ if all components in x_t are I(1), and the variables in x_t are thus cointegrated of order (1,1), denoted as $x_t \sim CI(1, 1)$ (Enders, 2014). Hence, by re-arranging $\beta_1 x_{1t} + \beta_2 x_{2t} + \dots + \beta_n x_{nt} = 0$ to $\beta_1 x_{1t} - \beta_2 x_{2t} - \dots - \beta_n x_{nt}$, I(1) variables can be included in an extended VAR framework in levels, as their linear combination is stationary. Cointegration thus suggests that in the long-run, two or more variables move simultaneously and together, even if exogenous shocks may cause them to temporarily deviate from their long-run equilibrium relationship. When the variables deviate, the economic relationship between the variables ensures a reversion back to the long-run equilibrium (Lütkepohl, 2005).

To be able to confirm the existence of one or more cointegrating relationship in the model, this study relies mainly on the Johansen procedure (Johansen, 1988) which focuses on the rank of the cointegrating matrix, using the maximum likelihood estimation method. This method has several advantages over the Engle-Granger methodology, as will be discussed in section 5.4. If the test of the rank of the cointegrating matrix confirms the existence of one or multiple cointegrating relationships among the variables, the VAR model in question is transformed to a VEC model. However, before turning to this test, we will present the model specification.

The reduced VECM specification with r cointegrating relationships is as follows:

$$\Delta \mathbf{y}_t = \boldsymbol{\alpha}\boldsymbol{\beta'}\boldsymbol{x}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \mathbf{y}_{t-i} + \boldsymbol{\gamma} + \boldsymbol{\tau} t + \boldsymbol{e}_t, \tag{4}$$

where $\mathbf{y}_t = (y_{1,t}, \ldots, y_{k,t})$ is a $(K \times 1)$ vector of variables, $\mathbf{x}_t = (y_{1,t}, \ldots, y_{k,t}, t)$ is a $((K+1) \times 1)$ vector of variables which includes a time trend t, and $\boldsymbol{\gamma}$ and $\boldsymbol{\tau}$ are $(K \times 1)$ vectors of parameters. Further, $\boldsymbol{\alpha}$ is a $(K \times r)$ matrix of speed of adjustment parameters, and $\boldsymbol{\beta'}$ is a $((K+1) \times 1)$ cointegrating matrix with the first parameter normalized to 1. Further, $\sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i$ represents the coefficient matrices for the lagged short-run effects of the variables in first differences, where $\boldsymbol{\Gamma}_i = -(\mathbf{A}_{i+1} + \cdots + \mathbf{A}_p)$. Finally, $\boldsymbol{e}_t$ is a $(K \times 1)$ vector of error terms with the same properties as in the standard VAR model. Equation 4 can also be written as;

$$\Delta \mathbf{x}_t = \boldsymbol{\Pi} \mathbf{x}_{t-1} + \sum_{i=1}^{p-1} \boldsymbol{\Gamma}_i \Delta \mathbf{x}_{t-i} + \boldsymbol{\gamma} + \boldsymbol{\tau} t + \boldsymbol{e}_t, \tag{5}$$

where the $(K \times r)$ matrix $\boldsymbol{\Pi} = \boldsymbol{\alpha}\boldsymbol{\beta'} = -(\mathbf{I}_K - \mathbf{A}_1 - \cdots - \mathbf{A}_p)$ represents the long-run cointegrated relationship(s). Thus, the $\boldsymbol{\Pi}$ and $\boldsymbol{\Gamma}_i$ matrices are based on the $\mathbf{A}_1, \ldots, \mathbf{A}_p$ coefficient matrices from the standard VAR model. Importantly, the $\boldsymbol{\alpha}$ vector show the speed and direction of adjustment towards the long-run equilibrium-the error correction-when the variables deviate from the equilibrium relationship(s). If a speed of adjustment coefficient is not significantly different from zero, the corresponding variable is said to be **weakly exogenous**. As all speed of adjustment parameters are coefficients of the I(0) term $\boldsymbol{\beta'}\boldsymbol{x}_{\boldsymbol{t-1}}$, it is possible to conduct inference through the standard t-test (Enders, 2014). Moreover, the constant $\boldsymbol{\gamma}$ denotes a linear time trend in the levels while $\boldsymbol{\tau}$ is a quadratic time trend in the levels of the data as equation 4 and 5 are estimated in first differences. Note that all terms in equation 4 and 5 are I(0) which makes the system of equations balanced. Finally, the stability condition of the VEC model is that the companion matrix of a model with K endogenous variables and the rank r has $K - r$ unit eigenvalues. [7]

Depending on the structure of the data, there are five variants of this model outlined by the Johansen framework. The model in this paper adheres to the second case with a **restricted trend**, where $\boldsymbol{\tau} = 0$. This implies allowing for a linear trend in the coin-

[7] The stability condition holds for all of our estimated models, see the results in appendix C.

tegrating relationship as well as a linear trend in the levels of the data, while excluding the possibility of a quadratic trend in the levels. This decision is made based on visual inspection of the data and because we do not reject the existence of a time-varying constant $(\mu + \rho t)$ in the long-run relationship(s) across the variables. The final model with one cointegrating relationship has the following form:

$$\Delta \mathbf{y}_t = \boldsymbol{\alpha}(\mu + \beta_1 y_{1,t-1} + \cdots + \beta_k y_{k,t-1} + \rho t) + \sum_{i=1}^{p-1} \boldsymbol{\Gamma_i} \Delta \mathbf{x}_{t-i} + \boldsymbol{\gamma} + \boldsymbol{e}_t. \tag{6}$$

This specification allows for trend stationarity in the cointegrating equation.

Regarding causality, we can investigate both short-run and long-run Granger causality in the VEC framework. As the variables are cointegrated and nonstationary in levels, the Granger causality test used in a standard VAR-framework cannot be used as that would exclude the long-run relationships across the variables. Instead, significant speed of adjustment terms provide evidence of long-run causality. If the speed of adjustment terms are insignificant, the variable is **weakly exogenous**; intuitively, this would suggest that the variable appurtenant to the insignificant speed of adjustment parameter drives the dependent variable but not necessarily the other way around. In order to investigate short-run Granger causality, we perform the Wald test of the short-run effects (Enders, 2014). Notably, this serves as an additional investigation of the short-run dynamics between the variables, on top of the estimated short-run lagged effects already incorporated in the VEC models.

As discussed, we are interested in the long-run relationship between financial sector development and economic growth in Sweden. This includes investigating the household channel, corporate channel and innovation channel through various models. In the simplest model there exists one cointegrating relationship, and $\mathbf{y_t} = (y_t, f_t)$ where y_t stands for log of GDP per capita and f_t stands for a proxy for financial sector development (in logs). Below we present the model in decomposed form, with the coefficient in front of the first variable in the cointegrating relationship normalized to 1:

$$\Delta y_t = \alpha_y(\mu + y_{t-1} + \beta_1 f_{t-1} + \rho t) + \lambda_y \Delta y_{t-i} + \lambda_f \Delta f_{t-i} + \gamma_y + e_{y,t}, \tag{7}$$

$$\Delta f_t = \alpha_f(\mu + y_{t-1} + \beta_1 f_{t-1} + \rho t) + \lambda_y \Delta y_{t-i} + \lambda_f \Delta f_{t-i} + \gamma_f + e_{f,t}. \tag{8}$$

These equations are quite intuitive. In order for the finance-growth relationship to be negative, the β_1 coefficient is estimated to be positive as $\mu + y_{t-1} + \beta_1 f_{t-1} + \rho t = 0$ can be rewritten as $y_{t-1} = -\mu - \beta_1 f_{t-1} - \rho t$.

4.3.1 Cointegration testing

As mentioned above, we use procedures from the Johansen methodology (1988) to establish any existence of one or more cointegrating relationships. After establishing that the variables are I(1), the procedure proceeds by identifying the rank of the cointegrating matrix Π_{t-1}. The rank corresponds to the number of cointegrating relationships in the system as the rank identifies number of linearly independent rows in the Π_{t-1} matrix. This is denoted by Johansen as the cointegrating space, and the estimation of the cointegrating space is based on Johansen's maximum likelihood estimator. We use the trace statistic, which is calculated based on the eigenvalues of the cointegrating matrix. After the rank of the cointegrating matrix is decided, we proceed by estimating the VEC model through maximum likelihood estimation.

To illustrate the method, the trace statistic is calculated as follows. Consider a standard VEC model of lag length 2:

$$\Delta x_t = A_0 + \Pi x_{t-1} + \Gamma \Delta x_{t-1} + e_t. \tag{9}$$

The characteristic roots of the Π matrix for a VEC model of this structure will generate three values; λ_1, λ_2 and λ_3. These values will then be inserted in the following equation and tested against the following hypothesis:

$$H_0(r_0) : \text{rank } (\Pi) = r_0 \text{ versus } H_1(r_0) : \text{ rank } (\Pi) > r_0.$$

The formula for the trace statistic is then as follows:

$$\lambda_{trace}(0) = -T[ln(1 - \lambda_1)] + ln(1 - \lambda_2) + ln(1 - \lambda_3)].$$

If the calculated value exceeds the critical value associated with the sample size T, we can reject the null hypothesis of no cointegrating vectors, and accept the alternative hypothesis of one or more cointegrating vectors in the system of equations. This procedure is then repeated until the test statistic does not exceed the associated critical value. This means that for the consecutive test, where the null hypothesis of one cointegrating relationship versus two or more cointegrating relationships is tested, the third term in the trace statistic is eliminated. As an illustration:

$$\lambda_{trace}(1) = -T[ln(1 - \lambda_1) + ln(1 - \lambda_2)].$$

The same logic follows if the test proceeds to conclude a higher rank (Enders, 2014).

Note that the number of lags used in the test is decided based on the following lag selection criteria; Final Prediction Error (FPE), Akaike's informaiton criterion (AIC), Quinn information criterion (HQIC) and Schwarz's Bayesian information criterion (SBIC).[8] These criteria are calculated based on an estimation of a simple VAR model in levels. The criteria and the rank testing results are presented for each model in appendix B.

4.4 The Gregory-Hansen test

As a robustness check, we apply the Gregory-Hansen test for cointegration in models with regime shifts, in order to investigate the presence of any structural breaks in our processes. This test is chosen in lieu of, for instance, the Chow test for several reasons. First, the Gregory Hansen test does not require the point of the fixed structural break to be known in advance (Gregory & Hansen, 1996). In addition, the Chow test is more suitable for linear regression models, and may fail to take into account important mechanisms in unit root processes (Enders, 2014). The Gregory-Hansen test instead is designed to discover structural breaks in cointegrating relationships, which makes it the more suitable choice. Further, standard cointegration tests may fail to acknowledge that the cointegrating vector may be time-variant. This residual-based test allows for the alternative hypothesis of a regime shift in either the intercept or the coefficient vector as an entirety; and can be considered as a multivariate extension of the univariate Perron test for example. Gregory and Hansen describe the test as particularly beneficial since it *"prevents informal data analysis (such as the visual examination of time series plots) from contaminating the choice of breakpoint"* (Gregory & Hansen, 1996, p. 100).

We apply the version of the test allowing for a regime shift and trend; this version allows for a change in slope of the relationship as well as a structural change in the relationship between the variables over time. This choice is made based on the character of the series. The regime change is modeled through a dummy variable, defined by the authors in the following way:

$$\phi_{t\tau} = \begin{cases} 0 \text{ if } t \leq [n\tau] \\ 1 \text{ if } t > [n\tau], \end{cases} \qquad t = 1, \ldots, n,$$

where the "unknown" parameter $\tau \in (0, 1)$ gives the relative point in time of the change. The model specification of the version in question is as follows:

$$y_{1t} = \mu_1 + \mu_2 \phi_{t\tau} + \beta t + \alpha_1^\top y_{2t} + \alpha_2^\top y_{2t} \phi_{t\tau} + e_t,$$

where y_1t and y_2t are I(1) and e_t is I(0). Further, μ_1 denotes the intercept before the shift, while μ_2 is the intercept at the shift point. βt denotes the time trend, and α_1 and α_2 represents the cointegrating slope coefficients before and after the regime change respectively (Gregory & Hansen, 1996). The null hypothesis is that of no cointegrating relationship between the variables. The relation is estimated by OLS, followed by a unit

[8]The number of lags that the majority of the criteria recommends are then used in the rank test. If this procedure provides two possible lag choices, we perform the cointegration testing with both lag options.

root test on the regression errors.

4.5 Engle-Granger procedure for estimating nonlinear VEC model

Based on the finding in the literature that the finance-growth relationship may be nonlinear, it is reasonable to alter the model to account for nonlinearities in the main relationship. We do this as a robustness check, as the estimated impact of finance on economic growth in the cointegrating relationship will be downward biased if the finance-growth relationship indeed takes a form similar to the inverted-u shape.

We take nonlinearity into account in the VEC framework by using the Engle-Granger methodology for cointegration (Engle and Granger, 1987) and adding a squared term to the model. In comparison to the Johansen methodology where the VEC model is estimated in one step, the Engle-Granger estimation involves two steps. This enables us to add a squared term in the cointegrating relationship to account for nonlinearity, without it being included as a dependent variable in the system of equations. The squared term used is the squared level financial sector development proxy, similar to the procedures used in cross-country studies (see e.g Cecchetti and Kharroubi, 2012 and Arcand et al. 2015).

Before presenting the methodology further however, it is important to highlight a limitation. Using a squared term for nonlinearity is based on the assumption that the finance-growth relationship is symmetric, as highlighted by Law and Singh (2014). This means that the impact of finance on growth decreases after the threshold level of financial development symmetrically to the increase before the threshold level. However, it could be that the relationship takes a different form, e.g., having a less steep slope after the threshold level. Indeed, Law and Singh (2014) find that the impact of finance on growth may be slightly smaller after the threshold level in absolute terms. Nonetheless, we will test for nonlinearity in the diagnostic checking by using a squared term as an indication of whether there exists a nonlinear cointegrated finance-growth relationship. It should be noted that an inverted-u shaped finance-growth relationship allows for negative values for GDP per capita at certain levels of financial development which is not plausible. If we do find a nonlinear cointegrated relationship, we will thus only discuss the estimated nonlinear relationship for the levels of financial development that exist in the data.

The Engle-Granger procedure for cointegration with I(1) variables is as follows, as explained by Enders (2014). After ensuring that all variables are integrated of order 1, the long-run relationship across the variables is estimated through ordinary least squares. In our case, this corresponds to the following estimation:

$$y_t = \alpha + \beta_1 f_t + \beta_2 f_t^2 + \tau t + e_t, \tag{10}$$

$$\hat{e}_t = y_t - \hat{\alpha} - \hat{\beta}_1 f_t - \hat{\beta}_2 f_t^2 - \tau t, \tag{11}$$

where y_t stands for log in GDP per capita, f_t stands for a level proxy for financial sector development, and t is a time variable. In contrast to Engle-Granger, we add the time variable to allow for trend stationarity, and the squared term to allow for nonlinearity as explained above. Note that we include the financial sector development proxy in levels in line with Arcand et al. (2015), in contrast to the earlier estimations.[9]

If the variables indeed are cointegrated, the residual series $\{\hat{e}_t\}$ must be stationary. Then the VEC model is estimated implicitly by adding the lagged residual series as an exogenous variable in a VAR estimation (Enders, 2014), i.e by estimating a VARX model. This VEC or VARX model in first differences with one cointegrating relationship can be written as;

$$\Delta \mathbf{y}_t = \mathbf{a} + \mathbf{A}_1 \Delta \mathbf{y}_{t-1} + \cdots + \mathbf{A}_p \Delta \mathbf{y}_{t-p} + \mathbf{B}\hat{e}_t + \mathbf{e}_t, \tag{12}$$

where $\hat{e}_t$ is the residual series estimated in the previous step, added as an exogenous term, and $\mathbf{B}$ is a vector of speed of adjustment parameters.

As mentioned, the residual series $\{\hat{e}_t\}$ must be stationary in order to estimate the VEC model through e.g. the Augmented Dickey-Fuller test (Enders, 2014). However, as equation 10 is estimated based on nonstationary variables, the estimated coefficients (α, β_1, β_2 and τ) converge faster to their probability limits (Stock, 1987). Consequently, the null hypothesis of a unit root in the residual series needs to be rejected based on larger critical values than those in the standard Dickey-Fuller table. Because of this, we use the critical values *Table C: Critical Values for the Engle-Granger Cointegration Test* provided by Enders (2014) as decision criteria. It is important to note that these critical values are aimed for estimations with linear variables, and hence we only use them as approximations.

Finally, the Engle-Granger methodology has its limitations. The procedure does not offer a systematic estimation method when there exists multiple cointegrating vectors (Enders, 2014). Naturally this is an issue as more than three dependent variables are used in several estimations here. Because of this, we mainly use the Johansen procedure when estimating the VEC models. It should moreover be taken into account that the residual series vary depending on which variable is used as dependent variable in the initial OLS regression of the long-run relationship. As a result, the testing for cointegration may vary depending on which residual series is used when using limited sample sizes (Enders, 2014).

[9]Note that we have performed Augmented Dickey-Fuller testing of the financial sector development proxies in levels and in squared terms as well, to be sure that all variables in the cointegrating relationship are I(1) variables. The results will not be presented, but can be obtained on request.

5 Results

In this section, we present the estimated baseline VEC models, including and excluding the interest rate, using the following proxies for financial sector development: Private sector credit, Corporate credit, and Household credit. This includes the estimated long-run relationships across the variables, the estimated speed of adjustment parameters, and constants, where the latter corresponds to the time trend of the variables in levels. For simplicity, the short-run estimates for each model are presented in appendix C, along with the results of short-run Granger causality tests. However, we do discuss the directions of short-run Granger causality in the text. All models presented in the first and second subsections have one cointegrated relationship, based on the Johansen rank test which is presented for each model in appendix B, along with the results from the lag selection procedure. Furthermore, results stemming from models including patent data are presented in section 5.3.

5.1 VECM estimations with Private sector credit

Below we display the estimated long-run relationships between Private sector credit and GDP per capita (baseline model), and between Private sector credit, interest rate and GDP per capita.

	Baseline model, Private sector credit		Interest rate added	
	0 lag	1 lags	0 lags	1 lags
α_y	-0.035***	-0.034***	-0.044***	-0.032***
α_f	0.039***	0.011	0.051***	0.010
α_r	NA	NA	-0.181	-0.130
β_0	-122.838	-140.528	-115.834	-134.5529
β_f	0.351***	0.499***	0.321***	0.539***
β_r	NA	NA	-0.001	0.002
ρ	-0.130***	-0.139***	-0.140***	-0.140***
c_y	0.115***	0.038*	0.215***	0.040***
c_f	0.102***	0.116**	-0.015	0.014
c_r	NA	NA	-0.057	-0.092

Table 6: The table displays the VECM estimation results for the estimated baseline model with Private sector credit as proxy and the model with the interest rate added (both have a restricted trend and rank 1). The α_y (α_f) (α_r) parameters denotes the estimated speed of adjustment parameters for the equation with Δ GDP per capita (Δ financial sector development proxy) (Δ interest rate) as dependent variable. β_0, β_f, β_r and ρ are the estimated parameters for the cointegrated relationship, with β_0 being the estimated constant, ρ being the estimated time trend and β_f and β_r showing the effect of lagged financial sector development proxy and lagged interest rate respectively. The effect of lagged GDP per capita is normalized to 1 in the cointegrating relationship. The c_y (c_f) (c_r) denotes the estimated constant for each equation. The *** denotes 1% significance level, ** denotes 5% significance level and * denotes 10% significance level. See appendix C For the estimated short-run coefficients.

The baseline model includes GDP per capita and Private sector credit to GDP. The estimated model reveals a negative and significant long-run relationship between GDP per capita and Private sector credit to GDP (as indicated by the positive β_f) for the period spanning from 1971 to 2020. The negative long-run relationship becomes more apparent when including one lag. Given that we have identified significant speed of adjustment parameters, it is crucial to include the cointegrating relationship in the model to capture the long-run dynamics accurately. At zero lags, both GDP per capita and Private sector credit are endogenous to the model as indicated by the significance of both speed of adjustment parameters, suggesting long-run impacts on one another. However, given the insignificance of α_f, Private sector credit to GDP appears to be weakly exogenous when adding one lag. This implies that while Private sector credit impacts GDP per capita in the long-run, the reverse causal direction is not clearly observed. This finding may seem surprising, as one might expect GDP and financial well-being to reinforce each other in the long-run, especially considering that economic growth often stimulates corporate investments and expansions. However, it is possible that growth in the financial system may instead be facilitated by foundational activities, such as the establishment of regulatory frameworks and institutions, which may not directly depend on the current state of the economy. Further, the estimated α_y parameter suggests that GDP per capita adjusts relatively slowly and negatively to deviations from the long-run equilibrium, for instance, in the presence of a credit boom.

Overall, these are intriguing findings. Similar to Hansson and Jonung (1997), we find that GDP per capita adjusts negatively to abnormally large credit booms; however, we do not find with certainty that finance and growth reinforce each other. In contrast to Hansson and Jonung, the long-run relationship between GDP per capita and Private sector credit is negative when using more recent data. This indicates notable changes, not only over time, but also as the financial sector has dramatically advanced simultaneously.

Further, the short run dynamics does not yield any significant effects of the variables on each other; the lagged differenced variables only yield significant effects on themselves. We do however observe that lagged changes in GDP per capita and Private sector credit jointly Granger causes current changes in GDP per capita. Similarly, the two variables jointly Granger causes changes in Private sector credit. That is, combined, lagged values of Private sector credit and GDP per capita are useful in predicting current changes in both variables respectively. Finally, we find significant estimated constants for both GDP per capita and Private sector credit, i.e an estimated trend in levels. This suggests that additional variables are needed to better explain changes in GDP per capita and in Private sector credit, as expected. We also note that the estimated constant for GDP per capita is smaller when including 1 lag.

When incorporating the interest rate, the significant and negative long term relationship between Private sector credit and GDP per capita persists. The relationship is almost as strong with 0 lags as in the baseline model, and it strengthens when adding one lag. The interest rate however does not have a significant effect in the cointegrating relationship. Similar to the baseline models, the significant speed of adjustment parameters suggest that the cointegrating relationship is important. These speed of adjustment terms are similar to the case in the baseline model in terms of size and strength. Again, Private sector credit appears to be weakly exogenous, which is also the case for the interest rate. This suggests that at one lag, GDP per capita adjusts negatively to changes in Private sector credit in the long-run, while the opposite effect is not observed. As the interest rate is neither significant in the cointegrating relationship, nor adjusts to deviations from this relationship, we cannot find any long-run dynamics between the interest rate and the other two variables. This either suggests that GDP per capita and Private sector credit is not impacted in the long-run by the interest rate, and that the interest rate is not impacted in the long-run by the other two variables, or that these findings may be caused by e.g. omitted variables.

Again, the short run dynamics now only yield significant effects of the variables on themselves, but not on each other. Regarding Granger causality however, we find strong evidence that lagged changes in Private sector credit, interest rate and GDP per capita jointly Granger causes all three variables respectively. We also find evidence that the interest rate Granger causes changes in GDP per capita, and strong evidence that changes in the variables Granger cause changes on themselves for all three variables. Further, the estimated constant for Private sector credit becomes insignificant when including the interest rate in the model, which suggests that this model better captures growth in Private sector credit to GDP. For GDP per capita however, the constant remains. Additionally, the constant for the interest rate is insignificant. This is expected as the interest rate does not inhibit a strong trend over time.

5.2 VECM estimations with Corporate credit and Household credit

	Baseline model, Corporate credit		Interest rate added	
	0 lag	1 lags	0 lags	1 lags
α_y	-0.040	0.035*	-0.055**	-0.001
α_f	0.400***	0.280***	0.395***	0.340***
α_r	NA	NA	-0.313	-1.445
β_0	-85.805	-72.863	-85.106	-77.243
β_f	-0.090**	-0.222***	-0.010***	-0.185***
β_r	NA	NA	0.010**	0.011**
ρ	-0.082***	-0.070***	-0.072***	-0.060***
c_y	0.117***	0.010***	0.174***	0.119***
c_f	0.012	-0.013	-0.355***	-0.298**
c_r	NA	NA	-0.477	-0.070

Table 7: The table displays the VECM estimation results for the estimated baseline model with Corporate credit as proxy and the model with the interest rate added (both have a restricted trend and rank 1). See table 6 for additional notes.

In the baseline model with Corporate credit as proxy for financial sector development, the long-run finance-growth relationship is positive, in contrast to the models using Private sector credit as proxy. Corporate credit adjusts positively and relatively fast to deviations from the long-run relationship, given the large significant estimates for α_f. The estimated the speed of adjustment parameters for GDP per capita provide conflicting results; α_y is negative and insignificant when using 0 lags and positive and significant at 10% level when using one lag. This suggests that GDP per capita may be weakly exogenous in the Corporate credit-Growth relationship; GDP per capita impacts Corporate credit positively in the long-run, but not vice versa. This stands in contrast to the baseline model, where Private sector credit appears to impact GDP per capita negatively, but not vice versa. In this case, this is quite intuitive; as the economy strengthens, so does corporate incentives to invest and expand. However, Corporate credit may not be a large enough factor explaining GDP per capita to impact it in the long-run. This will be discussed further in section 7.1.

Regarding short-run causality we find strong evidence that lagged changes in Corporate credit Granger causes current changes in Corporate credit and GDP per capita. Furthermore, we find strong evidence that lagged changes in the two variables jointly Granger cause current changes in GDP per capita and Corporate credit. Moreover, the estimated constant is significant and positive for GDP per capita, while insignificant for Corporate credit.

When adding the interest rate to the baseline model with Corporate credit as proxy, we immediately observe that the constants for GDP per capita and Corporate credit are significant and large. In particular, the constant for Corporate credit is large and negative, which is not in line with the underlying data process as Corporate credit increases over time. Hence, this indicates that this model may be misspecified or that important variables are missing. Nevertheless, seeing to the results, we find the following long-run mechanisms. GDP per capita increases with Corporate credit – i.e the baseline results persist – and decreases with the interest rate; GDP per capita is higher when the interest rate is low, which is intuitively pleasing. Turning to the speed of adjustment parameters, we observe a strong and positive adjustment for Corporate credit to deviations from the long-run relationship. Further, GDP per capita adjusts negatively when using 0 lags, but this effect disappears when using 1 lag. In contrast, both speed of adjustment parameters the interest rate respectively are insignificant.

Regarding short-run causality, we find strong evidence that the variables jointly Granger cause changes in the interest rate and Corporate credit. Furthermore, we find evidence that Corporate credit (GDP per capita) Granger causes current changes in GDP per capita (interest rate). Finally, we find strong evidence that changes in the variables Granger cause changes in the variables for the interest rate and for Corporate credit. Also note that the estimations provide evidence of a negative effect of Corporate credit on GDP per capita in the short run.

Although the model with interest rate should be interpreted with care, the two models overall suggest that GDP per capita may be weakly exogenous in the GDP per capita-Corporate credit relationship, while Corporate credit increases fast when there is a positive deviation from the long-run relationship. When there is an economic boom, credit extended to non-financial corporations increase as firms invest in times of high overall demand. This response is faster than when using Private credit to GDP as proxy, i.e firms are more responsive to changes in the economic climate than the entire private sector. In contrast, it is slightly surprising that changes in Corporate credit does not precede changes in GDP per capita. This may be explained by Corporate credit constituting a smaller share of the factors impacting GDP per capita, compared to Private sector credit.

Moreover, the results show that Corporate credit behaves counter-cyclically in respect to itself – low levels of borrowing in the previous period appears to generate higher levels in the next. Further, we find the positive response in Corporate credit to an abnormally high interest rate in the previous period slightly unintuitive. If we are to speculate, this may be explained by the fact that the interest rate impacts firms' profits through multiple channels, and it being less instrumental in firms' borrowing and investment decisions. For example, a high interest rate may generate higher return on investments, and it indicates that the future economic climate may be more favorable. Further, the interest rate appears to be weakly exogenous to the long-run relationship; neither GDP per capita nor Corporate credit impacts the interest rate in the long-run. This is slightly surprising as one would expected the interest rate to be highly dependent on those two variables. However, the robustness check may reveal additional mechanisms further on.

Importantly, both models with Corporate credit as proxy for financial sector development have a positive finance-growth relationship. This suggests that the negative long-run relationship in the baseline model may be driven by the other factor included in the Private sector credit variable – Household credit. To verify this, we estimate a model with Household credit as proxy for financial sector development below. Note that we do not find a cointegrating relationship between GDP per capita and Household credit to GDP when estimating the model with these two variables only. However, when adding the interest rate we find a cointegrating relationship – hence we will display the output of this estimated VEC model in table 8. The intuition behind this disparity may be that this relationship depends relatively more on the interest rate than that between GDP per capita and Corporate credit or Private sector credit. Indeed, firms' borrowing decisions most likely depend relatively more on conditions in the economy, as that impacts whether their investments will be successful or not. In contrast, the decision to borrow for households in order to e.g. buy real estate is less sensitive to the direct effects of booms and recessions in the economy in terms of the overall demand and supply of goods, while the interest rate directly impacts the cost of borrowing and consequently the borrowing decision. This is also in line with the overall trend in the Household credit data process, which is less volatile than that of Private sector credit and Corporate credit.

	Baseline model (Household credit), interest rate added	
	0 lag	1 lags
α_y	0.006	0.016
α_f	0.111***	-0.000
α_r	2.866***	4.258***
β_0	-110.180	-111.122
β_f	0.228***	0.248***
β_r	-0.050***	-0.055***
ρ	-0.170***	-0.180***
c_y	0.104***	0.110***
c_f	0.148***	0.032
c_r	-0.006	-0.000

Table 8: The table displays the VECM estimation results for the estimated baseline model with Household credit as proxy and the model with the interest rate added (both have a restricted trend and rank 1). See table 6 for additional notes.

When using Household credit as proxy for financial sector development, we find that GDP per capita decreases as Household credit increases and the interest rate decreases in the long-run relationship. This shows that GDP per capita and Household credit move in the opposite directions to one another in the long-run, as in the case for Private sector credit. Seeing to the speed of adjustment parameters, we note that α_y is insignificant, α_f is significant and positive at 0 lags but insignificant at 1 lag, while α_r is overall positive and significant. At 0 lags, reasonably, the long-run mechanisms show that Household credit increases in response to abnormal GDP per capita growth or abnormal Household credit growth in the previous period. Hence, Household credit growth does not appear to behave counter-cyclically as Corporate credit does, which is sensible given that the underlying data process for Household credit is not very volatile. Further, at 0 lags it is observed that Household credit logically increases as the interest rate is abnormally low in previous period. However, at 1 lag, these long-run impacts of GDP per capita, Household credit and the interest rate on Household credit cannot be found, and hence Household credit may be weakly exogenous similar to GDP per capita. On the other hand, the interest rate adjusts positively at both 0 and 1 lag to abnormal large economic booms or Household credit booms in the previous period, and positively to a relatively low interest rate in the previous period.

In terms of short-run Granger causality, we find that changes in the variables Granger cause changes in themselves for Household credit and the interest rate. Furthermore, we find strong evidence that Household credit Granger cause the interest rate. Finally, we find strong evidence that all variables jointly Granger cause Household credit and the interest rate.

5.3 The innovation channel

In this section we discuss our results when incorporating our innovation proxies in the model. The corresponding tables can be found in appendix C for one of our patent variables.[10] For simplicity, we will comment both the baseline model, as well as the model with all control variables (the interest rate, CPI and unemployment). This differs from the estimated models without innovation, where the corresponding results with all control variables are presented in section 6. As the results in section 5.2 indicate that the long-run relationship between Corporate credit and GDP per capita is positive, we do not expect to find evidence in line with the theory presented in section 3. Indeed, this investigation is performed based on the hypothesis the GDP per capita-Corporate credit relationship being negative – if we do find results in line with the theoretical prediction by Cecchetti and Kharroubi (2019), this would contradict our earlier findings.

In order to support the theory by Cecchetti and Kharroubi (2019), we would need to make the following findings; first, the GDP per capita – Patent – Corporate credit cointegrating relationship would have to have a positive estimate for Corporate credit and negative estimate for patent. If so, GDP per capita decreases with Corporate credit and increases with patent (innovation). Secondly, the short-run impact of Corporate credit on patent would need to be negative. If so, the negative GDP per capita-Corporate credit relationship may be driven by growth in credit reducing the incentive to innovate, which in turn has a negative impact on GDP per capita in the long-run.

When estimating the VEC model with Patent, GDP per capita and Corporate credit we find one cointegrating relationship. At 0 lags, we find a significant long-run relationship, with GDP per capita decreasing with patent applications *and* with Corporate credit. This cointegrating relationship displays a negative long-run relationship between patents and GDP per capita and a negative long-run relationship between patents and Corporate credit. At 0 lags, only patents respond to this long-run relationship, and do so negatively. These results are inconvenient in multiple ways; they do not align with theory that innovation decreases with growth, and while the negative Corporate credit-growth relationship is in line with the theory by Cecchetti and Kharroubi, it contradicts our earlier findings. However, when adding one lag these results change dramatically. This estimation reveals a significant long-run relationship, where GDP per capita increases with Corporate credit and with Patents, and Patents decrease with Corporate credit. Further, Patents, Corporate credit and potentially GDP per capita all adjust positively to this relationship. As an example, innovation may adjust upwards in the event of an economic boom. Regarding the short-run impact of Corporate credit on Patents, we do not find any significant effect. These results are intuitive but do not support the hypothesis.

[10] We have estimated the model for both variables, but for simplicity we only include the results when using the *prv_patstat* variable. The results obtained from using the patstat variable can be obtained on request.

When adding all control variables, we again find inconvenient results at 0 lags; GDP per capita decreases with patent applications and with Corporate credit in the long-run relationship that includes the three variables. At one lag, we find that GDP per capita decreases with patent, while the estimate for Corporate credit is insignificant. Further, the short-run impact of Corporate credit is insignificant as well. These overall findings consequently does not support the theory outlined in section 2.3, based on Cecchetti and Kharroubi (2019).

6 Robustness

In this section, we display the results of additional models, allow for a structural break in the main long-run relationship and perform the nonlinearity investigation as a robustness check of our findings and methodology. Initially, we estimate the finance-growth relationship with Private sector bank credit as proxy for financial sector development in a smaller model. This allows us to investigate whether the findings regarding the GDP per capita-Private sector credit relationships may be mainly driven by lending from the domestic bank sector or from other actors. We display the result of the VECM estimations with and without the interest rate to present a robust comparison with the main results. Secondly, we proceed to present the estimated error correction terms for solely the relevant finance-growth relationship in models with all control variables. These estimated models are presented in their entirety in appendix C. Thirdly, we discuss the outcome of the Gregory Hansen test for structural breaks in the cointegrating relationship. Finally, we allow for nonlinearities in the main finance-growth relationship.

6.1 VECM estimations with Private sector bank credit

	Baseline model, Private sector bank credit		Interest rate added	
	0 lag	1 lags	0 lags	1 lags
α_y	-0.026***	-0.023***	-0.032***	-0.026***
α_f	0.026***	0.002	0.033***	-0.002
α_r	-	-	-0.231	-0.032
β_0	-113.882	-141.4806	-109.092	-118.643
β_f	0.235	0.458***	0.233*	0.455***
β_r	-	-	-0.010	-0.008
ρ	-0.105***	-0.109***	-0.117***	-0.118***
c_y	0.097***	0.005	0.181***	0.541***
c_f	0.097***	0.059	0.012	0.024
c_r	-	-	-0.023	-0.438

Table 9: The table displays the VECM estimation results for the estimated baseline model with Private sector bank credit as proxy and the model with the interest rate added (both have a restricted trend and rank 1). See table 6 for additional notes.

When using the Private sector bank credit variable as a proxy for financial sector development, the estimation yields similar results as when using the main proxy. At a lag length of one quarter, the long-run relationship between Private sector bank credit and GDP per capita is negative and significant both when including and excluding the interest rate in the model. The coefficient for Private sector bank credit in the long-run relationship is only slightly smaller than when using the standard proxy. The nature of the speed of adjustment parameters remains the same as well, although the speed of adjustment parameters are slightly smaller than in the case with the standard proxy. Further, at one lag, the speed of adjustment parameter for private sector bank credit α_f is insignificant as in the model using the Private sector credit variable as proxy, suggesting that Private sector bank credit too may be weakly exogenous. This stays true when adding the interest rate. Note however, that when adding the interest rate, the constant for GDP per capita is significant and relatively large – suggesting that the model omits several important factors impacting GDP per capita growth. Further, the interest rate does not add any long-run dynamics.

Regarding short-run causality, we find evidence of the following; In the estimation without the interest rate, we find strong evidence that Private sector bank credit and GDP per capita jointly Granger causes changes in Private sector bank credit and in GDP per capita. Further, we find strong evidence that the variables Granger causes changes in themselves. When including the interest rate, these results are extended; we find evidence that that all variables jointly Granger cause changes in each of the three variables respectively, as well as changes in the variables themselves.

Based on these results, we cannot rule out that the negative finance-growth relationship is driven by credit from the domestic banking sector. In particular, the results indicate that credit provided by the domestic banking sector may be an important contributor to the negative relationship. However, as with the previous results we need to investigate whether these results hold when adding further variables to the model.

6.2 VECM estimations with all control variables

Below we present the results when including all control variables – the interest rate, CPI and unemployment rate – in order to investigate whether our main findings are driven by the omitted variables, or if they remain. These models are based on estimations of many parameters and should thus be carefully interpreted. For simplicity, we display only the first cointegrating relationship with the main relationship of interest. However, we will discuss some of the other relationships for our main proxy in order to interpret the results in a comprehensive way. All models can be viewed in their entirety in appendix C.

Model with Private sector credit as proxy and all controls		
	0 lags	1 lag
$\alpha_{1,y}$	-0.029**	-0.019
$\alpha_{1,f}$	0.050*	0.026
$\alpha_{1,r}$	2.657***	3.783***
$\alpha_{1,i}$	-7.804**	-4.994
$\alpha_{1,u}$	-1.159*	-1.454**
β_0	-128.743	-144.106
β_f	0.420***	0.527***
β_r	0.000	0.000
β_i	0.000	0.000
β_u	-	0.000
ρ	-0.137***	-0.141***
c_y	0.130***	0.015
c_f	0.100***	0.114**
c_r	-0.004	-0.004
c_i	-0.001	-0.001
c_u	-0.002	-0.007

Table 10: The table displays the main estimation results for a model that includes all control variables and use Private sector credit as proxy (restricted trend, rank 4). Note that this table only presents one estimated cointegrating relationship; see appendix C for the full estimated model. The α_y (α_f) (α_r) (α_i) (α_u) parameters denotes the estimated speed of adjustment parameters for the displayed cointegrating relationship. β_0, β_f, β_r and ρ are the estimated parameters for the cointegrated relationship displayed, with β_0 being the estimated constant, ρ being the coefficient for the time trend and β_f, β_r, β_i and β_u showing the effect of the lagged variables. The effect of lagged GDP per capita is normalized to 1 in the cointegrating relationship. The c_y (c_f) (c_r) (c_i) (c_u) denotes the estimated constants for each equation. The *** denotes 1% significance level, ** denotes 5% significance level, * denotes 10% significance level.

When we extend the Private sector credit-GDP per capita relationship to include the interest rate, CPI rate and unemployment rate as endogenous variables, we find four cointegrating relationships. The first cointegrating vector includes both GDP per capita and Private sector credit, and is hence our main interest. This cointegrating relationship, along with the corresponding speed of adjustment terms and constants, is displayed in table 10.

Interestingly, the main result of a negative long-run finance-growth relationship persist when adding all controls. We also note that the speed of adjustment parameter for GDP per capita is negative and significant when using zero lags, and slightly less negative and insignificant with one lag. This estimated speed of adjustment parameter is slightly smaller than in model 1 and 2, but nonetheless in the same direction. Based on all estimations with Private sector credit as proxy for financial sector development, we consequently find evidence that GDP per capita adjusts slowly and negatively to deviations from this long-run relationship. Hence, Private sector credit seem to impact GDP per capita negatively in the long-run. However, we cannot rule out weak exogeneity given the insignificant estimate at one lag in table 10. Further, the estimated speed of adjustment for Private sector credit is small but positive, as in models 1 and 2. However, this effect is only significant at 10% level at 0 lags, and insignificant at 1 lag. Because of this, together with insignificant speed of adjustment parameters for Private sector credit at 1 lag in the previous models, we conclude that Private sector credit appears to be weakly exogenous in the Private sector credit-GDP per capita relationship. Thus, the long-run Private sector credit-growth relationship runs from Private sector credit to GDP per capita only. Moreover, we note that the estimated trend in the main long-run relationship remains; the finance-growth relationship shifts upwards over time.

Regarding the other speed of adjustment parameters attributed to the first cointegrating relationship, we observe the following: First, the interest rate adjusts positively to abnormal GDP per capita or Private sector credit increases. This result was not obtained in the baseline models and hence it seems that the inflation and unemployment variables are needed to capture this endogenous adjustment. The positive adjustment for the interest rate is intuitively satisfying both due to central banking operations and as banks profit maximize by increasing interest rates in times of high credit demand. Second, we observe that unemployment naturally adjusts negatively during such times. Further, we note that CPI adjusts negatively and significantly when estimating the model with one lag. This is not necessarily intuitive – nevertheless, the Swedish inflation rate has structurally decreased over time while the economy at large has been growing, which may be what the model captures in this case. Note however that we do find an expected positive long-run relationship between inflation and Private sector credit in the second cointegrating relationship.

The additional cointegrating vectors can be found in appendix C in their entirety, and will only be briefly addressed below. The third cointegrating vector has a significant coefficient for Private sector credit to GDP. This suggests that there exists a negative long-run relationship between unemployment and Private sector credit. This is reasonable given that one can expect firms and households to invest more when the unemployment rate is low. Regarding the speed of adjustment parameters we find, for example, that Private sector credit decreases as unemployment deviates upwards. A result that stands out regarding this cointegrating relationship is that inflation adjusts downwards in response to positive deviation caused by the Private sector credit channel. However, one should keep in mind that all cointegrating vectors in a VEC model are at work simultaneously. If we again observe the second cointegrating relationship, there is a strong positive long-run relationship between inflation and Private sector credit, where inflation adjusts downwards as expected. Hence, this relationship behaves in accordance with theory. Finally, the fourth cointegrating vector suggests a negative relationship between the interest rate and Private sector credit. This is reasonable given that the cost of borrowing increases as the interest rate increases, hence reducing the incentive for firms and households to borrow credit.

Overall, the results in table 10 show that inflation, unemployment and the interest rate adjust much faster to deviations from the long-run equilibriums than that of Private sector credit and GDP per capita. This is an expected result as these variables are to varying degrees subject to tools available to economic actors, and adjust to the conditions of the overall economy. The former is especially true for the interest rate, which is directly determined by economic decision makers, while the latter is especially true for inflation. It should also be noted that the positive constant term for GDP per capita becomes insignificant when estimating the model with one lag, which differs from the previous models. Moreover, the estimated constant is insignificant for CPI, the interest rate and unemployment, as expected. However, the constant for the Private sector credit variable is positive and significant, suggesting that there are factors that impact credit positively that are not captured in this model.

Regarding short-run causality, we find that lagged changes in all variables jointly Granger cause current changes in all variables respectively, with the exception of unemployment. Furthermore, we find strong evidence that lagged changes in the variables Granger cause current changes in themselves, except for unemployment. Finally, we find that lagged changes in the interest rate Granger cause current changes in CPI and unemployment, where the evidence is strong for CPI.

As an additional robustness check, estimations using the remaining three proxies for financial sector development are displayed in table 11 in a similar manner.

	Private sector bank credit, all controls		Corporate credit, all controls		Household credit, all controls	
	0 lags	1 lag	0 lags	1 lag	0 lags	1 lag
α_y	-0.021	-0.011	-0.013	0.014	-0.060**	-0.020
α_f	0.055**	0.043*	0.226***	0.308***	-0.042	0.025
α_r	3.046***	4.361***	4.982***	3.686**	2.986*	4.861***
α_i	-8.024**	-3.978	-0.830	-10.070**	0.649	-8.106**
α_u	-1.187*	-1.297**	-1.686	-1.439	-3.415**	-1.229
β_0	-106.963	-122.977	112.433	-65.929	-101.875	-113.949
β_f	0.232*	0.339***	-2.299***	-0.329***	0.106***	0.310***
β_r	-0.017*	-0.028***	0.055	0.023***	-0.023***	-0.077***
β_i	-	-	-	0.000	0.000	0.000
β_u	0.000	0.000	-	-	-	0.000
ρ	-0.123***	-0.139***	0.232	-0.032*	-0.128***	-0.213***
c_y	0.215***	-0.027	0.097***	0.112***	0.102***	0.124***
c_f	-0.023	0.021	0.313***	0.031	0.171***	0.018
c_r	0.026	-0.000	0.078	-0.003	-0.011	0.001
c_i	-0.011	-0.000	-0.032	0.002	-0.002	-0.000
c_u	0.135	0.003	0.288	-0.011	-0.014	0.003

Table 11: The table displays the main estimation results for the models that include all control variables and use Private sector bank credit or Corporate credit proxy or Household credit as proxy (restricted trend, rank 3). See table 10 for additional notes.

Overall, table 11 confirms our previous findings. For simplicity, we only comment the main cointegrating relationship for each proxy. We will also not address the short-run direction of causality, but the results are presented in the appendix C.

We immediately observe some overall consistencies across the estimations using the different proxies. We find a positive adjustment to the main long-run relationship for the interest rate, a negative adjustment for the inflation in all cases when the adjustment parameter is significant, and a negative adjustment for unemployment. Once again the adjustment for CPI is not very intuitive, see the comments below table 10. These adjustment mechanisms are all relatively strong in terms of size and they are consistent to when estimating the model with Private sector credit as proxy and all controls.

When estimating the model with Private sector bank credit and all controls, we observe the following. Firstly, the interest rate now enters the long-run relationship, so that GDP per capita decreases with Private sector bank credit and increases with the interest rate. The added interest rate mechanisms show for instance (together with the significant α_f term) that Private sector bank credit increases when the interest rate is abnormally low in the previous period. Overall this estimation is consistent with table 9, and suggests that credit provided by domestic banks can explain an important part of the finance-growth relationship. Furthermore, the speed of adjustment terms for GDP per capita and Private sector bank credit are in the same direction as in the corresponding baseline model and in the full model with Private sector credit as proxy. However, the estimated speed of adjustment parameter for GDP per capita is insignificant. In comparison to when using Private sector credit as proxy and all controls, Private sector bank credit appears to respond positively and endogenously to deviations from the main long-run relationship. This suggests that GDP per capita impacts Private sector bank credit in the long-run but not vice versa, which is slightly surprising, given the overall results from using the main proxy.

Regarding the model with Corporate credit as proxy and all controls, we immediately observe that the estimated constant for Corporate credit is now positive – suggesting that this model serves a better fit than the baseline model with the interest rate. Further, the long-run relationship between GDP per capita and Corporate credit is again estimated to be positive. At 0 lags, there exists only a long-run relationship between Corporate credit and Growth – where the effect is estimated to be very large – however, when adding one lag the interest rate is added as a significant term in the cointegrating relationship. The latter suggests that GDP per capita increases with Corporate credit and decreases with the interest rate, as in table 7. Furthermore, Corporate credit adjusts positively and fast to deviations from the long-run equilibrium. GDP per capita on the other hand appears to be weakly exogenous, suggesting that GDP per capita affects Corporate credit but not vice versa, consistent with the baseline model with Corporate credit.

Finally, when using Household credit as proxy, we again find a long-run relationship where GDP per capita decreases with Household credit and increases with the interest rate. This is consistent with previous findings in table 8. Once again the speed of adjustment parameters for GDP per capita and Household credit are insignificant. Instead, the cointegrating relationship enters the model through the adjustment of inflation, the interest rate and (potentially) unemployment.

6.3 Testing for structural breaks

As an additional robustness check, we perform the Gregory Hansen test (Gregory and Hansen, 1996) for structural breaks to ensure that our results persist even when controlling for large economic events that may have altered the structural levels of our series over time. Given the nature and time span of our variables, it would be reasonable to assume the presence one or more structural breaks. For simplicity, we only perform this test for the model including GDP per Capita, interest rate and Private sector credit. The Gregory Hansen procedure typically tests for the presence of *one* structural break. However, as we suspect there may be two, we perform two separate tests; one where we exclude all observations post 2007Q3 and one where we exclude all observations pre 1994Q3. These time periods are chosen based on the two major economic crises Sweden has experienced over the course of our time sample. The results do not identify any viable structural breaks during the two time periods.

6.4 Allowing for nonlinearities

As mentioned in the methodology section, we investigate the possibility of nonlinearities in the main cointegrating relationship as a robustness check through the Engle-Granger procedure. As the Engle-Granger procedure only allows for one cointegrating relationship, we can only perform this for our baseline models (including and excluding the interest rate). Below we present the results of step 1 of the Engle-Granger procedure for each proxy.

When estimating the model with Private sector credit in logs, using the regular Engle-Granger methodology without a squared term, both with and without the interest rate, we find no cointegrating relationship. When adding a squared term to the model and estimating the long-run relationship with GDP per capita and Private sector credit (with the linear term not being logarithmized), not all estimated coefficients are significant. However, when adding the interest rate to this non-linear relationship, the estimated long-run relationship is as follows:[11]

$$y_{t-1} = 82.2675 + 0.0247r_{t-1} + 0.0306f_{t-1} - 0.0003f_{t-1}^2 + 0.1576t \tag{13}$$

This relationship has an inverted-u shape, considering the impact of Private sector credit on GDP per capita only. Taking the partial derivative of GDP per capita (index) w.r.t

[11] Rounded to four decimals.

Private sector credit (index) reveals a threshold of 51, corresponding to $\sim$ 67% of GDP. However, the threshold point lies outside the range of the dataset and can thus only be regarded as a rough estimate.[12] We do note however that all the data points for Private sector credit in our sample have a higher value than the estimated threshold, so that data ranges within the negative part of the inverted-u shaped relationship. This aligns with our main results and the literature. Further, the relationship shifts upward over time.

Before estimating the VEC model, we perform the Augmented Dickey-Fuller test of the residual series. Using case 1 and five lags, the test statistic is -3.149. If we were to use the standard Dickey-Fuller critical values, we would be able to reject the null hypothesis of a unit root at 1% level and continue to the VEC estimation. As mentioned in the methodology section however, we are required to use the critical values for the Engle-Granger Cointegration Test as the variables are nonstationary. In this instance, we cannot reject the null hypothesis at 1%, 5% or 10% level. We consequently find no cointegrating relationship when including squared Private sector credit in the long-run relationship between GDP per capita, Private sector credit and the interest rate.

Overall, we are unable to proceed with estimating a VEC model with a nonlinear cointegrating relationship. As we are unable to do so as well when excluding the squared term, we cannot definitively determine whether a nonlinear cointegrating relationship exists. However, due to the significant squared term we cannot rule out the possibility.

[12] Naturally, the estimate may also suffer from bias as the OLS regression does not take the issue of e.g. reverse causality into account.

7 Discussion

7.1 Discussion and policy implications

The main finding of this study is that there exists a negative long-run relationship between financial sector development appears and economic growth in Sweden for the period 1971-2020. This relationship is relatively large, and GDP per capita adjusts negatively to this relationship in all estimations with our main proxy but one. Hence, financial development in terms of credit appears to have impacted the Swedish economy negatively for the period 1971-2020. This is highly interesting given that Sweden has experienced a much lower overall economic growth rate during the past 50 years compared to the pre-1971 period, and that the Swedish financial sector has expanded simultaneously. Considering that the findings of Hansson and Jonung (1997) underline the important role of finance in promoting Swedish, our results show a remarkable difference, as we use similar techniques but data from different time periods. From these findings it follows that the Swedish financial sector has surpassed the threshold level above which further financial development no longer promotes growth, in line with Arcand et al. (2015), Cecchetti and Kharroubi (2019), Hassan et al. (2011), Law and Singh (2014), Rousseau and Wachtel (2011), Samargandi et al. (2015) and Zhu et al. (2020). Note that this does not mean that the financial sector does not provide benefits in terms of allocation of resources. However, when the financial sector becomes too large relative to the size of the economy, there are considerable potential downsides (e.g. misallocation of resources as well as increased risks and macroeconomic instability).

In turn, we observe that the long-run relationship between Household credit and economic growth is negative, while the relationship between Corporate credit and economic growth is positive. This finding aligns with previous research stating that the excessive household lending hampers economic growth, as mentioned in e.g. Jappelli & Pagano (1994); Sassi & Gasmi (2014); Beck et al. (2012). It should be noted that there is less clear evidence of endogeneity in the adjustment mechanisms in the models with these two variables. Nevertheless, as Private sector credit is composed of Corporate credit and Household credit, the estimates should still be regarded as strong indicators of a negative effect of Household credit on GDP per capita, and a positive effect of Corporate credit on GDP per capita. Moreover, the positive Corporate credit-Growth relationship is not in line with the theoretical framework outlined by Cecchetti and Kharroubi (2019), stating that a negative relationship between growth in finance and growth in output is mainly driven by Corporate credit when using cross-country data from advanced countries. Hence the Swedish Corporate credit-growth relationship seems to have differed from other advanced countries during the period 1971-2020.

In terms of long-run causal direction between finance and growth, we get differing results depending on the proxy for financial sector development. Using our main proxy, Private sector credit, we find unidirectional long-run causality from finance to growth. This stands in contrast to the findings of Hansson and Jonung (1997), that find bidirectional causality. However, when using Private sector bank credit, the relationship is unidirectional from growth to finance. Regarding Corporate credit, we observe that GDP per capita strongly impacts Corporate credit unidirectionally. For Household credit, the results yield conflicting results in terms of long-run causality. Hence, we only find long-run causality from finance to growth for our main proxy. The reason for this may be that the other variables capture a smaller share of the overall investments in the economy, and hence they only impact GDP per capita in the long-run jointly (as Household credit and Corporate credit together composes Private sector credit). Overall, taking all proxies into account, we should hence not reject the possibility that the long-run relationship between finance and growth may be bidirectional.

Moving on; as we do not find a negative Corporate credit-Growth relationship, we do not expect to find support for the hypothesis based on the theory of Cecchetti and Kharroubi (2019). Indeed, our findings regarding both the credit-patent channel and the patent-growth channel are inconclusive. As mentioned, Hansson and Jonung (1997) find a positive long-run relationship between GDP per capita and total lending and a positive between GDP per capita and patent applications for the post WWII period. Hence, it seems that the role of innovation proxied by patent applications as a contributing factor to long-run Swedish growth have diminished in between our respective time samples. Instead, this is in line with the findings of Zhu et al. (2020); that the impact of growth in Private sector credit on growth in patent applications as well as that of growth in patent applications on economic growth is lower for countries with well-developed financial sectors. Note however that the type of activities that are the most innovative in countries with well-developed financial sectors may not be those for which actors apply for patent protection. Finally, these findings are not in line with Pradhan et al.(2016), who find an important role of patent in the finance-growth relationship for 18 Eurozone countries. This disparity is slightly surprising given that Pradhan et al. use data from similar countries; however this difference may be explained by that Pradhan et al. use a wider proxy for innovation.

Overall, our findings suggest that the negative impact of finance on growth during the period 1971-2020 has mainly been driven by Household credit. As Household credit is mainly composed of private mortgages, there is reason for policymakers and regulators to oversee tools that regulate Household credit, such as loan-to-value ratios for private lending. Naturally, this needs to be combined with ensuring a stable supply of rental properties. In turn, there is reason to overview the Swedish housing market to thoroughly address the factors driving the compositional change in housing, as well as the legal factors impacting the incentive for households to invest in tenant owned dwellings.

7.2 Limitations and future research suggestions

This study is subject to some limitations. First, the VEC framework involves estimations of many parameters in multivariate analysis. Hence, the larger the sample the better fit of the model, requiring very long time series. We have aimed to use a relatively long time series to mitigate these problems, but naturally it would have been beneficial if the dataset extended further back in time. This aspect also constricted the number of lags in the estimations. This limited our findings in terms of short-run causality; we did not find short-run causality across the variables on many occasions. It is likely that we would have found short-run causality across more variables had we increased the lag length, as the relationships across (most of) the variables used are well established in theory – but as mentioned, this comes at a cost of risking to overparameterisize the model.

A second limitation of our methodology concerns the VAR and VECM frameworks, which neither allows for dynamic systems where the relationships across the variables can vary over time, nor thorough non-linearity investigations. The non-linear investigation was mainly limited because it did not allow for estimations with multiple cointegrating relationships, but also as our investigation is based on a (rather conventional) assumption of the functional form of the non-linear relationship. Hence it is of interest to further analyze the finance-growth relationship with methodologies that are more sophisticated in terms of dynamics and functional form. For instance, it would be of interest to perform recursive VEC estimations in order to investigate how the relationships across the variables have changed over time, if one would have access to time series of greater length.

The final shortcomings concerns the data and our choice of variables. First, none of the proxies for financial sector development take equity markets into account. This is a substantial part of the financial system, and future analyses would benefit from including it if possible. Nevertheless, the proxies used do capture a considerable part of the financial system, and should be considered viable and adequate measurements of the size of the financial sector. Secondly, the number of patent applications is not an ideal proxy for innovation – especially today when many innovative activities focus on e.g. using trade secrets, network effects, consumer data as well as and building platforms. Thirdly, the GDP per capita variable consist of estimated values for all observations until 1992Q4, and we are thus aware of the possibility for measurement error and uncertainty. Finally, there is the ever-present issue of whether the estimations suffer from omitted variable bias. In particular, we considered adding the USD/SEK exchange rate to the estimations. However, as the robustness estimations already have the drawback of estimating a large number of parameters, we decided to not include additional variables to our system.

For future inquiries it may be interesting to investigate the innovation channel with other, more adequate proxies. In addition, the long-run relationship between economic growth and financial sector development can be invested further using methods that are better aimed for capturing non-linear relationships. Further, it is unlikely that Household credit is the only driver in the negative long-run relationship between economic growth and financial sector development, and more attention should be directed towards uncovering what exactly composes this relationship.

8 Conclusion

This paper has aimed to investigate the nature of the relationship between economic growth and financial sector development in Sweden over the course of 1971Q1-2020Q3. Further, we have attempted to understand potential drivers of this relationship. The study relies on the Vector Error Correction (VEC) framework, which allows us to investigate the long-run and short-run relationships across multiple endogenous macroeconomic variables. The baseline models include GDP per capita and various proxies for financial sector development, and are estimated with and without the interest rate. As robustness checks we add Consumer Price Index (CPI) and unemployment as control variables, and investigate whether the main finding is driven by non-banking activities. Further, we also allow for structural breaks as well as nonlinearity in the main cointegrating relationship.

Our efforts yield several interesting results. Importantly, we find that financial sector development measured by credit allocated to the private non-financial sector have negatively impacted long-run economic growth in Sweden for the period 1970-2022. In addition to being a novel finding, given that previous studies have underlined the importance of finance in promoting Swedish growth, this has serious policy implications. In particular, our results indicate that credit allocated to households rather than the corporate sector drives this negative impact of finance, directing attention towards household lending behavior. Further, we cannot rule out that bank lending activity is responsible for a considerable part of this negative impact of finance. In terms of causality, the results indicate unidirectional causality from finance to growth in the long-run when using the main proxy. However, based on the findings using the other proxies, we cannot reject the possibility of bidirectional long-run causality. Finally, our results provide strong evidence that finance and growth impacts the interest rate, unemployment and CPI in the long-run. There is less evidence of short-run Granger causality across the variables, which may be explained by the limited number of lags.

Another aspect of this investigation concerned whether innovation drives the negative finance-growth relationship. This is based on the theoretical framework outlined by Cecchetti and Kharroubi (2019), suggesting that periods of high credit levels hampers growth through less investments in innovative activities. We do not find support for this hypothesis, which aligns with the finding of a positive Corporate credit-growth relationship. Further, this investigation does not yield any consistent long-run impact of innovation, proxied by patents, on growth. This stands in contrast with previous findings using earlier time samples, and we conclude that the impact of innovation on growth in Sweden may have decreased over time. Lastly, allowing for nonlinearities did not yield any telling results. However, we cannot rule out the possibility of an inverted-u shaped Swedish finance-growth relationship, and we consequently encourage future research in this area.

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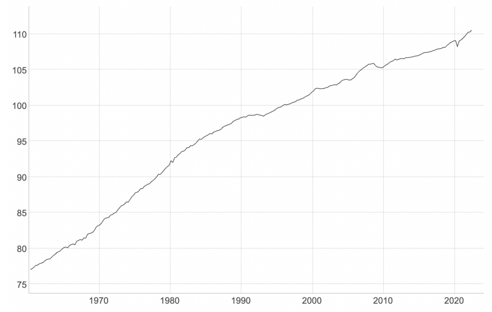
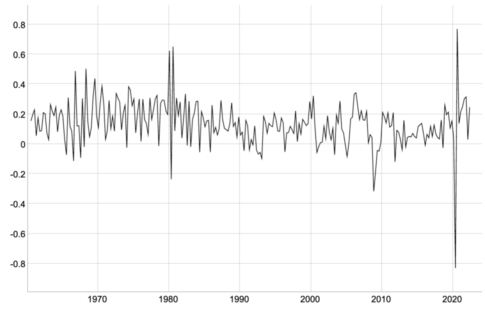
A Appendix-Data

A.1 Visualisations of original series and their first differences

GDP Per Capita



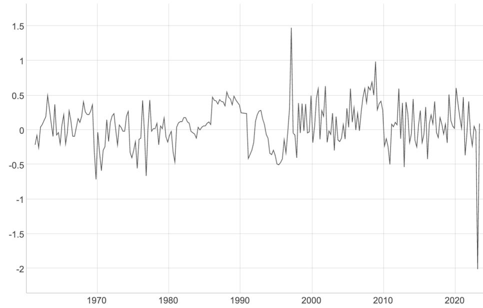
(a) GDP Per Capita in Logs and indexed at 1995Q4=100



(b) GDP Per Capita in Logs and indexed at 1995Q4=100 in First difference

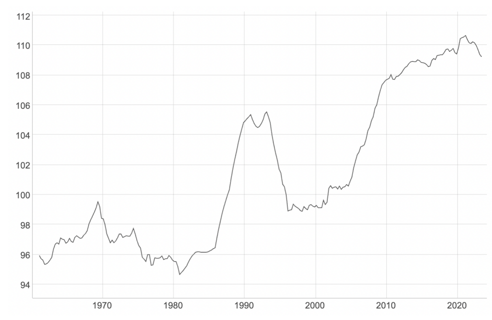
Private sector credit to GDP

(a) Private sector credit to GDP in Logs and indexed at 1995Q4=100

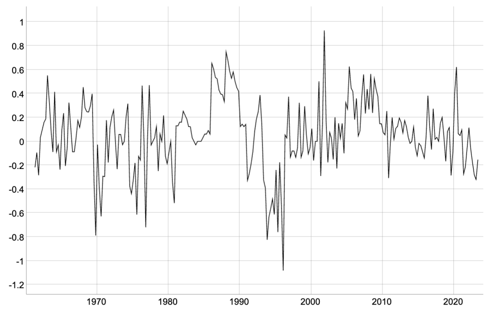


(b) Private sector credit to GDP in Logs and indexed at 1995Q4=100 in first difference

Private Sector Bank Credit to GDP



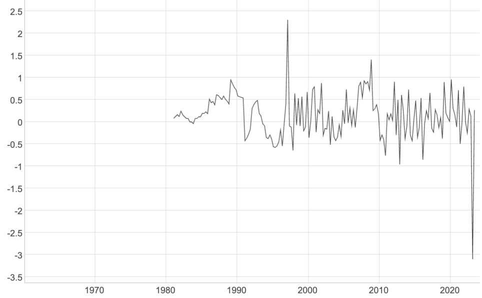
(a) Private Sector BankCredit to GDP in Logs and indexed at 1995Q4=100



(b) Private Sector Bank Credit to GDP in Logs and indexed at 1995Q4=100 in first difference

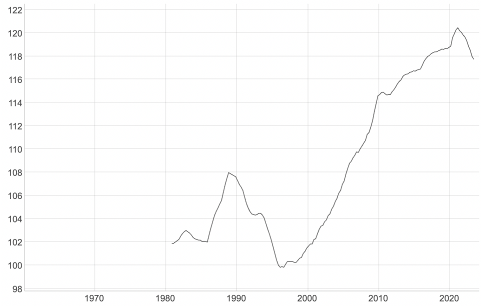
Corporate credit to GDP

(a) Corporate credit to GDP in Logs and indexed at 1995Q4=100

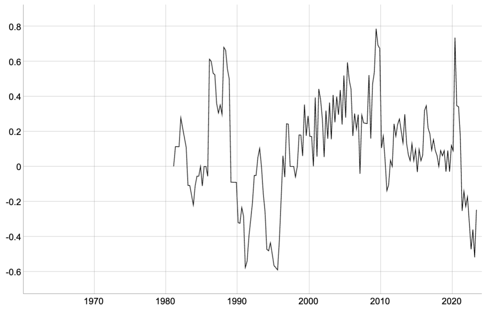


(b) Corporate credit to GDP in Logs and indexed at 1995Q4=100 in first difference

Household credit to GDP

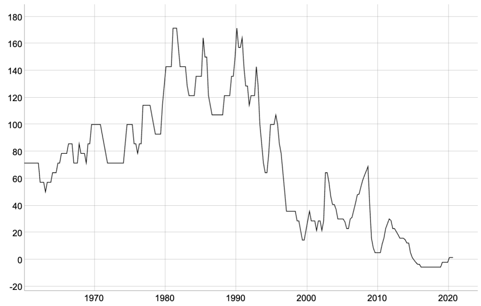


(a) Household credit to GDP in Logs and indexed at 1995Q4=100

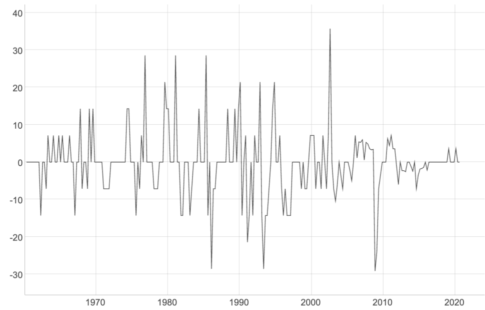


(b) Household credit to GDP in Logs and indexed at 1995Q4=100 in first difference

Interest rate



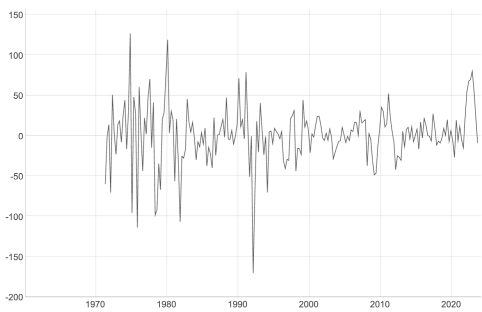
(a) Interest rate, indexed at 1995Q4=100



(b) Interest rate, indexed at 1995Q4=100 in first difference

Inflation (Consumer Price Index)

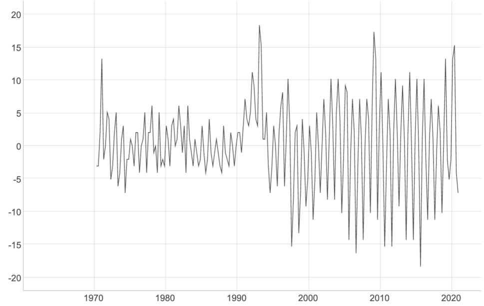
(a) Consumer price index, indexed at 1995Q4=100



(b) Consumer price index, indexed at 1995Q4=100 in first difference

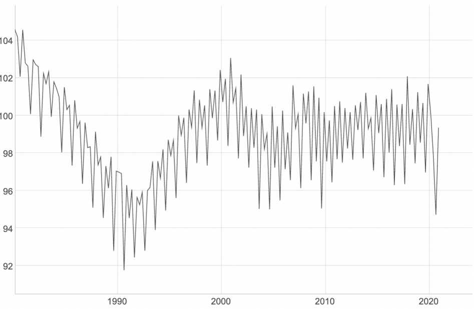
Unemployment

(a) Unemployment, indexed at 1995Q4=100

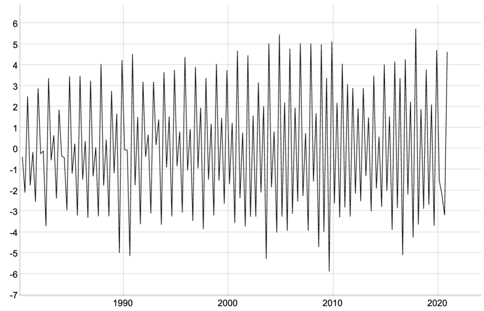


(b) Unemployment, indexed at 1995Q4=100 in first difference

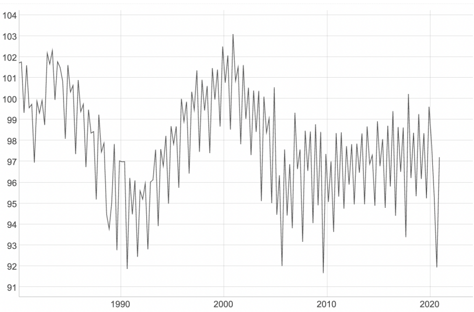
Patents



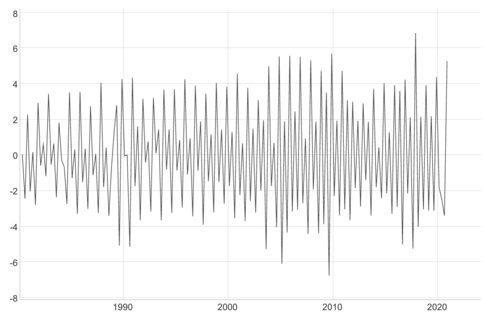
(a) Full patent data, including data from PRV and EUIPO, indexed at 1995Q4=100



(b) Full patent data, including data from PRV and EUIPO, indexed at 1995Q4=100 in first difference



(a) Patstat, indexed at 1995Q4=100



(b) Patstat, indexed at 1995Q4=100 in first difference

B Appendix-Pretesting: lag selection, Johansen cointegration test and Gregory Hansen test

B.1 Model 1

Lag selection-Model 1				
Lags	FPE	AIC	HQIC	SBIC
0	290.799	11.3484	11.3621	11.3822
1	0.00193	-0.574663	-0.533587	-0.473233
2	0.001662	-0.72371	-0.655249	**-0.554658**
3	0.001576	-0.77286	-0.681441	-0.540614
4	0.001616	-0.752109	-0.628881	-0.447817
5	**0.001491**	**-0.832904**	**-0.682291**	-0.460991

Table 12: The table displays the lag selection for a VAR model with GDP per capita and Private sector credit, using four lag selection criteria. These are final prediction error (FPE), Akaike's information criterion (AIC), Quinn information criterion (HQIC) and Schwarz's Bayesian information criterion (SBIC). For each criteria, the lowest statistic is denoted in bold.

Johansen tests for cointegration-Model 1			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	36.7287	25.32	30.45
1	**12.2408**	12.25	16.26

Table 13: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 5 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.2 Model 2

Lag selection-Model 2				
Lags	FPE	AIC	HQIC	SBIC
0	299362	21.123	21.1436	21.1738
1	0.155213	6.65066	6.73281	6.85352
2	0.124874	6.43308	**6.57685**	**6.78809**
3	**0.120998**	**6.40137**	6.60675	6.90853
4	0.128946	6.46465	6.73165	7.12395
5	0.123234	6.41882	6.74743	7.23026

Table 14: The table displays the lag selection for a VAR model with GDP per capita, Private sector credit and interest rate, using four lag selection criteria.

Johansen tests for cointegration-Model 2			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	58.1696	42.44	48.45
1	**21.6523**	25.32	30.45
2	5.7450	12.25	16.26

Table 15: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 3 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.3 Model 3

Lags	FPE	AIC	HQIC	SBIC
0	91.5305	10.1924	10.2084	10.2317
1	0.004082	0.174483	0.222335	**0.292293**
2	0.003782	0.098146	0.177899	0.294496
3	0.003597	0.047923	0.159578	0.322813
4	0.003756	0.091217	0.234772	0.444647
5	**0.003288**	**-0.04205**	**0.133406**	0.38992

Table 16: The table displays the lag selection for a VAR model with GDP per capita and Corporate credit, using four lag selection criteria.

Johansen tests for cointegration-Model 3			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	28.3950	25.32	30.45
1	12.0808	12.25	16.26

Table 17: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 5 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.4 Model 4

Lags	FPE	AIC	HQIC	SBIC
0	49607.9	19.3255	19.3495	19.3844
1	0.30674	7.33184	7.42755	**7.56746**
2	0.268113	7.1971	**7.36458**	7.60944
3	0.265426	7.18667	7.42593	7.77572
4	0.279141	7.23641	7.54745	8.00217
5	**0.263541**	**7.17787**	7.56069	8.12035

Table 18: The table displays the lag selection for a VAR model with GDP per capita, Corporate and interest rate, using four lag selection criteria.

Johansen tests for cointegration-Model 5			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	46.0222	42.44	48.45
1	25.1620	25.32	30.45
2	7.4848	12.25	16.26

Table 19: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 5 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.5 Model 5

Lags	FPE	AIC	HQIC	SBIC
0	112688	20.146	20.1699	20.2049
1	0.107459	6.28295	6.37865	6.51857
2	0.038185	5.24813	5.41561	**5.66047**
3	**0.035203**	**5.16646**	**5.40572**	5.75551
4	0.03578	-5.96326	5.49313	5.94785
5	0.035644	-5.96811	5.56005	6.11972

Table 20: The table displays the lag selection for a VAR model with GDP per capita, Household credit and the interest rate, using four lag selection criteria.

Johansen tests for cointegration-Model 5			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	63.1357	42.44	48.45
1	**21.9333**	25.32	30.45
2	3.8274	12.25	16.26

Table 21: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 3 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.6 Model 6

Lag selection-Model 6				
Lags	FPE	AIC	HQIC	SBIC
0	309.862	11.4119	11.4256	11.4457
1	0.001912	-0.583856	-0.54278	-0.482425
2	0.001305	-0.96593	-0.89747	**-0.796879**
3	0.00126	-1.00122	-0.905378	-0.76455
4	0.001185	-1.0621	**-0.938873**	-0.757809
5	**0.001179**	**-1.06736**	-0.916752	-0.695452

Table 22: The table displays the lag selection for a VAR model with GDP per capita and Private sector bank credit, using four lag selection criteria.

Johansen tests for cointegration-Model 3			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	33.9920	25.32	30.45
1	**10.1391**	12.25	16.26

Table 23: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 5 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.7 Model 7

Lag selection-Model 7				
Lags	FPE	AIC	HQIC	SBIC
0	410206	21.438	21.4586	21.4888
1	0.152761	6.63473	6.71689	6.83759
2	0.098067	6.19143	**6.33519**	**6.54644**
3	0.095454	6.16424	6.36962	6.67139
4	**0.093577**	**6.14405**	6.41104	6.80335
5	0.095196	6.16067	6.48928	6.97212

Table 24: The table displays the lag selection for a VAR model with GDP per capita, Private sector bank credit and interest rate, using four lag selection criteria.

Johansen tests for cointegration-Model 4			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	58.9595	42.44	48.45
1	**22.5662**	25.32	30.45
2	4.6794	12.25	16.26

Table 25: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 4 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.8 Model 8

Lags	FPE	AIC	HQIC	SBIC
0	3.5+11	40.7689	40.801	40.8534
1	5048.91	22.7162	22.9216	**23.2234**
2	4511.56	22.6032	22.9797	23.5329
3	2473.56	22.009	22.5486	23.3533
4	2504.41	22.0109	22.7197	23.7859
5	**1033.15**	**21.1215**	**22.0115**	23.3192

Table 26: The table displays the lag selection for a VAR model with GDP per capita, Private sector credit to GDP, interest rate, CPI rate and unemployment rate, using four lag selection criteria.

Johansen tests for cointegration-Model 8			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	134.5343	87.31	96.58
1	85.6193	62.99	70.05
2	50.8559	42.44	48.45
3	30.4703	25.32	30.45
4	**12.2404**	12.25	16.26

Table 27: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 5 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.9 Model 9

Lags	FPE	AIC	HQIC	SBIC
0	3.8e+10	38.5407	38.5806	28.6389
1	7665.1	23.1336	23.3729	**23.7227**
2	7141.38	23.0619	23.5005	24.1418
3	3348.94	22.3021	22.9401	23.8729
4	3633.56	22.379	23.2164	24.4406
5	**1596.49**	**21.5489**	**22.5857**	24.1015

Table 28: The table displays the lag selection for a VAR model with GDP per capita, Corporate credit, interest rate, CPI rate and unemployment rate, using four lag selection criteria.

Johansen tests for cointegration-Model 10			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	121.6852	87.32	96.58
1	80.6043	62.99	70.05
2	**45.4690**	42.44	48.45
3	**21.9774**	25.32	30.45
4	10.4553	12.25	16.26

Table 29: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 5 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.10 Model 10

Lags	FPE	AIC	HQIC	SBIC
0	7.5e+10	39.229	39.2691	39.3274
1	1766.12	21.666	21.905	22.2538
2	894.626	20.984	21.4227	22.064
3	381.626	20.130	20.7682	**21.7009**
4	353.624	20.049	20.8866	22.1109
5	**165.587**	**19.283**	**20.3197**	21.8354

Table 30: The table displays the lag selection for a VAR model with GDP per capita, Household credit, interest rate, CPI rate and unemployment rate, using four lag selection criteria.

Johansen tests for cointegration-Model 11			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	145.6970	87.32	96.58
1	92.8594	62.99	70.05
2	49.8627	42.44	48.45
3	**18.6787**	25.32	30.45
4	5.5607	12.25	16.26

Table 31: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 5 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.11 Model 11

Lags	FPE	AIC	HQIC	SBIC
0	5.2e+11	41.1626	41.1968	41.2471
1	4319.68	22.5602	22.7656	23.0674
2	3140.85	22.241	22.6175	23.1708
3	1815.61	21.6917	22.2393	23.0441
4	1659.51	21.5993	22.3182	23.3744
5	**769.048**	**20.8263**	**21.7163**	**23.024**

Table 32: The table displays the lag selection for a VAR model with GDP per capita, Private sector bank credit, interest rate, CPI rate and unemployment rate, using four lag selection criteria.

Johansen tests for cointegration-Model 9			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	136.1161	87.31	96.58
1	85.6033	62.99	70.05
2	52.4409	42.44	48.45
3	**24.7833**	25.32	30.45
4	7.8476	12.25	16.26

Table 33: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 5 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.12 Patent

Lags	FPE	AIC	HQIC	SBIC
0	408.018	14.5249	14.5489	14.5838
1	0.019054	4.55309	4.6488	4.78871
2	0.011501	4.04809	4.21557	4.45043
3	0.011164	4.01799	4.25725	4.60704
4	0.003048	2.71909	3.03013	3.48485
5	**0.002359**	**2.46203**	**2.84485**	**3.40451**

Table 34: The table displays the lag selection for a VAR model with GDP per capita, Corporate credit and Prv_patstat, using four lag selection criteria.

Johansen tests for cointegration-Patent (using Prv_patstat)			
Maximum rank	Trace statistic	Critical value, 5%	Critical value, 1%
0	43.3831	42.44	48.45
1	**18.2754**	25.32	30.45
2	4.2761	12.25	16.26

Table 35: The table displays Trace statistics and critical values at 5% and 1% significance level for Johansen cointegration tests, using 5 lags. Null hypothesis: the rank of the cointegrating matrix is equal to or less than the minimum rank.

B.13 Testing for structural break (excluding data after 2007-Q3): Gregory Hansen test and Johansen test

Gregory Hansen test results, excluding data after 2007Q3			
	Test statistic	Structural break date	Critical value, 5%
ADF (regime and trend)	-4.83	1991-Q4	-5.96
Z_t (regime and trend)	-4.85	1991-Q4	-5.96
Z_a (regime and trend)	-42.54	1991-Q4	-68.43

Table 36: The table displays the results from performing the Gregory Hansen test when excluding data after 2007-Q3. The null hypothesis is no cointegration, while the alternative hypothesis is cointegration in the presence of a possible regime shift. The regime and trend test allows a structural break in the constant and slope. The test is based on a model with the following variables: GDP per capita, Private sector credit and the interest rate.

B.14 Testing for structural break (excluding data before 1994-Q3): Gregory Hansen test and Johansen test

Gregory Hansen test results, excluding data before 1994-Q3			
	Test statistic	Structural break date	Critical value, 5%
ADF (regime and trend)	-5.75	2006-Q2	-5.96
Z_t (regime and trend)	-5.78	2006-Q2	-5.96
Z_a (regime and trend)	-50.46	2006-Q2	-68.43

Table 37: The table displays the results from performing the Gregory Hansen test when excluding data before 1994-Q3. The null hypothesis is no cointegration, while the alternative hypothesis is cointegration in the presence of a possible regime shift. The regime and trend test allows a structural break in the constant and slope. The test is based on a model with the following variables: GDP per capita, Private sector credit and the interest rate.

C Appendix-Estimation results: short-run effects, short-run Granger causality and diagnostic checking

C.1 Model 1 and 2

	Baseline model, Private sector credit		Interest rate added	
	0 lag	1 lags	0 lags	1 lags
α_y	-0.035***	-0.034***	-0.044***	-0.032***
α_f	0.039***	0.011	0.051***	0.010
α_r	-	-	-0.181	-0.130
β_0	-122.838	-140.528	-115.834	-134.5529
β_f	0.351***	0.499***	0.321***	0.539***
β_r	-	-	-0.001	0.002
ρ	-0.130***	-0.139***	-0.140***	-0.140***
c_y	0.115***	0.038*	0.215***	0.040***
c_f	0.102***	0.116**	-0.015	0.014
c_r	-	-	-0.057	-0.092
L_y	-	-0.226***;-0.138	-	-0.255***; -0.150; 5.316
L_f	-	-0.050; 0.350***	-	-0.048; 0.353***; 0.222
L_r	-	-	-	0.002*; 0.000; 0.246***
Eigenvalue	1, 0.979	1, 0.983, 0.358, -0.245	1, 1, 0.974	1, 1, 0.984, 0.360, -0.293, 0.266
Modulus	1, 0.979	1, 0.983, 0.358, 0.245	1, 1, 0.974	1, 1, 0.984, 0.360, -0.293, 0.266

Table 38: The table displays the VECM estimation results for the estimated baseline model and the model with the interest rate added (both have a restricted trend and rank 1). The α_y (α_f) (α_r) parameters denotes the estimated speed of adjustment parameters for the equation with Δ GDP per capita (Δ Private sector credit) (Δ interest rate) as dependent variable. β_0, β_f, β_r and ρ are the estimated parameters for the cointegrated relationship, with β_0 being the estimated constant, ρ being the estimated time trend and β_f and β_r showing the effect of lagged Private sector credit and lagged interest rate respectively. The effect of lagged GDP per capita is normalized to 1 in the cointegrating relationship. The c_y (c_f) (c_r) denotes the estimated constant for the equation with Δ GDP per capita (Δ Private sector credit) (Δ interest rate) as dependent variable. The L_y (L_f) (L_r) denotes the coefficient for lagged Δ GDP per capita (Δ Private sector credit) (Δ interest rate) in the model with Δ GDP per capita as dependent variable in the first case, Δ Private sector credit in the second case and Δ interest rate in the third case, (the three cases are separated by ";"). Finally, the eigenvalue and modulus show the results when investigating the Eigenvalue stability condition. The *** denotes 1% significance level, ** denotes 5% significance level, * denotes 10% significance level.

Dependent Variable	Lagged variable(s)	χ^2	Prob > χ^2
GDP per capita	All	10.93	0.0042
GDP per capita	GDP per capita	9.50	0.0021
GDP per capita	Private sector credit	2.25	0.1333
Private sector credit	All	27.81	0.0000
Private sector credit	GDP per capita	0.84	0.3601
Private sector credit	Private sector credit	25.76	0.0000

Table 39: The table presents the results from the Wald test based on the baseline model with Private sector credit as proxy for financial sector development. The null hypothesis is that the lagged variable(s) in first differences has a coefficient set to 0 in the equation with the corresponding dependent variable.

Dependent Variable	Lagged variable(s)	χ^2	Prob > χ^2
GDP per capita	All	14.06	0.0028
GDP per capita	GDP per capita	11.57	0.007
GDP per capita	Interest rate	2.78	0.0954
GDP per capita	Private sector credit	2.08	0.1494
Private sector credit	All	28.05	0.0000
Private sector credit	GDP per capita	0.94	0.3323
Private sector credit	Interest rate	0.09	0.7648
Private sector credit	Private sector credit	25.96	0.0000
Interest rate	All	15.48	0.0014
Interest rate	GDP per capita	1.22	0.2690
Interest rate	Interest rate	11.93	0.0006
Interest rate	Private sector credit	0.01	0.9177

Table 40: The table presents the results from the Wald test based on model with Private sector credit as proxy for financial sector development and the interest rate added. The null hypothesis is that the lagged variable(s) in first differences has a coefficient set to 0 in the equation with the corresponding dependent variable.

C.2 Model 3 and 4

	Baseline model, Corporate credit		Interest rate added	
	0 lag	1 lags	0 lags	1 lags
α_y	-0.040	0.035*	-0.055**	-0.001
α_f	0.400**	0.280***	0.395***	0.340***
α_r	-	-	-0.313	-1.445
β_0	-85.805	-72.863	-85.106	-77.243
β_f	-0.090*	-0.222***	-0.010***	-0.185***
β_r	-	-	0.010**	0.011**
ρ	-0.082**	-0.070***	-0.072**	-0.060***
c_y	0.117**	0.010***	0.174***	0.119***
c_f	0.012	-0.013	-0.355***	-0.298***
c_r	-	-	-0.477	-0.070
L_y	-	-0.116;-0.428	-	-0.068; -0.364; 10.825
L_f	-	-0.059**; 0.206***	-	-0.050**; 0.173**; 0.865
L_r	-	-	-	0.001; 0.000; 0.241***
Eigenvalue	1, 0.924	1, 0.934, 0.304, -0.174	1, 1, 0.903	1, 1, 0.872, 0.335, 0.220, -0.161
Modulus	1, 0.924	1, 0.934, 0.304, 0.174	1, 1, 0.903	1, 1, 0.872, 0.335, 0.220, 0.161

Table 41: The table displays the VECM estimation results for the estimated baseline model with Corporate credit as proxy and the model with the interest rate added (both have a restricted trend and rank 1). See the table 38 for additional notes.

Dependent Variable	Lagged variable(s)	χ^2	Prob > χ^2
GDP per capita	All	6.56	0.0376
GDP per capita	GDP per capita	1.55	0.2126
GDP per capita	NFC index	5.89	0.0153
NFC index	All	11.61	0.0030
NFC index	GDP per capita	2.23	0.1353
NFC index	NFC index	7.52	0.0061

Table 42: The table presents the results from the Wald test based on the baseline model with Corporate credit as proxy for financial sector development. The null hypothesis is that the lagged variable(s) in first differences has a coefficient set to 0 in the equation with the corresponding dependent variable.

Dependent Variable	Lagged variable(s)	χ^2	Prob > χ^2
GDP per capita	All	5.72	0.1262
GDP per capita	GDP per capita	0.55	0.4564
GDP per capita	Interest rate	1.43	0.2318
GDP per capita	NFC index	3.95	0.0469
NFC index	All	8.55	0.0360
NFC index	GDP per capita	1.76	0.1840
NFC index	Interest rate	0.00	0.9602
NFC index	NFC index	5.27	0.0217
Interest rate	All	14.91	0.0019
Interest rate	GDP per capita	3.61	0.0573
Interest rate	NFC index	0.31	0.5803
Interest rate	Interest rate	9.64	0.0019

Table 43: The table presents the results from the Wald test based on model with Corporate credit as proxy for financial sector development and the interest rate added. The null hypothesis is that the lagged variable(s) in first differences has a coefficient set to 0 in the equation with the corresponding dependent variable.

C.3 Model 5 and 6

	Baseline model (Household credit), interest rate added	
	0 lag	1 lags
α_y	0.006	0.016
α_f	0.111***	-0.000
α_r	2.866***	4.258***
β_0	-110.180	-111.122
β_f	0.228***	0.248***
β_r	-0.050***	-0.055***
ρ	-0.170***	-0.180***
c_y	0.104***	0.110***
c_f	0.148***	0.032
c_r	-0.006	-0.000
L_y	-	-0.073; -0.082; -0.066
L_f	-	0.005; 0.789***; -5.835**
L_r	-	0.002; -0.001; 0.305***
Eigenvalue	1, 1, 0.887	1, 1, (0.705 + 0.040i), (0.705-0.040i), 0.467, -0.071
Modulus	1, 1, 0.887	1, 1, 0.706, 0.706, 0.467, 0.971

Table 44: The table displays the VECM estimation results for the estimated baseline model with Household credit as proxy and the model with the interest rate added (both have a restricted trend and rank 1). See the table 38 for additional notes.

Dependent Variable	Lagged variable(s)	χ^2	Prob > χ^2
GDP per capita	All	2.46	0.4833
GDP per capita	GDP per capita	0.61	0.4349
GDP per capita	Interest rate	2.13	0.1444
GDP per capita	Household credit	0.01	0.9176
Household index	All	208.63	0.0000
Household index	GDP per capita	0.33	0.5682
Household index	Interest rate	0.30	0.5839
Household credit	Household credit	182.80	0.0000
Interest rate	All	25.62	0.0000
Interest rate	GDP per capita	0.00	0.9875
Interest rate	Interest rate	18.67	0.0000
Interest rate	Household index	4.88	0.0272

Table 45: The table presents the results from the Wald test based on model with Household credit as proxy for financial sector development and the interest rate added. The null hypothesis is that the lagged variable(s) in first differences has a coefficient set to 0 in the equation with the corresponding dependent variable.

C.4 Model 7 and 8

	Baseline model, Private sector bank credit		Interest rate added	
	0 lag	1 lags	0 lags	1 lags
α_y	-0.026***	-0.023***	-0.032***	-0.026**
α_f	0.026***	0.002	0.033***	-0.002
α_r	-	-	-0.231	-0.032
β_0	-113.882	-141.4806	-109.092	-118.643
β_f	0.235	0.458***	0.233*	0.455**
β_r	-	-	-0.010	-0.008
ρ	-0.105***	-0.109***	-0.117***	-0.118**
c_y	0.097***	0.005	0.181***	0.541**
c_f	0.097***	0.059	0.012	0.024
c_r	-	-	-0.023	-0.438
L_y	-	-0.210**; -0.123	-	-0.233***; -0.140; 5.469
L_f	-	-0.004; 0.543**	-	-0.007; 0.542***; -0.596
L_r	-	-	-	0.002; 0.001; 0.246***
Eigenvalue	1, 0.980	1, 0.985, 0.541, -0.215	1, 1, 0.978	1, 1, 0.985, 0.539, 0.266, -0.259
Modulus	1, 0.980	1, 0.985, 0.541, 0.215	1, 1, 0.978	1, 1, 0.985, 0.539, 0.266, 0.259

Table 46: The table displays the VECM estimation results for the estimated baseline model with Private sector bank credit as proxy and the model with the interest rate added (both have a restricted trend and rank 1). See the table 38 for additional notes.

Dependent Variable	Lagged variable(s)	χ^2	Prob > χ^2
GDP per capita	All	7.87	0.0195
GDP per capita	GDP per capita	7.81	0.0052
GDP per capita	Private sector bank credit	0.01	0.9090
Private sector bank credit	All	82.91	0.0000
Private sector bank credit	GDP per capita	0.83	0.3629
Private sector bank credit	Private sector bank credit	78.58	0.0000

Table 47: The table presents the results from the Wald test based on model with Private sector bank credit as proxy for financial sector development. The null hypothesis is that the lagged variable(s) in first differences has a coefficient set to 0 in the equation with the corresponding dependent variable.

Dependent Variable	Lagged variable(s)	χ^2	Prob > χ^2
GDP per capita	All	10.24	0.0166
GDP per capita	GDP per capita	9.29	0.0023
GDP per capita	Interest rate	2.44	0.1182
GDP per capita	Private sector bank credit	0.04	0.8343
Private sector bank credit	All	83.01	0.0000
Private sector bank credit	GDP per capita	1.02	0.3115
Private sector bank credit	Interest rate	0.25	0.6172
Private sector bank credit	Private sector bank credit	77.49	0.0000
Interest rate	All	15.66	0.0013
Interest rate	GDP per capita	1.28	0.2571
Interest rate	Private sector bank credit	0.08	0.7820
Interest rate	Interest rate	11.93	0.0006

Table 48: The table presents the results from the Wald test based on model with Private sector bank credit as proxy for financial sector development and the interest rate added. The null hypothesis is that the lagged variable(s) in first differences has a coefficient set to 0 in the equation with the corresponding dependent variable.

C.5 Model 8

Model 8: GDP per capita, Private sector credit and all controls		
	0 lags	1 lag
$\alpha_{1,y}$	-0.029**	-0.019
$\alpha_{1,i}$	-7.804**	-4.994
$\alpha_{1,u}$	-1.159*	-1.454**
$\alpha_{1,r}$	2.657***	3.783***
$\alpha_{1,f}$	0.050*	0.026
ECM_1	(1, 0.000, -, 0.000, 0.420***, -128.743(const), -0.137t***)	(1, 0.000, 0.000, 0.000, 0.527***, -144.106(const), -0.141t***)
$\alpha_{2,y}$	0.000	0.000
$\alpha_{2,i}$	-0.221***	-0.231***
$\alpha_{2,u}$	-0.008	-0.013
$\alpha_{2,r}$	0.017	0.023*
$\alpha_{2,f}$	-0.001***	-0.001***
ECM_2	(0.000, 1, -, 0.000, 1.400, -431.431(const), 1.498t)	(-, 1, -, 0.000, -13.843, 1000.746(const), 3.216t***)
$\alpha_{3,y}$	0.000	-0.000
$\alpha_{3,i}$	-0.474***	-0.393**
$\alpha_{3,u}$	-0.036	-0.052*
$\alpha_{3,r}$	-0.079**	-0.042
$\alpha_{3,f}$	-0.007***	-0.007***
ECM_3	(0.000, -, 1, 0.000, 1.937**, -588.737(const), -0.400t**)	(0.000, 0.000, 1, 0.000, 5.638**, -558.826(const), -0.779t*))
$\alpha_{4,y}$	-0.000	-0.001
$\alpha_{4,i}$	0.442***	0.330**
$\alpha_{4,u}$	0.084***	0.097***
$\alpha_{4,r}$	-0.148***	-0.201***
$\alpha_{4,f}$	0.000	0.000
ECM_4	(0.000, 0.000, 0.000, 1, 8.057*, -911.343(const), 0.220t)	(-, 0.000, -, 1, 6.557*, -868.142(const), 0.547t)
c_y	0.130***	0.015
c_i	-0.001	-0.001
c_u	-0.002	-0.007
c_r	-0.004	-0.004
c_f	0.100***	0.114**
L_y		-0.294***; 16.047; 1.670; -1.746; -0.186;
L_i		0.001; 0.150**; -0.008; 0.006; 0.000;
L_u		-0.000; 0.445; 0.069; 0.0347; 0.003
L_r		0.002; 1.041***; -0.102*; 0.321***; -0.002
L_f		-0.043; -4.223; -0.457; -1.270; 0.185**
Eigenvalue	1, 0.975, (0.940 + 0.073i), (0.940-0.073i), 0.716	1, 0.962, (0.901 + 0.050i), (0.901-0.050i), 0.655, -0.332, (0.281 + 0.010i), (0.281-0.010i), (0.135 + 0.076i), (0.135-0.076i)
Modulus	1, 0.975, 0.943, 0.943, 0.716	1, 0.962, 0.903, 0.903, 0.655, 0.332, 0.281, 0.281, 0.155, 0.155

Table 49: The table displays the VECM estimation results for the model with all control variables and Private sector credit as proxy for financial sector development (restricted trend, rank 4). The α_y (α_i) (α_u) (α_r) (α_f) parameters denotes the estimated speed of adjustment parameter for Δ GDP per capita (Δ CPI rate) (Δ unemployment rate) (Δ interest rate) (Δ Private sector credit) and c_y (c_i) (c_u) (c_r) (c_f) denotes the estimated constant for the VECM model with Δ GDP per capita (Δ CPI rate) (Δ unemployment rate) (Δ interest rate) (Δ Private sector credit) as dependent variable. The L_y (L_i) (L_u) (L_r) (L_f) denotes the coefficient for lagged Δ GDP per capita (Δ CPI rate) (Δ unemployment rate) (Δ interest rate) (Δ Private sector credit) in the model with Δ GDP per capita as dependent variable in the first case, Δ CPI rate in the second case, Δ unemployment rate in the third case, Δ interest rate in the fourth case, Δ Private sector credit in the fifth (the five cases are separated by ";"). The ECM columns show the estimated error-correction vectors, with the coefficients for the lagged level variables displayed in the following order: coefficient for GDP per capita, coefficient for CPI, coefficient for unemployment, coefficient for interest rate, coefficient for Private sector credit constant and coefficient · time trend. Finally, the eigenvalue and modulus show the results when investigating the Eigenvalue stability condition. The *** denotes 5% significance level, ** denotes 5% significance level, * denotes 10% significance level.

Dependent Variable	Lagged variable(s)	χ^2	Prob > χ^2
GDP per capita	All	19.06	0.0019
GDP per capita	CPI	2.93	0.0869
GDP per capita	Unemployment	0.05	0.8177
GDP per capita	Interest rate	2.23	0.1354
GDP per capita	Private sector credit	1.29	0.2564
GDP per capita	GDP per capita	14.29	0.0002
Private sector credit	All	14.54	0.0125
Private sector credit	CPI	0.00	0.9486
Private sector credit	Unemployment	0.85	0.3570
Private sector credit	Interest rate	0.71	0.4002
Private sector credit	GDP per capita	1.48	0.2231
Private sector credit	Private sector credit	6.21	0.0127
CPI	All	26.64	0.0001
CPI	GDP per capita	0.81	0.3679
CPI	Unemployment	1.31	0.2532
CPI	Interest rate	13.71	0.0002
CPI	Private sector credit	0.24	0.6262
CPI	CPI	4.83	0.0279
Unemployment	All	6.04	0.3024
Unemployment	GDP per capita	0.00	0.9632
Unemployment	CPI	0.34	0.5600
Unemployment	Interest rate	3.19	0.0739
Unemployment	Private sector credit	0.07	0.7952
Unemployment	Unemployment	0.76	0.3848
Interest rate	All	22.29	0.0005
Interest rate	GDP per capita	0.00	0.9704
Interest rate	CPI	0.11	0.7434
Interest rate	Unemployment	0.11	0.7376
Interest rate	Private sector credit	0.30	0.5816
Interest rate	Interest rate	18.40	0.0000

Table 50: The table presents the results from the Wald test based on model with all control variables and Private sector bank credit as proxy for financial sector development. The null hypothesis is that the lagged variable(s) in first differences has a coefficient set to 0 in the equation with the corresponding dependent variable.

C.6 Model 9

Model 9: GDP per capita, Corporate credit and all controls		
	0 lags	1 lag
$\alpha_{1,y}$	-0.013	0.014
$\alpha_{1,i}$	-0.830	-10.070**
$\alpha_{1,u}$	-1.686	-1.439
$\alpha_{1,r}$	4.982***	3.686**
$\alpha_{1,f}$	0.226***	0.308***
ECM_1	(1, -, -, 0.055, -2.299***, 112.433(const), -0.232t)	(1, 0.000, 0, 0.023***, -0.328***, -65.929(const), -0.032t*)
$\alpha_{2,y}$	0.000	0.000*
$\alpha_{2,i}$	-0.153***	-0.176***
$\alpha_{2,u}$	-0.027**	-0.032***
$\alpha_{2,r}$	0.043***	0.036**
$\alpha_{2,f}$	-0.001**	-0.001
ECM_2	(-, 1, -, -10.487, 276.755***, -24615.2(const), -41.476t**)	(0.000, 1, -, -7.050***, 36.606***, -2810.285(const), -9.830t***)
$\alpha_{3,y}$	0.001**	0.001**
$\alpha_{3,i}$	-0.347***	-0.396***
$\alpha_{3,u}$	-0.033	-0.053*
$\alpha_{3,r}$	0.006	-0.011
$\alpha_{3,f}$	-0.007***	-0.005***
ECM_3	(-, 1, 0.000, 3.468, -120.204***, 10698.46(const), 17.457t**)	(0.000, -, 1, 1.859***, -15.557***, 1190.079(const), 3.544t***)
c_y	0.097***	0.112***
c_i	-0.032	0.002
c_u	0.288	-0.011
c_r	0.078	-0.003
c_f	0.313***	0.031
L_y		-0.148; 24.548; -2.602; 5.718; -0.291
L_i		0.000; 0.249***; -0.013; -0.010; -0.001
L_u		-0.001; 0.178; 0.073; -0.003; 0.000
L_r		0.002; 0.649***; -0.090; 0.295***; -0.001
L_f		-0.033; 0.125; 0.402; 0.298; 0.109
Eigenvalue	1, 1, (0.948 + 0.058i), (0.948 + 0.058i), 0.713	1, 1, 0.896, 0.870, 0.669, (0.337 + 0.187i), (0.337-0.187i), -0.207, 0.151, 0.075 (0.189 + 0.251i), (0.189-0.251i), -0.116
Modulus	1, 1, 0.950, 0.950, 0.713	1, 1, 0.896, 0.870, 0.669, 0.386, 0.386, 0.207, 0.151, 0.075

Table 51: The table displays the VECM estimation results for the model with all control variables and Corporate credit as proxy for financial sector development (restricted trend, rank 3). See table 49 for additional notes.

C.7 Model 10

Model 10: GDP per capita, Household credit and all controls		
	0 lags	1 lag
$\alpha_{1,y}$	-0.060**	-0.020
$\alpha_{1,i}$	0.649	-8.106**
$\alpha_{1,u}$	-3.415**	-1.229
$\alpha_{1,r}$	2.986*	4.861***
$\alpha_{1,f}$	-0.042	0.025
ECM_1	(1, 0.000, 0, -0.023***, 0.106***, -101.874(const), -0.128t***)	(1, 0.000, 0.000, -0.077***, 0.310***, -113.949(const), -0.213***)
$\alpha_{2,y}$	0.000	0.000
$\alpha_{2,i}$	-0.173***	-0.271***
$\alpha_{2,u}$	-0.022**	-0.024*
$\alpha_{2,r}$	0.027**	0.016
$\alpha_{2,f}$	-0.002***	-0.001
ECM_2	(0.000, 1, 0, -5.042***, 3.813, 116.551(const), -4.222t***)	(0.000, 1, 0.000, 5.159***, -33.966***, 2342.908(const), 11.531t***)
$\alpha_{3,y}$	-0.001	0.002**
$\alpha_{3,i}$	-0.385***	-0.519***
$\alpha_{3,u}$	-0.039	-0.103***
$\alpha_{3,r}$	-0.008	-0.020
$\alpha_{3,f}$	-0.008***	-0.003***
ECM_3	(0.000, 0.000, 1, 1.706***, -2.667*, -17.497(const), 1.796t***)	(0.000, -, 1, -1.564***, 9.505***, -752.460(const), -3.225t***)
c_y	0.102***	0.124***
c_i	-0.002	-0.000
c_u	-0.014	0.003
c_r	-0.011	0.001
c_f	0.171***	0.018
L_y		-0.100; -6.198; -2.639; 2.339; -0.029
L_i		0.001; 0.286***; -0.021; -0.009; -0.001
L_u		-0.001; 0.537*; 0.085; 0.048; 0.003
L_r		0.003**; 0.733***; -0.136**; 0.318***; -0.002
L_f		0.066; -23.499***; -3.924; -5.728*; 0.653**
Eigenvalue	1, 1, 0.922, 0.903, 0.691	1, 1, 0.935, (0.779 + 0.214i), (0.779-0.214i), (0.413 + 0.223i), (0.413-0.223i), (0.189 + 0.251i), (0.189-0.251i), -0.116
Modulus	1, 1, 0.922, 0.903, 0.691	1, 1, 0.935, 0.808, 0.808, 0.470, 0.470, 0.314, 0.314, 0.116

Table 52: The table displays the VECM estimation results for the model with all control variables and Household credit as proxy for financial sector development (restricted trend, rank 3). See table 49 for additional notes.

C.8 Model 11

Model 11: GDP per capita, Private sector bank credit to GDP and all controls		
	0 lags	1 lag
$\alpha_{1,y}$	-0.021	-0.011
$\alpha_{1,i}$	-8.024**	-3.978
$\alpha_{1,u}$	-1.187*	-1.297**
$\alpha_{1,r}$	3.046***	4.361***
$\alpha_{1,f}$	0.055**	0.043*
ECM_1	(1, -, -, -0.017*, 0.232*, -106.963(const), -0.123t***)	(1, -, 0.000, -0.028***, 0.339***, -122.977(const), -0.139t***)
$\alpha_{2,y}$	0.000	0.000**
$\alpha_{2,i}$	-0.180***	-0.168***
$\alpha_{2,u}$	-0.019**	-0.033***
$\alpha_{2,r}$	0.020**	0.025**
$\alpha_{2,f}$	-0.002***	-0.001***
ECM_2	(-, 1, -, -3.425***,-17.053, 1707.716(const), -1.309t)	(0.000, 1, 0.000, -2.768***, -27.258***, 3328.124(const), -0.413t)
$\alpha_{3,y}$	0.000	0.000
$\alpha_{3,i}$	-0.510***	-0.552***
$\alpha_{3,u}$	-0.027	-0.097***
$\alpha_{3,r}$	-0.080**	-0.077*
$\alpha_{3,f}$	-0.010***	-0.008***
ECM_3	(-, -, 1, 0.488**, 3.989, -468.184(const), 0.149t)	(0.000, 0.000, 1, 0.383**, 6.299***, -835.196(const), -0.003t)
c_y	0.215***	-0.027
c_i	-0.011	-0.000
c_u	0.135	0.003
c_r	0.026	-0.000
c_f	-0.023	0.021
L_y		-0.268***; 14.999; -1.631; -0.909; -0.225*;
L_i		0.000; 0.114; -0.002; 0.003; 0.000
L_u		-0.001; 0.401; 0.140*; 0.052; 0.007**
L_r		0.002; 0.954***; -0.091; 0327***; -0.000
L_f		0.013; -10.235; -5.151***; -3.471; 0.286***
Eigen-value	1, 1, 0.978, 0.915, 0.720	1, 1, 0.978, 0.917, 0.587, 0.393, (0.168 +0.273i), (0.168 -0.273i), -0.295, 0.183
Modu-lus	1, 1, 0.978, 0.915, 0.720	1, 1, 0.978, 0.917, 0.587, 0.393, 0.320, 0.320, 0.295, 0.183

Table 53: The table displays the VECM estimation results for the model with all control variables and Private sector bank credit as proxy for financial sector development (restricted trend, rank 3). See table 49 for additional notes.

C.9 Patent estimations

	GDP per capita – Patent (*prv_patstat*) – Corporate credit estimation	
	0 lag	1 lags
α_y	-0.004	0.019*
α_f	-0.001	0.129***
α_p	-0.741***	0.410***
β_0	-300.4336	6.802
β_f	0.699**	-0.528***
β_p	1.444**	-0.532***
ρ	-0.208**	-0.020
c_y	0.103***	0.122***
c_f	0.164***	0.162***
c_p	-0.001	-0.057
L_y	-	-0.088; -0.173; 0.833
L_f	-	-0.052**; 0.265***; -0.203
L_p	-	0.004; 0.040***; -0.702***
Eigenvalue	1, 1, -0.076	1, 1, -0.796, 0.794, 0.309, -0.099
Unit modulus	1, 1, 0.076	1, 1, 0.796, 0.794, 0.309, 0.099

Table 54: The table displays the VECM estimation results for estimated model with GDP per capita, *prv_patstat* as proxy for innovation and Corporate credit as proxy for financial sector development. See the table 38 for additional notes.

Model 12: GDP per capita – Patent (*prv_patstat*) – Corporate credit estimation with all controls		
	0 lags	1 lag
$\alpha_{1,y}$	0.002	0.028
$\alpha_{1,i}$	-1.502	-5.782*
$\alpha_{1,u}$	-1.332	-0.034
$\alpha_{1,r}$	3.719***	1.831*
$\alpha_{1,f}$	0.274***	0.237***
$\alpha_{1,p}$	-0.528*	-0.199
ECM_1	(1, -, 0.000, 0.031***, 0.543***, 1.395***, -285.685(const), -0.153t***)	(1, 0.000, 0.000, 0.060***, -0.146, 0.656***, -151.0921(const), -0.028t)
$\alpha_{2,y}$	0.001**	0.001*
$\alpha_{2,i}$	-0.353***	-0.352***
$\alpha_{2,u}$	-0.034	-0.047
$\alpha_{2,r}$	0.007	-0.008
$\alpha_{2,f}$	-0.007***	-0.007***
$\alpha_{2,p}$	-0.001	-0.006
ECM_2	(-, 0.000, 1, 2.167***, 35.374***, 77.068***, -111169.32(const), -3.663t***)	(0.000, 0.000, 1, 2.920***, 1.010, 30.760***, -3501.801(const), 2.096t*)
$\alpha_{3,y}$	0.001***	0.001***
$\alpha_{3,i}$	-0.163***	-0.172***
$\alpha_{3,u}$	-0.026***	-0.203*
$\alpha_{3,r}$	0.034***	0.030**
$\alpha_{3,f}$	-0.001*	-0.001
$\alpha_{3,p}$	0.002	-0.002
ECM_3	(0.00, 1, 0.00, -7.309***, -90.156***, -180.907***, 26858.24(const), 8.429t***)	(0.000, 1, 0.000, -9.557***, -12.820, -85.823***, 10517.83(const), -4.950t)
c_y	0.094***	0.125***
c_i	-0.034	-0.009
c_u	0.310	0.056
c_r	0.081	-0.006
c_f	0.296***	-0.045
c_p	0.039	0.160
L_f on p	-	0.055
Eigenvalue	1, 1, 1, 0.908, 0.775, -0.119	1, 1, 1, 0.901, 0.793, -0.740, 0.661, (0.348 +0.166i), (0.348 -0.166i), -0.213, 0.130, 0.049
Modulus	1, 1, 1, 0.908, 0.775, 0.119	1, 1, 1, 0.901, 0.793, 0.740, 0.661, 0.386, 0.386, 0.213, 0.130, 0.049

Table 55: The table displays the VECM estimation results for the model with all *prv_patstat* as proxy for innovation, Corporate credit as proxy for financial sector development and all control variables (restricted trend, rank 3). See table 49 for additional notes. Note that this table only shows the short-run impact of lagged changes in Corporate credit on current changes in Patent.

C.10 Nonlinear estimation results

Nonlinear relationship	
	Coefficient
Constant	82.267***
Private sector credit (level)	0.031**
Squared Private sector credit	-0.0003***
Interest rate	0.0247***
Time	0.158***

Table 56: The table displays the estimated coefficients in the first step of the Engle-Granger procedure, with GDP per capita as dependent variable. *** and ** show 1% and 5% significance level.

Augmented Dickey-Fuller test	
Test statistic	-3.149
Approximated critical value	-3.785

Table 57: The table displays the test statistic of the Augmented Dickey-Fuller test of the residual series generated from the estimated model in table 57. The critical value is an approximation, from Table C: Critical Values for the Engle-Granger Cointegration Test.