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Essays in Empirical Macroeconomics

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Declaration

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Abstract

This thesis is a collection of three independent essays. The objective of the research is to answer three key questions faced by Central Banks and policy makers in Europe which have arisen since the Global Financial Crisis.

The first essay examines the "wage puzzle" in Europe in the period from 2012 to 2017, where wage growth remained markedly subdued despite significant reductions in conventional measures of labour market slack. The contribution of this chapter is to generate a "non-employment index" for a selection of European countries using novel dataset that allows us to exploit the panel structure of the European Labour Force Survey. The NEI includes discouraged workers and those marginally attached to the labour market, but crucially their weight in the index is determined by their estimated probability of transitioning back into employment. We demonstrate that using the NEI in a wage Phillips curve more accurately accounts for the wage dynamics across several Euro-zone countries. The implication is that conventional measures of labour market slack understate the available pool of labour when cyclical conditions tighten. We show that the effect is stronger in those countries most affected by the sovereign debt crisis.

The second essay makes two significant contributions to the literature on capital misallocation and the broader debate on productivity divergence across Europe. First, we provide a comprehensive measurement and decomposition of the sources of capital misallocation across 19 European countries. Using a novel dataset that contains firm-level balance sheet data from the manufacturing sector, we employ the methodological framework of David and Venkateswaran (2019), which accounts for adjustment costs and firm-level uncertainty. In contrast to previous studies, which primarily focus on country-level estimates, we extend the analysis to industry-level variation. By decomposing misallocation at the two-digit NACE industry level, we document substantial heterogeneity in the factors driving misallocation across sectors and countries. Our findings show that most of the observed dispersion is driven by permanent firm-specific factors, particularly in Southern European countries that were more severely impacted by the sovereign debt crisis. We also identify significant contributions from adjustment costs and uncertainty, whereas firm-specific distortions play a more limited role. The second contribution is to show that financial variables and productivity-related industry characteristics are closely linked to the

persistent distortions observed in our analysis. This provides new insights into the role of financial and macroeconomic conditions in driving productivity differences across Europe, highlighting the importance of targeted policy interventions to address these sources of misallocation.

The third chapter addresses whether macroprudential policies designed to stabilise traditional banks inadvertently shifted credit activity into less-regulated non-bank financial intermediaries (NBFIs), and if so, how does this shift affect the transmission of monetary policy? Using a panel of European countries from 2009 to 2021 and comprehensive data on macroprudential policies the IMF, I show that a tightening of macroprudential policies on traditional banks is associated with an increase FVC loans. This finding supports the "cross-sectoral arbitrage" hypothesis á la Farhi and Tirole (2017). Second, I find that loan-targeted macroprudential measures do not appear to significantly influence this shift, suggesting that policies aimed at systemic risk, such as capital requirements and the use of bank profits are the main drivers of the result. Third, the chapter investigates whether how FVC loans respond to monetary policy shocks. Contrary to the traditional bank lending channel, FVCs are found to expand their lending following a monetary policy shock. This finding provides suggestive evidence that the expansion of FVCs, spurred by macroprudential tightening, may also dampen the transmission of monetary policy transmission to the broader financial system.

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I am grateful to my parents, whose unwavering support has been crucial throughout my years in education. I particularly wish to remember my mother, whose encouragement profoundly influenced my educational journey.

I dedicate this thesis to my wife, Niamh, whose unwavering support and encouragement over the years have helped me balance family life with work and study. Your own achievements during the years of this PhD, both educational and professional, have been a constant source of inspiration. The birth of our son, Harry, in June 2022, has brought immense joy to our lives. Harry, your love, energy and sense of fun have kept everything in perspective.

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Chapter 1

General Introduction

This thesis addresses important macroeconomic questions faced by central banks and policymakers in Europe in the years following the Global Financial Crisis. The financial crisis, followed by the sovereign debt crisis in Europe, exposed several unresolved issues regarding the interaction between policy and the real economy. Three key questions, in particular, emerge. Firstly, why did wage growth remain persistently weak in the post-crisis years despite a sharply declining unemployment rate? Second, while it is well established that capital misallocation has played an important role in the divergence of productivity growth across European countries, what are the specific sources of this misallocation? Do these sources differ across countries and sectors? What policy interventions might alleviate them, and what would be the resulting increase in aggregate total factor productivity? Lastly, in the aftermath of the global financial crisis most developed economies have instituted macroprudential policies to curb excessive credit growth and preserve financial stability (Cerutti et al., 2017). Over the same period, however, there has been a substantial expansion of non-bank financial institutions (NBFIs) in Europe, particularly financial vehicle corporations (FVCs). This raises the question: have macroprudential policies aimed at stabilising traditional banks inadvertently shifted credit activity to less regulated NBFIs. If so, do these entities respond in the same way as traditional banks to monetary policy shocks?

The second chapter of this thesis addresses the persistent ”wage puzzle” observed in the European Monetary Union. Despite significant improvements in employment figures and a reduction in conventional measures of labour market slack from 2013 onwards, wage growth remained remarkably subdued. This outcome contradicts the predictions of the wage Phillips curve, which posits that as labour market slack decreases, wage inflation should rise. A tighter labour market is expected to put upward pressure on wages, driven by increased bargaining power among workers. This chapter re-evaluates the adequacy of traditional measures of labour market slack, such as the unemployment rate, in capturing the true conditions in the labour market. The first contribution of this chapter is the construction of the Non-Employment Index (NEI), a broader measure of labour market slack developed for the US by Hornstein et al. (2015), for a comprehensive panel of Euro member countries. Using a novel dataset collected from Central Banks in the monetary union that allows us to exploit the panel element of Labour force surveys in Europe, this chapter is the first to compute the NEI in a comparable way across European countries. The NEI incorporates wider cohorts of individuals who are not officially classified as unemployed, weighting them using their estimated probability of transitioning back into employment. This group includes discouraged workers and those marginally attached to the labour market. The second contribution is demonstrating that the NEI outperforms other measures of labour market slack, such as the unemployment rate, unemployment gap, and broader measures like U6, in predicting wage dynamics. In a conditional forecast comparison exercise, the NEI proves to be a more accurate indicator of labour market conditions - with the most significant improvement in countries most affected by the eurozone sovereign debt crisis. These findings suggest that traditional measures can misrepresent the true level of slack, while the NEI offers new insights into wage-setting dynamics in the post-crisis period.

The third chapter makes two significant contributions to the literature on capital misallocation and the broader debate on productivity divergence across Europe. First, we provide a comprehensive measurement and decomposition of the sources of capital misallocation across 19 European countries. Using a novel dataset that contains firm-level balance sheet data from the manufacturing sector, we employ the methodological framework of David and Venkateswaran (2019), which accounts for adjustment costs and firm-level uncertainty. In contrast to previous studies, which primarily focus on country-level estimates, we extend the analysis to industry-level variation. By decomposing misallocation at the two-digit NACE industry level, we document substantial heterogeneity in the factors driving misallocation across sectors and countries. Our findings show that most of the observed dispersion is driven by permanent firm-specific factors, particularly in Southern European countries that were more severely impacted by the sovereign debt crisis. We also identify significant contributions from adjustment costs and uncertainty, whereas firm-specific distortions play a more limited role. Second, we explore the macroeconomic determinants of misallocation by matching our industry-level misallocation estimates to a range of potential predictors using micro-aggregated cross-country panel data from CompNet. To handle the high dimensionality of the data, we also employ a penalised regression approach. Across both approaches, the results indicate that firm demographics, financial variables and productivity-related industry characteristics are closely linked to the persistent distortions observed in our analysis.

The fourth chapter addresses the question: Have macroprudential policies designed to stabilise traditional banks inadvertently shifted credit activity into less-regulated non-bank financial intermediaries (NBFIs), and if so, how does this shift affect the transmission of monetary policy? In this chapter, I provide evidence of a link between the tightening of macroprudential policies banks and growth in loan claims of Financial Vehicle Corporations (FVCs) in Europe. Using a panel of Euro-area countries from 2009 to 2021, the analysis shows that regulatory constraints on traditional banks may have inadvertently shifted credit activity to less-regulated sectors, supporting the "cross-sectoral arbitrage" hypothesis Farhi and Tirole (2017). Second, the chapter extends this analysis by examining which specific macroprudential policies drive these shifts. I find that loan-targeted macroprudential measures do not appear to significantly influence this shift, suggesting that policies aimed at systemic risk, such as capital requirements and the use of bank profits are the main drivers of the result. Third, the chapter investigates how these shifts in credit activity to non-bank financial intermediaries affect the transmission of monetary policy. Contrary to the traditional bank lending channel, FVCs are found to expand their lending following a monetary policy shock. This finding suggests that the expansion of FVCs, spurred by macroprudential tightening, may alter the effectiveness of monetary policy transmission to the broader financial system. This chapter underscores the need for macroprudential and monetary policy authorities to coordinate efforts to mitigate these unintended spillover effects.

Finally, chapter 5 summarises the overall findings and provides general conclusions and policy recommendations arising from this thesis, along with suggestions for future research.

Chapter 2

Solving the Wage Puzzle: Does the Non-Employment Index Explain European Wage Dynamics Since the Global Financial Crisis? [1]

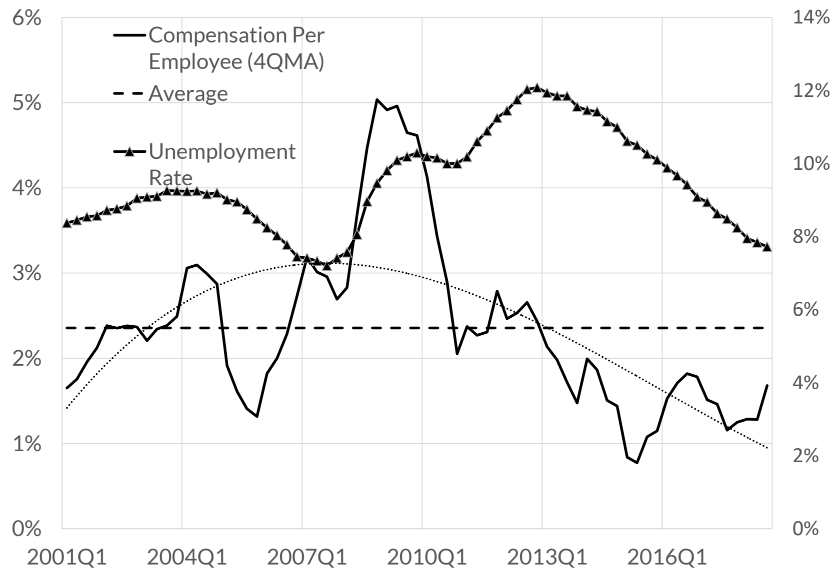
2.1 Introduction

A puzzling fact of the growth experience in the euro area during 2012 to 2017 is that wage growth remained consistently lower than forecast. This is despite a notable fall in the unemployment rate and other standard measures of labour market slack since 2013 (Figure 2.1). This phenomenon is puzzling because the wage phillips curve documents an inverse relationship between the degree of labour market slack and the pace of wage growth. In search and matching models of the labour market, wages are set in negotiations where the bargaining power of workers depends on

[1] Co-authored with Shayan Zakipour-Saber. This paper was published as Central Bank of Ireland Research Technical Paper RTP/2020/05. The opinions expressed in this paper are those of the authors and do not necessarily represent the views of the Central Bank of Ireland, the European System of Central Banks or the ECB. This research was carried out as part of the ECB's Expert Group on Low Wages (WEG) and a Box outlining a summary of the work is contained in Nickel et al. (2019a). We thank Agustín Bénétrix, Reamonn Lydon, Gerard O'Reilly, John FitzGerald, the members of the WEG, seminar participants at the 2019 Congress of the European Economics Association, the Irish Economics Association Conference 2019, and participants in the Central Bank and Trinity College Dublin seminar series for helpful comments that greatly improved the paper. All remaining errors are our own.

the tightness of the labour market. In this framework, a tighter labour market implies greater bargaining power for the employees meaning they can demand higher wages.[2]

Figure 2.1: Euro Area Compensation Per Employee and Unemployment



Source: Eurostat and Authors' Calculations.

This episode has raised questions about whether slack in the labour market is accurately measured. Recent studies such as Bell and Blanchflower (2018b) and Blanchard (2018) have asked whether accounting for those outside of the labour force may give us a better understanding of the availability of labour and hence a more accurate view of the relative bargaining power of workers.

In this paper, we seek to answer this question in two steps. First, we construct a non-employment index (NEI) for a group of euro-area countries in the spirit of Hornstein et al. (2015). These authors constructed a NEI for the US labour market. The non-employed are the group of individuals who are not in employment, but do not meet the strict definition of unemployed

[2]The propogation mechanism for this is typically through the wages of new hires in the Diamond (1982) Mortensen (1982) and Pissarides (1990) framework (see Lydon and Lozej (2018)

as set out by the official statistical agencies. The ILO define "the unemployed" as persons of working age who were: a) without work during the reference period; b) currently available for work; and c) seeking work, i.e. had taken specific steps in a specified recent period to seek paid employment or self-employment. Second, we show that the constructed NEI outperforms other traditional measures of labour market slack in a conditional forecast comparison exercise in the countries affected by the european sovereign debt crisis. We argue that currently used indicators of labour market slack such as the unemployment rate, unemployment gap, and even more recently established broader measures such as "U6" can misrepresent the "true" level of slack available in a particular economy. Only a subset of workers who are outside of the labour force workers are comparable with the unemployed, which may under-represent the "true" level of slack. Brandolini et al. (2006) find that these are individuals whose last search effort dates back to no more than 6 months before the reference period.

There was a significant increase in discouraged workers in Europe during and after the global financial crisis. This is due to workers becoming discouraged and exiting the labour force after prolonged employment searches. As the labour market improves, these workers represent an additional pool of slack available to firms, reducing the wage bargaining power of incumbent workers. We show that, particularly in the countries worst hit by the european sovereign debt crisis, the missing wage growth is explained when the Phillips curve is re-specified to account for this additional pool of non-employed workers.

Understanding the drivers of wage developments is of considerable importance in assessing the appropriate stance of monetary policy. Labour represents a significant fraction of costs in most industries, hence wage growth is one of the primary drivers of consumer price inflation. Accordingly, there has been considerable research into this puzzle in recent times. Many have questioned whether the the phillips curve is still relevant (Blanchard (2018); Moretti et al. (2019), Leduc and Wilson (2017a); Murphy (2018)). Some have suggested the possibility that the phillips curve may be non-linear (Byrne and Zekaite (2018); Ho and Njindan Iyke (2018)). Many papers have suggested that the unemployment rate is not a comprehensive enough indicator of the pool of available labour.

The paper that is most closely related to ours is that of Bell and Blanchflower (2018b) who develop an underemployment index and show that underemployment in the UK and US labour markets is resulting in a flattening of the wage phillips curve. Underemployed workers are those who would like to work more hours. We go further and suggest that all those who are not working represent, with heterogeneous probability, individuals who could transition into employment in the next quarter. To do this, we use the methodology of Hornstein et al. (2015) who have developed a "non-employment index" for the US.

While the work to explicitly estimate a non-employment index is recent, it follows on a large body of previous research that points to the importance of considering job seekers who are outside of the labour force as well as the unemployed when analysing the labour market. Recent policy work such as ECB (2017) assessed developments in wider measures of labour market slack in comparison with the narrow definition of the unemployment rate. Blanchard (2018) also argued that if some workers become less employable or become discouraged, then the unemployment statistics will fail to capture hysteresis effects fully, because many of these workers will drop out of the labour force.

Our paper also contributes to the rapidly expanding literature on the importance of accounting for heterogeneous job searchers (Hall and Schulhofer-Wohl (2018), Ahn and Hamilton (2016)). In the context of estimating matching efficiency of the labour market, Veracierto (2011), Diamond (2013)and Elsby et al. (2013) show that it is important to account for the job seekers out of the labour force in addition to the unemployed. Hornstein and Kudlyak (2016) motivated this in a theoretical framework, by estimating a model where they introduce endogenous search effort into the standard matching function of Diamond, Mortenson and Pissardes with job seeker heterogeneity.

The structure of the rest of the paper is as follows. Section 2 details the data sources used in our empirical analysis. In section 3 we document the calculation of the NEI - using the case of Ireland as an illustrative example. Section 4 discusses the heterogeneous dynamics in the non-employment indices across Europe. Section 5 details the conditional forecasting performance of our measure relative to other measures of slack traditionally used in estimating the phillips curve, while section 6 concludes.

2.2 Data

The analysis in this paper is based on data from the Labour Force Survey (LFS) which is a large-scale, harmonised survey of households carried out by each member state of the European Union. It is designed to produce quarterly labour force estimates that include the official measure of employment and unemployment on a consistent basis set down by the International Labour Organisation (ILO). In most countries, one fifth of the households in the survey are replaced each quarter. The longitudinal nature of the LFS makes it possible to track the labour market status of individuals over consecutive quarters during which they remain in the survey sample. This detailed information on worker flows allows us to calculate the probability of workers moving between different states, i.e. from unemployment to employment or from inactivity to unemployment, and these probability weights are used in constructing our non-employment index. This data is primarily available from the European Statistical Agency, Eurostat. We also gathered additional data from national central banks of the eurosystem, as data on transition probabilities are available only back to 2011 in the publicly available dataset. [3]. This allowed us to compile the series back as far as 2005 for a selection of countries. One regrettable shortcoming of this work is the lack of availability of data for Germany. Longitudinal data from the German Labour Force survey was not available from Eurostat or the Federal Employment Agency. Accordingly, Germany are excluded from the analysis.

2.3 The Non-Employment Index

The financial crisis of 2008-2012 had a severe and lasting effect on the European labour market (Table 2.1). The headline unemployment rate - which peaked at 12.1 per cent in the 1st quarter of 2013 for the euro area and 11.5 per cent for the EU28 - is a commonly cited measure of the impact of the crisis. However, this captures only part of the effect of the economic downturn on the labour market. As well as the workers who lost their jobs, a large number also exited

[3] This exercise was carried out as part of the authors' work on the European Central Bank's Expert Group on Low Wages

Table 2.1: Peak to trough percentage point change in standard measures of labour slack (2008-2013)

	Unemployment Rate	Labour Force Participation
Austria	1.2	-1.6
Belgium	1.3	-1
Cyprus	8.2	-0.9
Spain	16.6	-2.5
Finland	2	-1.5
France	2.4	-1
Ireland	10.5	-4.5
Italy	4.6	-1.5
Lithuania	13.5	-3.9
Latvia	13.4	-1.8
Netherlands	2.1	-2.3
Portugal	7	-0.5
Slovenia	4.5	-1.5
Slovakia	4.9	-1.1

the labour force entirely, particularly in the countries which were worst hit by the crisis in the periphery. Among those who dropped out of the labour force, some returned to education or training, while a significant number became discouraged as the recession persisted and stopped searching for work. In Ireland, one of the countries which was worst affected by the crisis, the overall labour force participation rate declined by four percentage points from Q4 2007 to Q4 2012 while the size of the inactive population - i.e. those neither employed or unemployed - increased by 13 per cent. Given the size of the pool of these non-employed individuals, a broader measure of labour utilisation than the standard unemployment rate may be needed to provide a fuller picture of labour market conditions.

A number of extended, or broader, measures of unemployment are published by statistical agencies such as Eurostat which include some individuals not usually counted as unemployed. The primary example of this is the “U6” measure, which has been widely used in the US and in Europe. These include passive job seekers, discouraged workers, students and individuals who report that they do not want a job. However, a key characteristic of these broader measures of unemployment is that they assign the *same weight* to all non-employed individuals outside the labour force. As a result, they do not take into account the substantial differences in the degree of labour force attachment of different types of individuals. For instance, looking at the transition rates of non-employed individuals who move back into work shows, unsurprisingly, that those who state that they are actively looking for work consistently have a much higher transition rate to employment than individuals who report that they are not engaged in job search.

This section shows how the NEI accounts for this by using the transition probablities of each cohort as a proxy for labour force attachment. The Labour Force comprises the population aged 15-74 who are either employed or unemployed. However, the unemployed are only a subset of the working age population who are not in work (hereafter non-employed). The definition of unemployment is based on the notion that the individual 'seeks work'. Seeking work, however, is not a clear-cut process and the job search process of different individuals will have varying degrees of intensity depending on their circumstances. Every individual not currently working has some non-zero probability of transitioning into employment in the next quarter, and this probability reflects their attachment to the labour force.

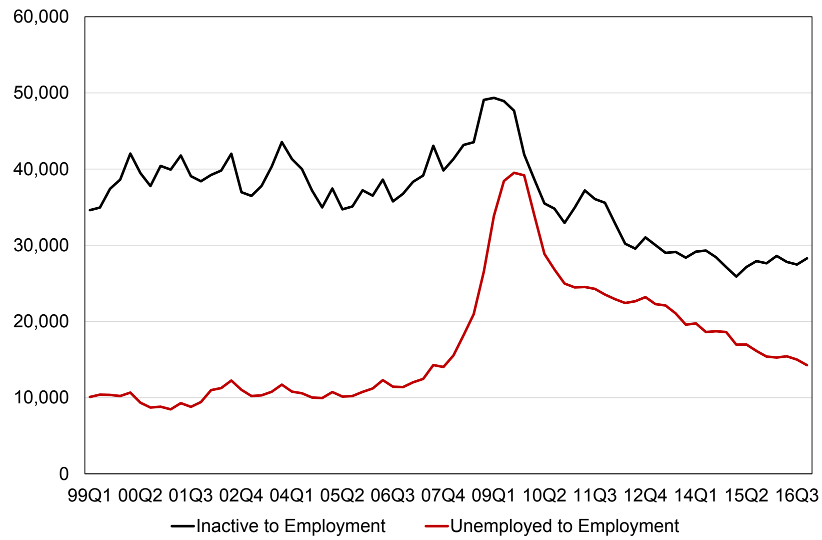
The LFS splits the non-employed into five different cohorts: short-term unemployed; long-term unemployed; available not seeking; seeking not immediately available; and others. The stock and proportion of individuals in each cohort in each country is described in Table 2.2.

Between 2008Q4 and 2012Q4, the number of persons in the inactive group (i.e. outside of the labour force but not classified as unemployed) grew significantly in each of the countries considered, particularly in countries worst affected by the crisis - Ireland, Spain, Portugal, Italy and Greece.

An examination of the flows into employment reveals another reason to consider a broader measure of labour utilisation than the standard unemployment rate. For example, the flows into employment in Ireland from unemployment and inactivity in each quarter are shown in Figure 2.2. As the chart shows, the flow of workers from inactivity into employment every quarter is significantly larger than the flow of workers from unemployment back to employment. The probability that an individual from each of these non-employed or inactive cohorts transitions into employment in the following quarter serves as a proxy for each of these cohorts' attachment to the labour force.

The average transition probabilities are described in Table 2.2. Short-term unemployed persons had the highest transition probability over the sample period in all countries. Interestingly, those

Figure 2.2: Flows into Employment (Ireland)



Source: Eurostat and Authors' Calculations.

who are *seeking but not immediately available* in many cases have an average transition probability greater than those who are classified as long-term unemployed. This category comprises individuals who have been actively seeking work in the previous four weeks but are not available in the next two weeks. Those who are not seeking because they are in education or training have an average transition probability of 8 per cent. Overall, the ranking of the employment probabilities in Table 1 is closely aligned with individual's self-reported desire to work as recorded in the LFS: those actively seeking work have a higher transition probability than those who want work but are not searching for a job. In Austria, Cyprus, Finland, Italy, Ireland and Slovakia, at least one of the cohorts outside of the labour force have significantly higher transition probabilities than the long-term unemployed. This feature of the data suggests that the unemployment rate may not fully capture the degree of slack in the labour market.

To address this potential under-estimation of slack, we propose the non-employment index which takes into account differences in the labour market attachment of non-employed groups. Our methodology follows closely that of Hornstein et al. (2015) who were the first to develop a NEI

Table 2.2: Transition probabilities

	short-term	long-term	available not seeking	seeking not immediately available	Others
Austria	32.00	14.50	14.67	9.33	4.67
Cyprus	23.33	9.67	5.00	25.83	1.33
Finland	28.33	13.33	8.67	14.67	6.00
France	26.67	13.17	7.17	10.50	2.17
Italy	19.65	10.30	12.79	7.55	3.45
Latvia	23.00	12.67	8.00	8.83	3.33
Lithuania	17.67	8.17	3.50	0.00	1.83
Netherlands	25.33	13.67	5.67	9.33	3.33
Ireland	18.50	8.00	6.50	8.50	3.00
Portugal	24.17	15.17	9.50	6.00	5.00
Slovakia	9.08	4.06	7.28	4.87	0.99
Slovenia	23.83	14.83	8.67	7.00	6.50
Spain	22.83	9.33	5.17	8.67	2.67

Source: Eurostat, National Central Banks, and Authors' calculations

for the United States. The NEI is a weighted average of the population shares of the cohorts outlined in Table 1, where the weights for each cohort is given by that group's average transition probability to employment over the labour force survey (Table 2.2). This index gives a measure of the available units of labour in the economy. We assign a weight of 1 to the short-term unemployed, who have the highest transition probability, and assign each of the other cohorts' weight relative to this. To take a concrete example, Irish individuals who are classified as *seeking but not immediately available* have an average probability of transitioning into employment over the sample of 10.98 per cent. In the same country, the average transition probability of someone who is short-term unemployed is 18.5 per cent. Combining these probabilities, the *seeking not immediately available* cohort are are given a weight of $\frac{8.5}{18.5} = 0.46$. In each quarter in our sample, the stock of workers in each cohort is reweighted using this method. More formally, the non-employment index for each period t is defined as:

$$\sum_{j=1}^{9} \theta_j \frac{Pop_j}{Pop}$$

where we multiply the population share of cohort j by their transition probability defined weight θ from Table 2.2. This yields the non-employment rate as a percentage of the *working age population*. The key contribution of the NEI is that each cohort is now weighted according to their probability of transitioning into employment. As a result, the NEI may represent a more accurate picture of slack remaining in a given economy since other measures of labour market slack do not account for these heterogeneous transition probabilities.

One caveat is that our measure still does not account for slack which is available in terms of workers coming from abroad, who may transition into employment from unemployment in a different region. This group represent a further source of slack, which may be more important in terms of the wage phillips curve when the labour market is tight. Obviously, this is also the case with more standard measures of labour market slack, but further work to incorporate this dimension would be a valuable contribution.

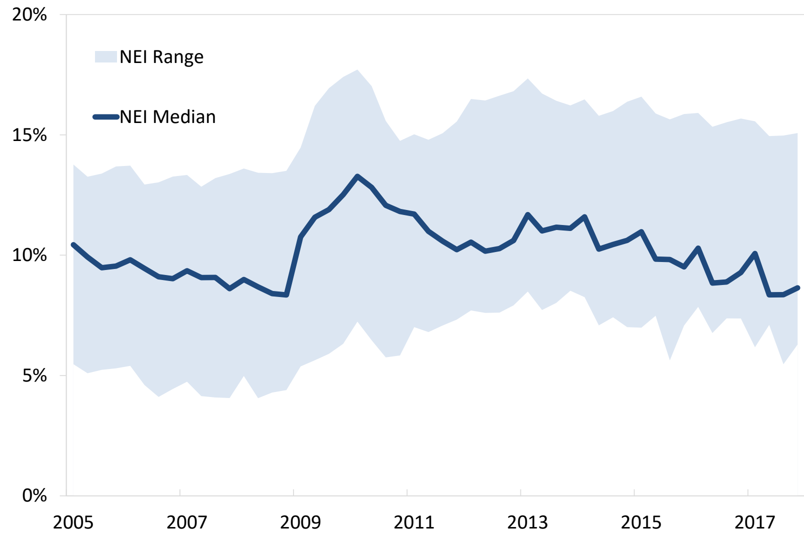
2.4 Non-Employment Indices for Europe

Figure 2.3 shows our estimates of the median Non-Employment Index (NEI) for the 13 countries in our sample. The shaded bands represent the highest and lowest NEI in the sample at any given time.

What is more important to our analysis however is the additional information that the NEI gives the researcher compared with the standard unemployment rate. It is important to note that different denominators are used in the calculation of the NEI and the standard unemployment rate. As such, they are not directly comparable - the NEI is calculated as a percentage of the *working age population* while the unemployment rate is expressed as a share of the *labour force*. In figure 2.4, we index both the median non-employment index and the median unemployment rate to 2005Q1, the beginning of our sample, in order to compare the dynamics in both series.

It is clear that during the post crisis period (2013 to 2017) the slope of the unemployment rate is much steeper than that of the non-employment index. Both series increase substantially during the crisis, but the pace of the subsequent decline in the Non-employment series is much slower than that of the unemployment rate.

Figure 2.3: Non-Employment Range



Source: Eurostat, National Central Banks and Authors' Calculations.
Note: The blue line represents the median of the cross country NEI

Figure 2.6 displays a decomposition of the NEI for each country. There is substantial heterogeneity in terms of the level and dynamics in non-employment, which is driven both by the structure of their respective labour markets and by the degree to which countries were hit by the European sovereign debt crisis between 2008 and 2013. Figure 2.6 shows that within these groups however, the NEI in certain countries was driven to a greater or lesser extent by movements in the cohorts outside of the labour force. In crisis-hit countries, there was a significant increase in the number of individuals who were *available but not seeking*. Portugal, for instance saw the number *available but not seeking* increase significantly after 2011. While the number of short and long-term unemployed has decreased, these discouraged workers remained outside of the labour force and, as such, kept their NEI higher than would have otherwise been the case. This was also the case in Italy, where those who are identified as "available but not seeking" have a higher transition probability (and hence weighting) than the long-term unemployed.

The non-employment index can also capture the way in which the standard unemployment rate can *overstate* the available pool of labour. In Spain for instance, the long-term unemployment

Figure 2.4: Non-Employment and Unemployment Indices

Dashed lines represent cubic trends

Source: Eurostat and Authors' Calculations.

rate expanded significantly in the wake of the great recession and has remained stubbornly high. Through the lens of the non-employment rate however, one can see that this pool of labour, when weighted by their attachment to the labour force, is lower than might be believed from an analysis of the standard unemployment rate. This is because the Spanish long-term unemployed have a very low transition probability relative to the short term unemployed, meaning that their weight in the NEI is lower. Specifically, 9 per cent of those classified as long-term unemployed transition back into employment each quarter, whereas 22.8 per cent of those who are short term unemployed make the same transition. The non-employment index properly accounts for this by assigning a weight of 0.41 to the stock of long-term unemployed in Spain.

There are structural differences in each country's labour market that result in these idiosynacrasies. An example would be the incentive structures around the timing of unemployment benefits. This means that in certain countries individuals are less incentivised to remain in the labour force. For example, in Italy, Austria and Slovakia the long-term unemployed actually have a lower transition probability than the *available not seeking.* In Finland, Ireland, Poland

and Sweden the long-term unemployed have a lower transition probability than those who are *seeking not immediately available*.

These differences may also arise out of differences in the measurement of those cohorts outside the labour market. For instance, those who are classified as *seeking not immediately available* are likely classified as such for heterogeneous reasons. The ILO definition of "unemployed" requires the individual to be available to start work within the next two weeks. This would mean that a person who was seeking work, but going on a holiday for two weeks, would not be classed as unemployed.

It is also likely that, despite the harmonised nature of the LFS, that there are country specific idiosyncrasies in the classification of different groups. For example, if an individual answering the survey in April is partaking in a course of study but wishes to take a job when the course breaks for summer in June they are more likely to be *seeking not immediately available*. If they do not break for summer, or if they plan to use the break for recuperation, they would likely be classified in "others".

2.5 Empirical Analysis: The NEI and Wage Dynamics

We have so far shown that the standard unemployment rate could give an underestimate of the potential available slack in the labour market. This has important implications for Central Banks, for whom the relationship between wages and slack forms an important part of the monetary policy decision making toolkit. In this section, we test whether including the non-employment index as the measure of the available level of labour market slack in a country's phillips curve improves wage projections in a pseudo out-of-sample wage forecast.

The traditional phillips curve denotes the relationship between nominal wage growth (π_t) and labour market slack (x_t)

$$\pi_t = \alpha + \delta X_t + \epsilon_t \tag{2.1}$$

Table 2.3: Wage and Slack Measures Used

Slack Measure	**Source**
Unemployment Rate	Eurostat
Unemployment Gap	Deviation of Unemployment from NAIRU (authors' calculations)
Output Gap	European Commission
U6	Eurostat
Non-employment Index	Eurostat, National Central Banks and Authors' calculations
Wage Measure	**Source**
Compensation Per Employee	Eurostat
Hourly Earnings	Eurostat
Unit Labour Costs	Eurostat

where α is a constant representing the long run rate of wage growth, and X_t is a measure of slack in each time period. Our aim is to test whether our measure of slack, the NEI, outperforms the other measures in forecasting wage growth after the crisis.

To test this, we use a framework that allows us to compare wage forecasts using traditional measures of labour market slack with the new NEI measure.

2.5.1 The model

We estimate a two-variable vector autoregression (VAR) to capture the relationship between each measure of slack and wage growth in each country between 2005Q1 and 2013Q4. We then conduct conditional forecasts of wage growth for the period 2014Q1 to 2017Q4, where the forecasts are conditional on the realised outturn of each slack measure over the forecast period. We estimate this equation for four alternative measures of slack and for three wage measures outlined in table 2.3. In total, for each wage measure there are five separate VAR models estimated for each country.

The VAR takes the following form:

$$\begin{pmatrix} x_t \\ wg_t \end{pmatrix} = C + B_1 \begin{pmatrix} x_{t-1} \\ wg_{t-1} \end{pmatrix} + ... + B_p \begin{pmatrix} x_{t-p} \\ wg_{t-p} \end{pmatrix} + \varepsilon_t,\ \ \varepsilon_t \sim N(0, \Omega). \tag{2.2}$$

where the vector x_t and wg_t represent the measure of slack and wage growth, respectively. The vector $C = (c_x, c_{wg})'$ contains the intercepts, $B_1, ..., B_P$ are 2×2 coefficient matrices, p denotes the lag length and the reduced form residuals $\mu_t = (\mu_t^x, \mu_t^{wg})'$. Ω denotes the residual variance-covariance matrix. The estimation and conditional forecasts of the model are generated with Bayesian methods. We adopt a Minnesota type prior as per Blake and Mumtaz (2012). This choice is consistent with the high persistence of euro area slack measures. Another advantage of our estimation strategy is that the use of Bayesian methods allows us to account for estimation uncertainty arising from the relatively short sample period.

The VAR conditional forecasts of wages are based on paths formed from the actual realizations of the selected slack measure. We use the method of Waggoner and Zha (1999) that generates predictive distributions from the VAR conditional on the path of the slack variable. The deviation between the conditional and unconditional forecasts is used as a source of information for deriving the conditional forecasts for the VAR errors over the forecasting sample. The distribution of conditional forecasts of wage growth is retrieved by iterating the VAR forward with draws of the residuals.

2.5.2 Estimation Results

We rank the forecast accuracy of each slack measure using the root-mean-squared errors (RMSE) of the conditional forecasts. The lower the RMSE, the more accurate the forecast of the wage measure, conditional on the outturns of the particular measure of slack over the projection period (2014Q1-2017Q4).

A summary of the results are outlined in Table 2.4. The first row of each of the panels outlines RMSE for the full sample, and we present the results for the three wage measures used in our estimation. Hourly earnings is a the most "pure" measure of changes in wages, in that it is not affected by changes in the number of employees. Compensation per employee and unit labour costs are both ratios which can be driven by dynamics in the number of employees and the level of output.

Table 2.4 shows that the NEI outperforms each of the other measures in the crisis countries when hourly earnings or unit labour costs are used as the measure of wage inflation. For compensation per employee, it is ranked second in the crisis countries and third in the overall sample. The reason for this is likely that the dynamics in compensation per employee are driven to a large extent by increases in hours worked. When workers increase their hours, aggregate wages increase but the wage of the individual worker does not.

As discussed in section 2, the additional benefit of the NEI particularly applies to countries that have been hit by an adverse labour market shock. Countries where the unemployment rate is very high, typically see large flows of workers out of the labour force and into inactivity as a result of becoming discouraged. If this is the case, we expect that countries' which were worst hit by the eurozone sovereign debt crisis, had larger numbers of individuals move out of the labour force due to discouragement and skills mismatch, etc.

To illustrate this, we restrict the sample to the crisis-hit countries in our sample (Italy, Ireland, Portugal, Spain and Cyprus) in the second row of each panel. Again, for the hourly earnings measure, the non-employment index outperforms the unemployment rate on average, as well as the unemployment gap and other standard measures.

Table 2.4: Forecast Comparison: RMSEs of conditional forecasts 2014Q1-2017Q3

	Hourly Earnings				
	Unemployment Rate (SA)	Output Gap	NEI	U6	UGap
Crisis Countries	2.690	2.115	**1.743**	1.792	2.117
Overall	2.696	2.186	**1.75**	1.866	2.218
	Compensation Per Employee				
	Unemployment Rate (SA)	Output Gap	NEI	U6	UGap
Crisis Countries	1.858	1.573	1.848	1.776	1.745
Overall	1.867	1.538	1.405	1.590	1.398
	Unit Labour Costs				
	Unemployment Rate (SA)	Output Gap	NEI	U6	UGap
Crisis Countries	3.684	3.887	3.503	5.464	4.133
Overall	2.778	2.815	2.733	3.976	3.147

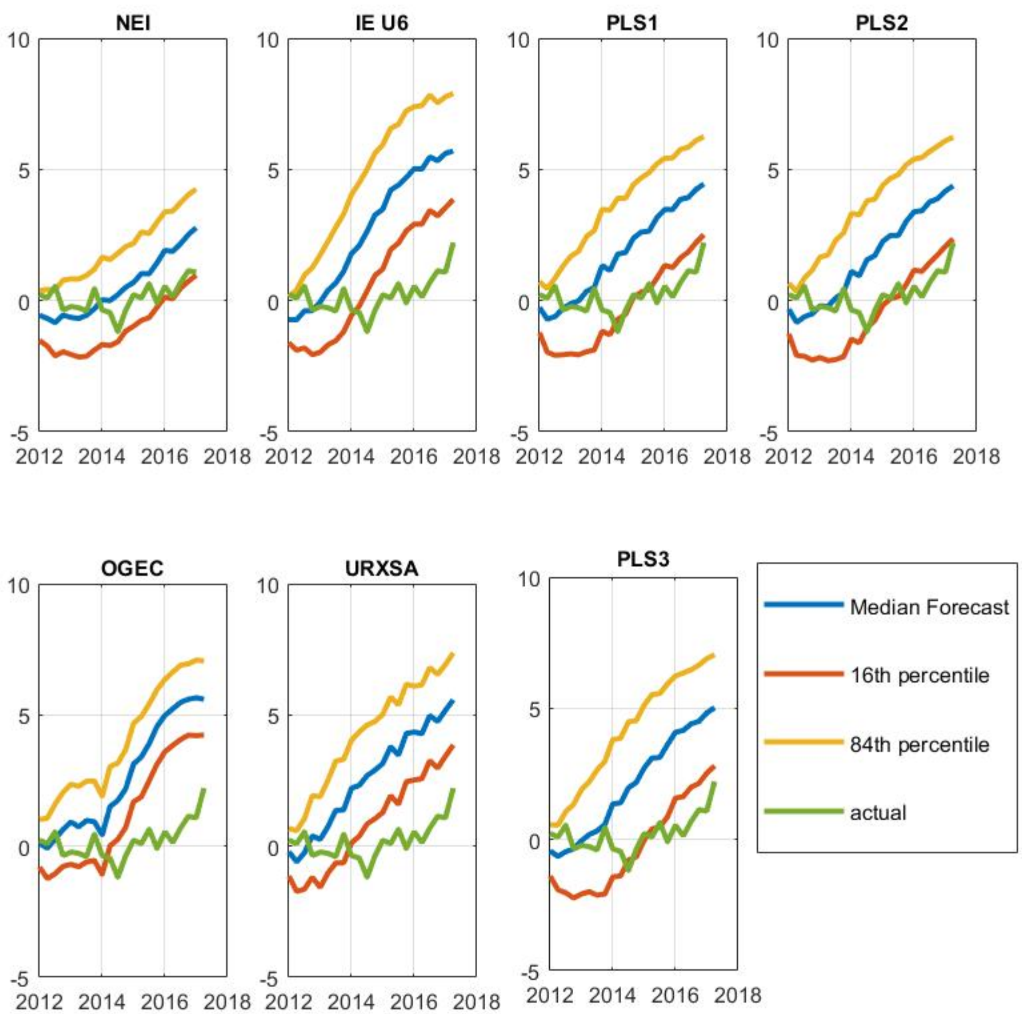
2.5.3 Forecast Distribution

While the point estimates show only the results in terms of forecast accuracy, our modelling approach also allows us to consider whether using broader measures of slack such as the NEI yields improvements in terms of forecast certainty. To illustrate this point, Figure 2.5 plots the median forecast, along with the 16th and 84th percentile of the forecast distribution and compare this to the outturn of the respective wage measure in the Irish case. The NEI is the only slack measure for which the wage forecast remains within the bands throughout the entire out-of-sample forecast period. To test this empirically by computing the log densities of the forecast distributions for each model. The log densities yield a measure of forecast certainty. The results of this estimation are outlined in Table 2.5, and the NEI performs well. For hourly earnings, the conditional forecasts from the models estimated using the NEI have the lowest density, this is also the case for Unit labour costs. In the case of compensation per employee, the output gap appears to perform marginally better. We speculate that this is related to the output gap capturing to some extent the "non-wage" component of compensation per employee in the short run, e.g. the rate of employment growth.

Table 2.5: Conditional Forecasts: Log Density Scores

		Hourly Earnings			
	URXSA	OGEC	NEI	U6	UGAP
Crisis	-2.597	-2.163	**-2.073**	-2.133	-2.364
Overall	-2.577	-2.197	**-2.025**	-2.101	-2.394
		Compensation Per Employee			
	URXSA	OGEC	NEI	U6	UGAP
Crisis	-3.473	**-1.927**	-1.998	-2.142	-2.122
Overall	-2.635	**-1.801**	-2.129	-1.821	-1.800
		Unit Labour Costs			
	URXSA	OGEC	NEI	U6	UGAP
Crisis	**-3.548**	-6.879	-3.694	-7.290	-6.141
Overall	**-2.679**	-4.516	-2.823	-4.946	-4.185

Figure 2.5: Forecast Horserace: Ireland



2.5.4 Panel Analysis

The analysis thus far demonstrates that the NEI outperforms other measures of slack in explaining the missing wage puzzle, particularly in crisis-hit countries. However, it could be the case that the parsimonious specification used to isolate the relative performance of each of the slack measures misses important dynamics. For example, productivity and a proxy for inflation expectations are typically included in a standard phillips curve framework. To investigate the performance of the NEI in this regard, we estimate an augmented version of the standard wage phillips curve akin to the theoretical work of Galí (2011) and the empirical work of Bonam et al. (2021) and Bulligan and Viviano (2017). We estimate a specification which regresses wages, w_it, on a measure of slack S_it, lagged nominal wage growth, and lagged consumer price inflation, π_t^e as a proxy for expected inflation:

$$w_{it} = \alpha_{it} + S_{it-1} + w_{it-1} + \pi_{it-1} + \mu_{it} \tag{2.3}$$

Lagged wage growth captures persistence in wage dynamics, whereas lagged consumer price inflation captures foward looking behaviour in wage setting. The model is estimated using the fixed-effects estimator with robust standard errors clustered at the country level. Table 2.6 outlines the results. In the baseline specification, we only include the non-employment index as our measure of slack and lagged compensation. In the second specification, we include lagged consumer price inflation to capture expectations[4]. In the third specification, we add a measure of productivity, output per worker, and the coefficient on non-employment remains largely unchanged. Under all specifications, including with lagged wages as a proxy for inflation expectations, the NEI remains a statistically and economically significant predictor of wage developments. Finally, we test each of these specifications with the unemployment rate as our measure of slack. In all cases the sign and statistical significance of the result is the same, however the magnitude of the coefficient on the NEI is statistically significantly larger than that on the unemployment rate.

[4] We test various lags of inflation, the results do not change significantly

Table 2.6: Panel Regression

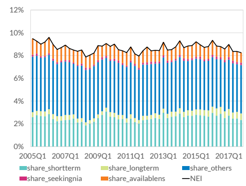
	Baseline	Productivity	Inflation	Unemployment
NEI_{t-1}	-0.281***	-0.331***	-0.321***	
	(0.061)	(0.079)	(0.072)	
CPE_{t-1}	0.984***	0.978***	0.971***	0.965***
	(0.003)	(0.004)	(0.009)	(0.011)
$hicp_{t-1}$		-0.107***	-0.0964***	-0.0840**
		(0.028)	(0.028)	(0.032)
$Prod_{t-1}$			0.0227	0.0436
			(0.023)	(0.029)
$Unemp_{t-1}$				-0.157***
				(0.044)
Constant	6.317***	7.812***	6.143***	1.497
	(1.031)	(1.451)	(1.213)	(1.751)
Observations	510	510	510	663
R-squared	0.985	0.985	0.986	0.986
Number of panelid	10	10	10	13

1 Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

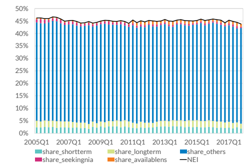
2.6 Conclusion

We generate a new measure of labour market tightness for a selection of euro area countries. We show that the non-employment index accounts well for the rather subdued wage dynamics evident in the euro-area during the recent expansion. Our analysis shows that policymakers should focus both on the stock of workers who are outside the labour force, but also their probability of transitioning into employment. The non-employment index has been slower to decline, and indeed remains elevated in many countries in contrast to the unemployment rate. This is particularly the case in the countries which were worst hit by the european sovereign debt crisis in 2009-2011. As the crisis persisted, large numbers of workers became discouraged, or otherwise marginally attached to the labour force. During the recovery, this additional pool of labour reduces the bargaining power of workers, placing downward pressure on wages. Our analysis shows that after a cyclical downturn non-employment could be a valuable addition to the policymakers toolkit when examining the level of available slack in the labour market.

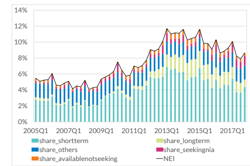
Figure 2.6: NEI Decompositions



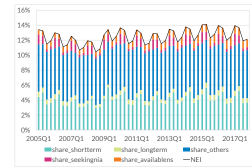
((a)) Austria



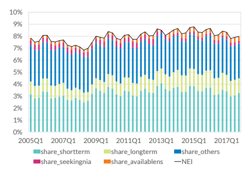
((b)) Belgium



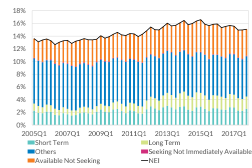
((c)) Cyprus



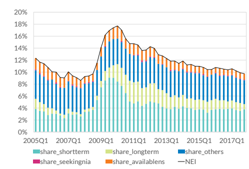
((d)) Finland



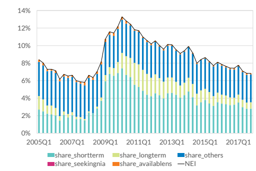
((e)) France



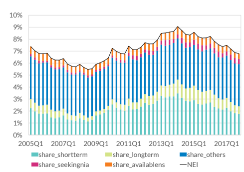
((f)) Italy



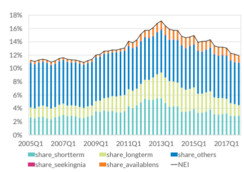
((g)) Latvia



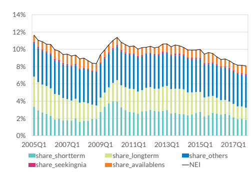
((h)) Lithuania



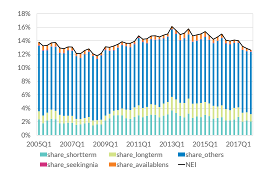
((i)) Netherlands



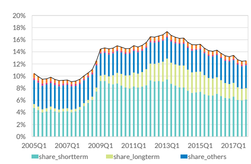
((j)) Portugal



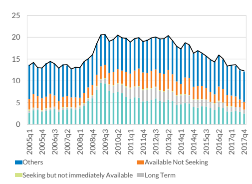
((k)) Slovakia



((l)) Slovenia



((m)) Spain



((n)) Ireland

Chapter 3

The Sources of Capital Misallocation in Europe [1]

3.1 Introduction

A large literature in macroeconomics seeks to analyse cross-country differences in income per capita across countries. Much of this literature focuses on productivity as the dominant source of these differences (Solow, 1957). Specifically, for a given quality and quantity of factor inputs (capital, labour and technology), some countries generate less output per worker than others. In Europe, productivity trends across countries have diverged in recent decades, particularly between northern and southern countries, as countries in the south experienced slower productivity growth (ECB, 2021).

But what causes these productivity differences across countries? A large body of literature focuses on the importance of firm-level misallocation of resources in explaining divergences in aggregate productivity.[2] Misallocation in this context refers to dispersion in the marginal revenue product of factor inputs across firms and sectors. In a standard model of monopolistic competition

[1] Co-Authored with Robert Goodhead. The opinions expressed in this paper are those of the authors and do not necessarily represent the views of the Central Bank of Ireland, the European System of Central Banks or the ECB. We thank Cian Ruane and Bruno Morando for helpful comments on earlier drafts of this paper, as well as seminar participants at the Irish Economics Association Conference, 2024 and Central Bank of Ireland Research Seminar Series. All remaining errors are our own.

[2] For review papers see Restuccia and Rogerson (2013), Restuccia and Rogerson (2017), and Hopenhayn (2014).

with heterogeneous firms, marginal revenue products of factors are equalised across firms in equilibrium. A strand of the misallocation literature pioneered by Hsieh and Klenow, 2009 posits that if we observe dispersion in marginal revenue products to factors across firms within given industries, then this dispersion must arise from distortions. A country can attain increases in aggregate productivity and output by removing these distortions in ways that reallocate factors to firms with relatively high marginal revenue products.

In Europe, where productivity growth has been weak in recent decades and particularly since the global financial crisis, researchers have pointed to rising levels of misallocation as an important determinant (see *inter alia* Gopinath et al. 2017, Gorodnichenko et al. 2021). A recurring theme in this literature speculates on the decline in the real interest rate, associated with the euro convergence process, being one causal driver of this rise in misallocation. Indeed, from a policymakers perspective, understanding the sources and drivers of misallocation is crucial to identifying policy prescriptions to remedy it.

In this vein, a more recent literature has focused on the role of specific determinants that generate misallocation of resources across firms. Examples include the role of adjustment costs, financial frictions, or imperfect information. Much of this literature focuses on the contribution of each factor in turn to dispersion in average products. But disentangling the precise nature and relative contribution of these factors is vital for policymakers to think about what impediments can be removed or policies can be instituted in order to increase productivity and spur output growth.

This paper contributes both to the literature on the sources of misallocation, and to the literature on the causes of productivity and output growth divergence in Europe. We make two main contributions. Firstly, we measure and decompose the sources of capital misallocation at the country in 19 European countries using a comprehensive dataset of the balance sheets of firms in the manufacturing sector. We use the method introduced in David and Venkateswaran (2019), which explicitly accounts for adjustment costs and firm-level uncertainty. Previous efforts to decompose misallocation have mostly focussed on country-level sectoral estimates, we extend these analyses by focussing on industry-level variation. We report key moments from the data and extend the analysis by decomposing the sources of misallocation at the two-digit NACE industry level, and document significant heterogeneity in the factors driving misallocation at the industry level. We find that most of the observed dispersion stems from permanent firm-specific factors. This is particularly true in the periphery countries. We also find an important role for adjustment costs and uncertainty at the country industry level, and a more limited role for idiosyncratic firm-specific distortions.

Our second contribution is to investigate which features of the macroeconomic environment are correlated with these sources of misallocation. We match our country-by-sector misallocation estimates to potential predictors using micro-aggregated cross-country panel data from CompNet. We find suggestive evidence that variation in firm demographics (size/age) and financial constraints are associated with country and sectoral differences in misallocation.

We now outline the organisation of our paper. Section 3.2 reviews the literature. Section 3.3 describes our dataset and the steps taken to generate a representative sample of European firms. Section 3.4 documents the methodology used to disentangle the sources of misallocation. Section 3.5 reports the results at the country and country-sector level. Section 3.6 documents our estimation approach to investigate which economic features of the European economies we study are correlated with the sources of misallocation. Section 4.5 concludes.

3.2 Literature Review

Our paper contributes both to the growing literature on the sources of capital misallocation and to the literature on productivity differences in Europe. Restuccia and Rogerson (2017) characterise the methods used in measuring misallocation as "indirect" and "direct" approaches. In this categorisation, the direct approach focuses on specific sources of misallocation and assesses their consequences. The indirect approach seeks to identify the extent of misallocation without identifying its underlying sources. The indirect approach can be traced back to the seminal studies of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009). Hsieh and Klenow (2009), henceforth HK, find large effects of misallocation on total factor productivity in China, India and the United States. These authors find that if misallocation were eliminated then total factor productivity in manufacturing would increase significantly in China and India (over 100 percent) and by between 30 and 40 per cent in the US. Following HK, there was a large wave of literature estimating misallocation using their methodology in different countries and settings.

However, there are notable constraints to the indirect approach, which prompted the emergence of a subsequent wave of literature aimed at addressing these limitations. These limitations could be summarised as reflecting model misspecification and mismeasurement in the data. Notably, the HK framework assumes an identical Cobb-Douglas production function for all producers in a given sector. However, if different production methods are employed within the sector, the capital shares in the production function would inevitably vary among producers. Consequently, deviations in capital-labour ratios could be mistakenly interpreted as misallocation, rather than an outcome of heterogeneity in production technologies. Another inherent limitation relates to adjustment costs. Cooper and Haltiwanger (2006) as well as Bloom (2009) present compelling evidence that models encompassing both convex and non-convex adjustment costs best fit the non-linear relationship between investment and profitability observed in the plant level data. The HK approach infers misallocation based on disparities in the marginal revenue product of capital. Nevertheless, these variations may arise due to adjustment costs or transient firm-specific shocks, rather than actual misallocation. Addressing this issue, Asker et al. (2014) demonstrate that differences in marginal revenue products of capital can align with efficient allocations in the presence of adjustment costs and volatile transitory firm-specific shocks, which tend to be more prevalent in poorer countries.

A key paper which seeks to address both of these issues in a unified framework is David and Venkateswaran (2019), henceforth DV. The question raised by the second wave of the literature is whether observed variation in input products stem from efficient sources such as adjustment costs or heterogeneous production technologies, or inefficient sources such as policy induced distortions or variations in markups. The study makes two main contributions. Firstly, these authors estimate a dynamic extension of the HK model in a framework that explicitly allows for the presence of adjustment costs, informational frictions in the form of imperfect knowledge about firm level fundamentals, and other firm-specific factors including unobserved heterogeneity in production functions or markups, financial frictions, or institutional/policy related distortions.

Secondly, they provide an empirical strategy that decomposes the contribution of each of these forces to observed variation in the average revenue product of capital ($arpk$).

Another issue with the indirect estimation approaches discussed thus far is the assumption that differences in plant-level average revenue products of capital reflect differences in true marginal products. If this assumption is inaccurate, then the estimates of misallocation presented in the papers discussed thus far are subject to measurement error. Bils et al. (2021) propose a methodology to estimate the gaps in true marginal products in the presence of measurement error. Their method exploits the fact that revenue growth is less sensitive to input growth when a plant's average products are overstated by measurement error. Their paper reduces the estimates of potential gains from reallocation by approximately 20 percent for India and more than 60 percent for the US compared with the standard HK framework using the same dataset. However, after accounting for measurement error they show that the contribution of misallocation to productivity differences between India and the US is the same as in HK. Another important finding in their paper is that the contribution of measurement error is becoming larger over time in the United states, but is stable in India.

Many other papers discuss model misspecification arising from the assumption that all of the cross sectional dispersion in marginal revenue products of capital reflect misallocation. Haltiwanger et al. (2018) suggest that when models deviate from the structural assumptions in HK then "distortions" recovered from the data may not be signs of allocative inefficiency, but instead reflect demand shifts or movements of the firm along its marginal cost curve. As such, the framework may be more likely to identify inefficiencies in firms that are better in some fundamental way to their competitors. Nishida et al. (2017) describe differences between measures of productivity in the US census of manufactures and what firms themselves report. They find substantially more extreme values of productivity in what firms report themselves. Many of the edits undertaken in the US census of manufactures are infeasible for researchers using datasets from other countries. When these authors use common data cleaning strategies, they find no evidence that allocative efficiency is lower in India than the United States.

The application of the methodologies discussed above to different countries and time periods has also yielded a wealth of empirical evidence on the importance of misallocation for understanding productivity differences. Many of these papers also look to understand the *causes* of misallocation, both in terms of real economy market failures such as credit-market imperfections, but also in terms of distortions introduced by government policy. For example, Busso et al. (2013) find that productivity heterogeneity and resource misallocation are much higher in Latin America than in the United States. These authors find that achieving an efficient allocation of resources could boost manufacturing TFP by between 45 and 127 percent, depending on the country considered. Their paper highlights that access to capital and restrictive labour regulations are important contributors to misallocation in the countries studied. Kalemli-Özcan et al. (2012) conduct a similar study for 10 African countries using the World Bank Enterprise Surveys. These authors find evidence of high variation in firms marginal product of capital, but with some countries in their analysis closer to developed country benchmarks. They also find that access to finance is an important contributor to misallocation. In their analysis, a firm with the worst access to finance has a marginal product of capital 45 percent higher.

Our paper is closest in methodological terms to David et al. (2021). These authors use data from ORBIS and utilise the model and estimation strategy developed in DV to study the sources of misallocation in a group of 11 developing and developed countries. As discussed, the advantage of this methodology is the ability to account for capital adjustment costs, firm-level uncertainty and a broad class of other firm specific factors to variation in average revenue products (*arpk*). David et al. (2021) find that "efficient" sources of *arpk* dispersion, such as adjustment costs, account for a modest share of observed misallocation. They find that heterogeneity in firm-level production technologies accounts for 25-50 percent of observed dispersion in *arpk* dispersion, and approximately 50 percent explained by the combination of a component that is correlated with firm size/productivity and a component that is permanent to the firm.

Many papers find that policy-induced distortions increase misallocation and thereby lower TFP. For example, similar to Kalemli-Özcan et al. (2012), García-Santana and Pijoan-Mas (2014) find evidence that some productive firms in India are too small. In this case, this is the result of size-dependent government policy. Using evidence from the small scale reservation laws, which "reserve" a number of manufacturing goods for exclusive production by small scale industries in India, they find that manufacturing TFP would be 3.6 percent higher in the absence of the distortion. López and Torres (2020) find that a payroll tax that increases with establishment size generates a reduction in plant-size and and output losses of 10 percent compared using data on size-dependent social security contributions in Mexico compared with the with the US. The distortionary effect of size-dependent policies is also found in developed countries, for example by Garicano et al. (2016) and Gourio and Roys (2014), who both exploit the fact that many labour regulations become binding once a firm reaches more than 50 employees in France. Lenzu and Manaresi (2018) use firm-level gaps between marginal revenue products and user costs in Italian firms to show that TFP in the Italian corporate sector could be increased by 3-4 percent if resources were reallocated from over-endowed producers towards higher value users.

The empirical evidence on whether resource misallocation can explain productivity differences in Europe has often focused on the divergence in TFP growth in "northern" and "southern" Europe. Gopinath et al. (2017) is a seminal contribution that finds a significant increase in the dispersion of the return to capital across firms in Spain, Italy and Portugal but not in Germany, France and Norway. Their paper develops an extension of HK to include financial frictions that depend on firm size, matching the positive relationship between firm size and leverage in the data. Larger firms, with higher net worth, increase their capital in response to a decline in the cost of capital. These firms experience a decline in their marginal product of capital. On the other hand, firms that have lower net worth despite being potentially productive delay investment until they can internally accumulate sufficient funds. These firms do not experience a decline in their marginal product of capital. Therefore MRPK dispersion between financially constrained and unconstrained firms increases. Gopinath et al. (2017) argue that the decline in the real interest rate, related to euro area convergence, lead to a decline in TFP as capital inflows to southern Europe are misallocated towards firms that have a higher net worth but are less productive. Indeed, evidence that credit booms decreased allocative efficiency in the EU as a result of a misallocation of capital inflows is also found by Borio et al. (2015) using EU KLEMS data.[3] This finding is similar to that of Reis (2013) who finds that misallocation of capital from abroad is responsible for the poor performance of the Portuguese economy between 2000 and 2007 and its sluggish recovery from the Eurozone Sovereign debt crisis. His paper also

[3]KLEMS is an EU project focusing on EU level Capital (K), Labour (L), Energy (E) and Materials (M).

highlights the importance of financial frictions, and shows that the Portugal's integration into European capital markets did not improve the ability of firms to allocate capital. As such, the most productive firms were not able to access the newly abundant funds available after Portugal joined the Euro. His findings are supported up by Dias et al. (2016) who conduct a similar exercise at the sectoral level for Portugal and find that the deterioration in allocative efficiency in Portugal between 1996 and 2011 is largest in the services sector. Contrary to the argument of Gopinath et al. (2017), Franco (2018) finds that higher availability of credit leads to a decline in capital and labour misallocation, while Albrizio et al. (2023) find that expansionary monetary policy shocks lead to a decrease in capital misallocation.

Gorodnichenko et al. (2021) also take a slightly different view. They utilise the Investment Survey conducted by the European Investment Bank and ORBIS data to analyze resource misallocation in European firms. Their approach is novel in that they show that as well as directly measuring distortions using dispersion in the marginal revenue product of capital; some firm characteristics such as demographics, quality of inputs, utilisation of resources and dynamic adjustment of inputs are themselves predictors of the marginal revenue product of capital. They show that some firm characteristics may reflect compensating differentials rather than constraints and hence the effect of constraints on on misallocation may be lower than in the literature. They estimate that removing distortions in resource allocation could increase productivity by 40 per cent or more.

3.3 Data and Descriptive Statistics

3.3.1 Firm-Level Data – ORBIS

We construct nationally representative firm-level data for each year from 2008 to 2018 for a number of European countries. Our data come from the ORBIS/AMADEUS database, compiled by Bureau Van Dijk. The dataset contains firm-level balance sheet and ownership data originally derived from business registers and other regulatory sources for approximately 14 million European firms. The dataset presents a detailed 4-digit industry classification (NACE Rev.2). There are significant benefits to using ORBIS/AMADEUS. Much of the literature on discussed in Section 2 applies the framework from HK, calculating dispersion in the marginal revenue product of capital of firms using only a subset of firms in a country's manufacturing sector. For example, David and Venkateswaran (2019) use data from Compustat for the US case, which contains data on large publicly listed firms. By contrast, ORBIS/AMADEUS contains data on small and private firms, with listed firms representing only around 1% of the sample. The data have further advantages over "census" type data used in other papers in the literature insofar that information on output and employment is contained alongside that relating to balance sheets and profit and loss accounts. Importantly for our analysis, in most European countries these filings are required by legislation for most firms. As such, the dataset is a rich source of information on the balance sheets of small and medium sized private enterprises as well as large publicly owned firms.

Cleaning the ORBIS Dataset

While ORBIS/AMADEUS is the foremost cross-country comparable source of data on firms in Europe, the data do have well documented limitations. We closely follow the comprehensive data collection and cleaning process developed in Kalemli-Özcan et al. (2015), which documents how best to generate serviceable micro-data for analysis from this source.

One of the primary issues affecting data coverage is that some versions of ORBIS drop data for firms who have not reported balance sheet information in the previous five years. This creates an artificial survivorship bias in the data. We accessed the dataset through Bureau Van Dijk's proprietary web platform. Fortunately this platform allows us to keep observations for firms who have not reported, but for whom Bureau Van Dijk have information from business registers that the firm is still active. These firms these enter our dataset as missing variables for that year. The platform also allows us to keep information on inactive companies who reported in previous years.

An additional issue faced by some researchers using ORBIS is that the web platform limits each data download to a maximum of one million cells (firms $\times$ variables). This is further complicated by the fact that the panel element of the raw dataset is "wide", i.e. each year is an additional variable. To avoid any missing observations, we downloaded our required set of variables for firms in each NACE two-digit sector by methodically downloading the data at NUTS3 administrative division. For example, downloading our dataset for firms in NACE sector 10 (manufacture of food products) located in a particular province in Italy, then moving on to food manufacturers in the next province, and so on until each NACE code is complete. This process ensures the best possible coverage and is similar to the process outlined in Kalemli-Özcan et al. (2015), who accessed the dataset using discs. In order to minimise challenges with the estimation of the production function, we restrict our analysis to the manufacturing sector (NACE sectors ten to thirty-three).

Some further important cleaning steps are required. Firstly, to remove duplicates we keep only unconsolidated accounts. We also adopt the convention in the literature that the current year is assigned only if the account closing date is after the 31st of May and the previous year is assigned otherwise. Our next step is to construct the "TFP Sample" outlined in Kalemli-Özcan et al. (2015). This step involves keeping only firms with positive values for employment or the wage-bill, and positive values for tangible fixed assets, gross output and materials. We clean the data further by dropping firm-year observations that are missing information on each of total assets and operating revenues, sales and employment. We drop firms if total assets, sales or fixed assets are negative in any year. We also drop firms where employment in the firm is negative or greater than 2 million in any year.

Crucially for estimating the average revenue product of capital central to our analysis, we drop firm-year observations with missing, zero or negative values for materials, operating revenue, or total assets. We then check the internal consistency of the balance sheet data by comparing the sum of the variables belonging to some aggregate to their respective aggregate. This involves generating a set of ratios for each country in our analysis, as outlined in detail in Appendix A.2 of Gopinath et al. (2017). For example, we construct the sum of tangible fixed assets, intangible fixed assets, and other fixed assets as a ratio of total fixed assets. Following Gopinath et al. (2017), we then drop extreme values from the analysis by excluding observations that are below the 0.1 percentile or above the 99.9 percentile of the distribution of ratios.

We conduct some further checks to examine the quality of the data, again following the steps in Appendix A.2 of Gopinath et al. (2017). These checks mostly involve verifying the internal consistency of the data. For example ensuring that the implied values for firm age, liabilities, or the wage bill are not negative or missing. We also implement checks to ensure that those variables that are most important for our estimation are of good quality, for example we test whether the difference between total assets and total liabilities is equal to shareholders funds, and drop observations where this identity does not hold. A full description of each of our cleaning steps and the number of firm-year observations that are dropped in each step is available on request.

Assessing the Representativeness of Our Sample

The ORBIS data we use provide us with relatively good coverage of employment and value added in the countries to be analysed. Table 3.1 shows the coverage of operating revenue and employment in the sectors we analyse in comparison to Eurostat's Structural Business Statistics (SBS). The SBS data represent census measures, i.e. the universe of firms in each country. With respect to revenue and employment, coverage is in line with other papers who have used the ORBIS dataset for Europe. The ratios presented in Table 3.1 represents the coverage of the data after completing the comprehensive cleaning steps outlined in Kalemli-Özcan et al. (2015). In Appendix 3.C, Tables 1 and 2, we show that our sample is also broadly representative in terms of the contribution of small and medium sized firms which account for much of the manufacturing activity across Europe. This is a significant advantage of our data.

3.3.2 Industry-Level Data – CompNet

The second part of our analysis uses data from the CompNet research network. The CompNet dataset contains aggregated firm-level information. The data are collected using firm-level datasets from national statistical institutes and central banks in 19 countries in the European Union. The data contain harmonised information on firm characteristics across a range of six categories: competitiveness, productivity, labour, trade, finance and other variables. The data are

Table 3.1: Coverage of the ORBIS Dataset

	AT	BE	DE	EE	ES	FI	FR	GR	LU	IE	IT	LT	LV	NL	SI	SK	PT
Operating Revenue																	
2010	36	75	24	46	65	15	67	32	48	19	57	1	32	18	79	39	79
2011	47	95	24	58	67	43	71	35	81	34	62	45	69	26	81	87	83
2012	50	98	24	59	70	42	72	35	71	37	62	46	68	28	83	89	84
2013	50	97	25	60	73	40	79	37	73	42	66	49	72	29	85	90	88
2014	55	98	25	62	75	45	83	37	72	50	70	55	77	29	86	90	89
2015	61	107	26	62	77	51	86	42	41	28	73	58	81	27	88	91	91
2016	63	103	27	64	79	48	83	50	38	51	75	62	83	30	90	94	92
2017	66	104	31	65	80	59	78	47	37	51	74	61	85	31	90	94	94
2018	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Employment																	
2010	0	51	16	46	56	14	38	.	32	22	37	1	27	9	67	32	66
2011	0	98	17	53	60	43	37	.	51	26	49	52	64	13	70	78	71
2012	1	72	18	54	62	44	33	.	50	29	52	48	67	14	73	77	76
2013	4	73	19	57	65	46	42	.	51	.	55	55	68	16	76	80	79
2014	30	75	17	59	66	50	52	.	51	32	59	58	74	17	73	83	80
2015	52	77	21	60	70	49	55	43	9	33	62	59	78	17	80	86	83
2016	52	78	23	62	70	61	59	44	2	50	64	63	80	17	82	85	85
2017	53	119	25	62	71	69	59	49	0	57	66	68	81	17	83	90	83
2018	53	79	24	63	69	57	54	40	0	51	68	71	81	16	86	88	84

Notes: Table displays coverage ratios for operating revenue and employment. We compare totals computed across our ORBIS/AMADEUS dataset, relative to totals from Eurostat Structural Business Statistics.

aggregated, but importantly for our matching to the results of our estimations using ORBIS, the data can be split by country and NACE two-digit sector. In order to ensure representativeness and harmonisation across countries, the variables are weighted by firm population weights.

There are nine vintages of the CompNet dataset, with each subsequent vintage incrementally adding new variables and countries. There are also two versions of the dataset available; the "20E" sample, which includes only firms who have twenty or more employees, and the "full" sample. We make use of the full sample version of the 8th vintage of the data, which covers the years 1999 to 2019 and contains all of the variables required for our analysis.

As well as the aggregated statistics for each country and sector, CompNet reports a number of moments of given sector-level variables (e.g. mean, standard deviation and percentiles of the distribution). The dataset also provides joint distributions from the data, i.e. summary statistics of variables by percentiles of the distribution of other variables. For example, productivity by size deciles. The dataset also contains "discrete conditional variables", i.e. calculations of variables for firms with certain characteristics. For example "zombie-firms", in which case the data file would contain all distributions of a summarised variable conditional on whether or not the firm was classified as a "zombie". Details on the classification of variables by certain firm characteristics are based on the literature and a comprehensive summary can be found in CompNet (2020).

3.4 Methodology

The environment is identical to that of David and Venkateswaran (2019), and is an extension of the HK framework, which explicitly accounts for dynamic considerations of the firms investment decision. The model allows for adjustment costs, firm-level uncertainty, as well as the components of the HK distortion τ, broken into permanent and transitory firm specific distortions. A full description of the model is provided in Appendix 3.D . We discuss the key elements here.

3.4.1 The Model

The model considers a discrete time, infinite horizon economy populated by a representative household and production in the economy is carried out by a continuum of firms who intermediate goods using capital and labour. Intermediate goods are bundled to produce the single final good using a standard constant elasticity of substitution (CES) aggregator. The final good is produced under perfect competition, frictionlessly, by a representative firm.

Firms are heterogeneous, and their productivity is modelled as a stochastic process. The functional form of their productivity draws is AR(1) in logs, with a time-varying idiosyncratic white noise shock with variance σ_μ^2. Adjustment frictions are modelled using a quadratic adjustment cost function, similar to Asker et al. (2014). Firm-level uncertainty is modelled using the framework of David et al. (2016) by assuming that the firm, at the time of making its investment choice for period t, observes a noisy signal of next periods productivity a_{t+1}. DV show that a sufficient statistic for this uncertainty is the posterior variance of the firm, denoted $\mathcal{V}$. Because productivity is assumed to follow an AR(1) process, $\mathcal{V}$ ranges between 0 and σ_μ^2. If $\mathcal{V} = 0$, the firm is perfectly informed about next periods productivity. If $\mathcal{V} = \sigma_\mu^2$, the firm only has information about current productivity but has no signal of next periods productivity innovation.

To model the other factors influencing investment decisions, DV follow HK by assuming that they take the form of an implicit proportional tax on the cost of capital, referred to throughout the literature as a "wedge". The model yields the following log-linearised law of motion for capital:

$$k_{it+1}((1+\beta)\xi + 1 - \alpha) = \mathbb{E}_{it}[a_{it+1} + \tau_{it+1}] + \beta\xi\mathbb{E}_{it}[k_{it+2}] + \xi k_{it}, \tag{3.1}$$

where ξ is a composite parameter that summarises the severity of adjustment costs and β is the discount rate. The productivity term a_{t+1} takes the expectation operator $\mathbb{E}$, reflecting the fact that the firm may have imperfect information about future productivity innovations. Here τ_{it} is a distortion or wedge that acts on the firm's investment decisions.

We assume that τ_{it} has two components:

$$\tau_{it} = \chi_i + \epsilon_{it}, \tag{3.2}$$

where χ_i represents permanent firm specific distortions while ϵ_{it} represents idiosyncratic firm-specific distortions and is i.i.d over time. So the factors other than adjustment costs and uncertainty are parameterised by σ^2_χ, which is the cross-sectional variation in the fixed component, and σ^2_ϵ, which is the volatility transitory firm specific component.

3.4.2 Identification – Disentangling the Misallocation Sources

Section 3.4.1 shows that five separate forces all contribute to dispersion in *arpk*: adjustment costs, uncertainty and the three components of the wedge (τ), parameterised by $\xi, V, \gamma, \sigma^2_\chi$ and σ^2_ϵ. In a detailed derivation for the special case where productivity follows a random walk, i.e. $\rho = 1$, DV prove that these parameters are uniquely identified by the following moments of the data: the variance and serial correlation of investment, the correlation of investment with lagged changes in productivity, a_{it}, the correlation of *arpk* with productivity and the cross sectional dispersion in *arpk*.

The intuition for this result provided in DV rests on the idea that while each of these moments is a function of multiple factors, making any single one insufficient for identification, analysing the moments in pairs is sufficient to pin down each of the parameters. For example, disentangling adjustment costs from other idiosyncratic factors that the response of investment to productivity rests on the insight that while both forces depress the variability of investment, they have opposing effects on its autocorrelation. Convex adjustment costs create incentives to smooth investment over time and so increase its serial correlation. A distortion that reduces the responsiveness to productivity, will lower the serial correlation of investment by raising the relative weight of other more transitory factors.

DV also show in their numerical analysis that that this result holds when productivity is assumed to follow an AR(1) process, (i.e. $\rho < 1$). We conduct the same exercise for European firms in this paper, but extending the analysis to both countries and sectors, this allows us to quantify the severity of various forces and their impact on *arpk* dispersion at a more granular level.

The model is estimated using the simulated method of moments (McFadden, 1989). We compute the variance-covariance matrix from the model and match the moments in the data.

3.4.3 Parameterisaton

We specify certain parameters on the basis of typical values in the literature. The discount rate is set to $\beta = 0.95$. The annual depreciation rate is assumed to be δ =0.1. We keep the elasticity of substitution θ common across countries and sectors and set its value to 6, following the literature. We assume constant returns to scale in production, but allow the parameters $\hat{\alpha}_1$ and $\hat{\alpha}_2$ to vary across country and sector. For each country, we assume a capital share of 0.62.

Firm-level productivity is given by $a_{it} = va_{it} - \alpha k_{it}$ where va_{it} denotes the log of value-added. Controlling for industry-year fixed effects to isolate the firm-specific component, we use a standard autoregression to estimate the persistence of the of the productivity process ρ and the variance of the innovation σ^2_μ. To estimate adjustment costs, ξ, the quality of information, $\mathcal{V}$, and the size of the other factors, γ and σ^2_ϵ, we follow DV and target a set of of moments as outlined in the previous subsection. Specifically, we target the correlation of investment growth with the lagged innovations in productivity ($\rho_{i,a-1}$), the autocorrelation of investment growth ($\rho_{i,i-1}$), the variance of investment growth (σ^2_i), and the coorelation of the average product of capital with productivity ($\rho_{arpk,a}$). Finally, to infer σ^2_χ, the variance of the fixed component, we match the overall dispersion in the average product of capital, σ^2_{arpk}. By construction, our estimation with the parameters outlined above, will match the observed *arpk* dispersion in the data. This allows for a decomposition of the contribution of each factor.

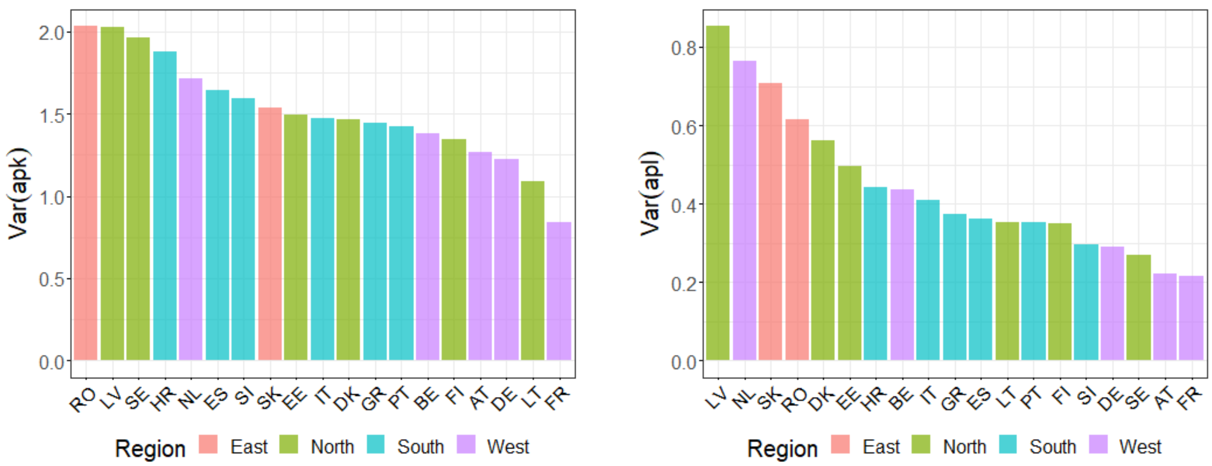
3.4.4 Target Moments

In Figure 3.1 we display our measures of the variance of (log) average factor products. These represent summary measures of misallocation in our dataset, and ultimately the key feature of the data we seek to explain. While our study focusses on the variance of the average product of capital, displayed in panel (a), we also display the variance of the average product of labour for reference (panel b). We subdivide the countries in our sample into four broad geographic regions.[4] Our findings on the level of *arpk* dispersion are broadly close to those found in the

[4]North includes Latvia, Sweden, Estonia, Denmark, Finland, and Lithuania. West includes the Netherlands, Belgium, Austria, Germany, and France. South include Croatia, Spain, Slovenia, Italy, Greece, and Portugal. East includes Romania and Slovakia.

Figure 3.1: Revenue Product Dispersion by Country

((a)) Var(APK) ((b)) Var(APL)



Notes: Panels (a) and (b) of the figure display the variance of (log) APK and (log) APL, respectively.

literature, including Gorodnichenko et al. (2021) and to those estimated using census data in CompNet. Looking across countries, *arpk* dispersion is highest in Romania, Latvia, and Sweden, but is also higher than average in Spain, the Netherlands, Slovenia, and Slovakia. We observe a clear distinction in between the countries sometimes labelled as the "core" (West) and the "periphery" (South). Specifically, the level of *arpk* dispersion is lower than average in France, Austria and Germany. The same stylised fact is apparent for the variance of the average product of labour, as can be observed in panel (b).

While we have established that the ORBIS/AMADEUS dataset broadly covers the manufacturing sector, there is still some scope for our misallocation measures deviating from the underlying aggregates. To investigate this, we check whether our estimated misallocation measures correlate with country-level TFP. We find this indeed to be the case, as can be seen in Figure 3.2. The correlation patterns we see are reassuring, particularly as the TFP measure is based on national statistics, and thus includes sectors outside of the manufacturing sector. This suggests our measures can be generally useful for explaining broad patterns of cross-country performance.

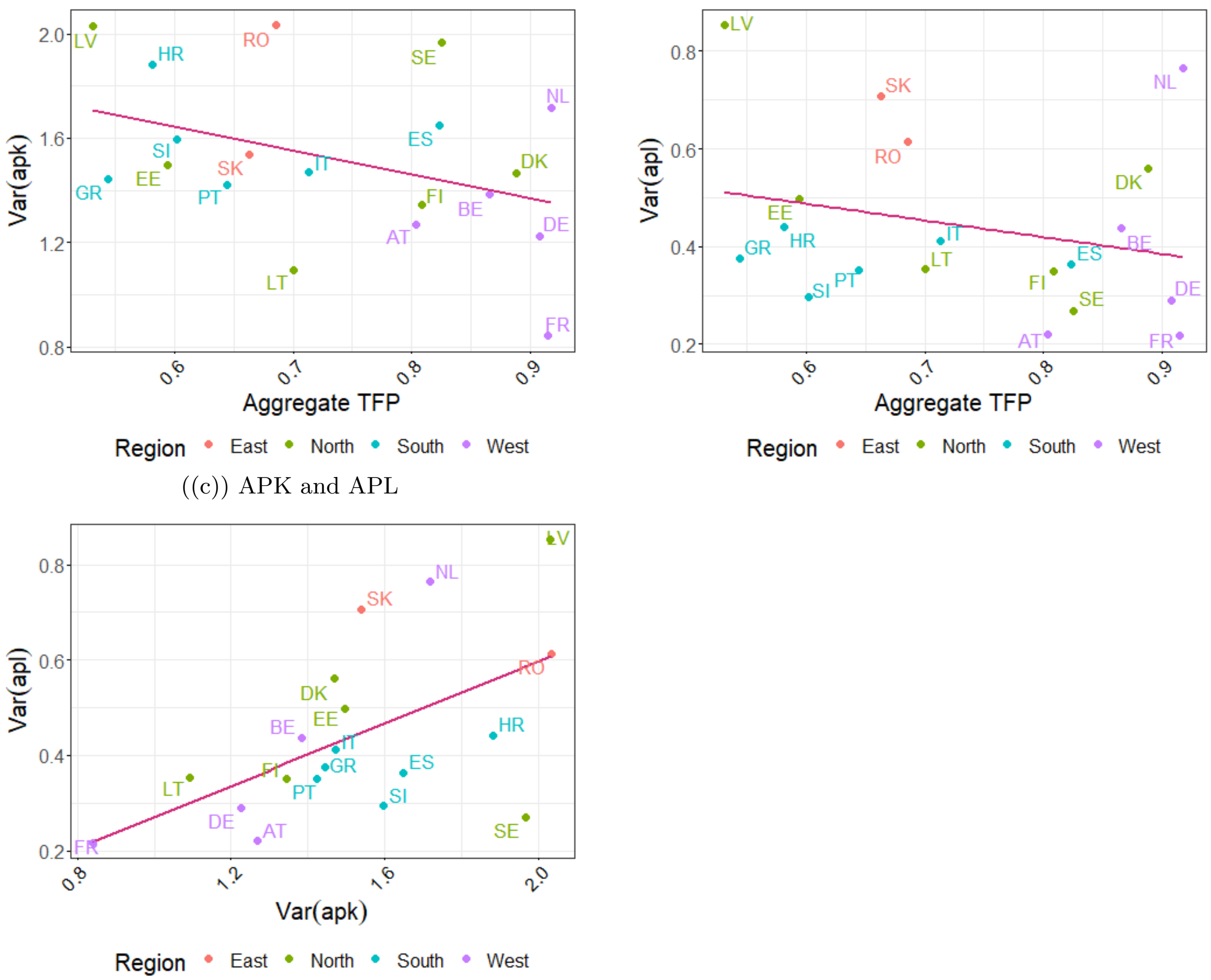
Figure 3.3 displays the other target moments across the countries in our sample. Panel (a) displays the estimated auto-correlation parameters for the (log) productivity process, which are broadly comparable across countries. Panel (b) demonstrates that the variance of productivity

Figure 3.2: The Relation Between Aggregate TFP and Revenue Product Dispersion

((a)) Var(APK)

((b)) Var(APK)

((c)) APK and APL

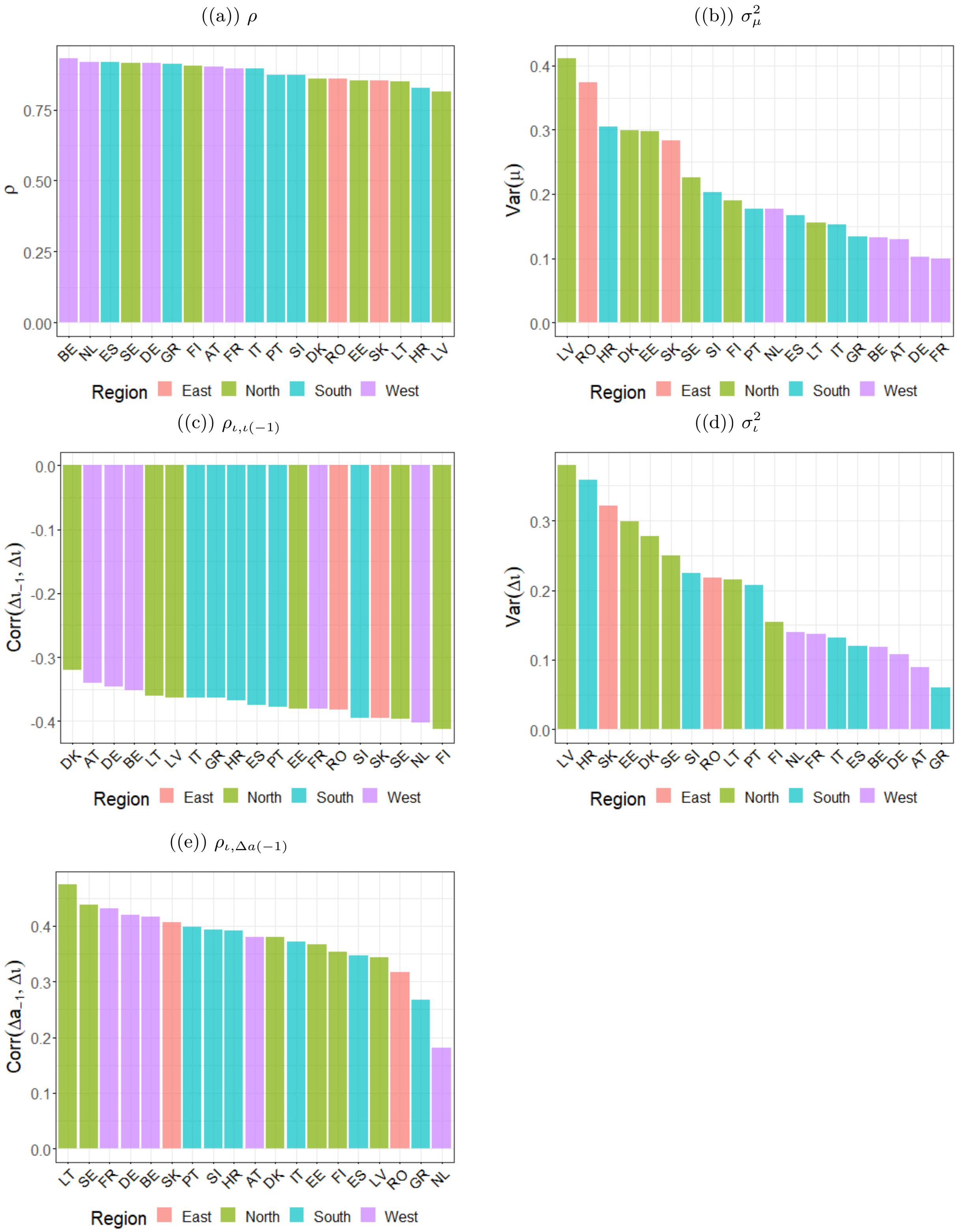


Notes: Panels (a) and (b) of the figure display the relationship between country-level TFP and the variance of (log) APK and (log) APL, respectively. Country-level TFP estimates are extracted from the Penn World Tables. Panel (c) displays the relationship between country-level (log) APK and (log) APL variance.

shocks is notably higher in the eastern European economies, as well as certain members of the Baltics. Investment growth rates show negative serial correlation and low variability across all countries, albeit with significant heterogeneity in the absolute levels of each. For example, investment growth rates are significantly more variable in certain Northern economies, and the Baltics. The variance of investment is lowest in Western Europe, as well as a number of Southern European economies. Table 3.4 reports the exact estimates for the target moments for each country, which have been displayed in Figures 3.1 and 3.3.

In the next section, we use these moments to shed light on the contributions to dispersion in *arpk*, our summary statistic for capital misallocation.

Figure 3.3: Moments by Country



Notes: Figure displays computed target moments for the countries in our sample.

3.5 Results

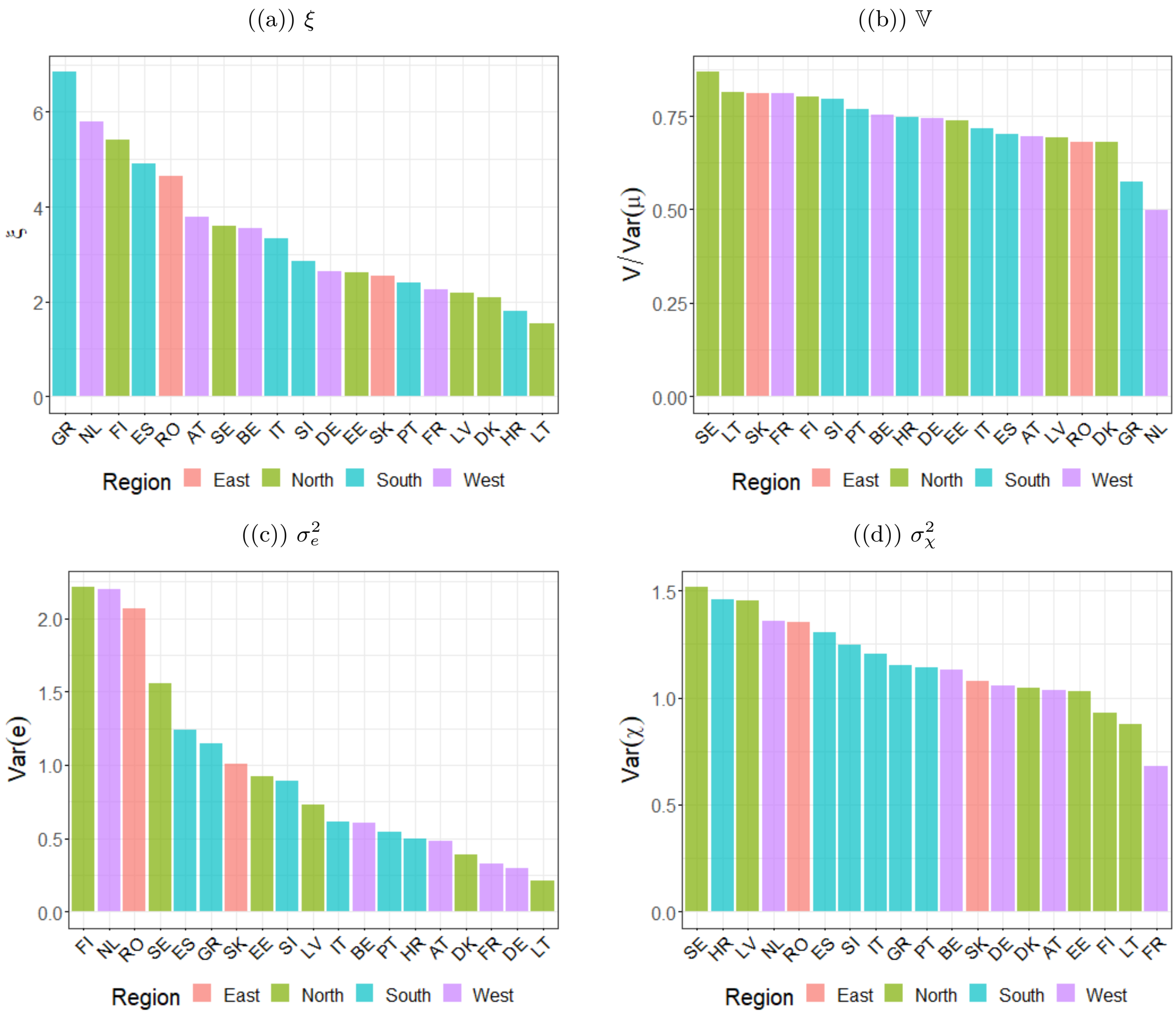
3.5.1 Country-Level Estimates

Figure 3.4 displays estimated parameters, across the countries in our sample. These estimates are reported also in Table 3.5 for reference. There are a number of interesting findings. Firstly, we can observe that the adjustment costs estimates do not obviously correlate by region. Each region appears to contain cases with both higher and lower adjustment cost estimates. Within the four largest euro area economies, we can observe that Spain and Italy have larger adjustment costs according to our estimates, while Germany and France have lower values. We find that adjustment costs are highest in Greece, the Netherlands, Finland, and Spain. Each of these economies was at the lower end of estimates for the variance of investment (see Panel d. of Figure 3.3). Adjustment costs act to reduce the variance of investment in the modelling framework we apply.

When we study levels of uncertainty across our sample, we again find little evidence for strong regional effects. For example, certain economies from Southern Europe have higher levels of uncertainty (Slovenia and Portugal), while Greece has one of the lowest levels of uncertainty. We estimate high levels of uncertainty in France, while our lowest estimate is from the Netherlands, suggesting that Western Europe displays heterogeneous uncertainty levels. The low uncertainty estimates for Greece and the Netherlands result from the low values of the correlation of investment with lagged productivity, as can be observed in Panel (b) of Figure 3.3.

Finally, turning to the two components of the distortion, τ, the estimates of the "permanent" distortion are reasonably heterogeneous across the countries in our sample. However, we do see greater evidence for variation by European region. With the exception of the Netherlands, estimates of the variance of idiosyncratic distortions tends to be lower in Western Europe. Sotuern European economies are congregated in the middle of the range of estimates, though Spain and Greece display estimates in the higher range. Turning to the permanent distortions, we also see greater evidence for a congregation of estimates by region. Western and Northern economies

Figure 3.4: Estimated Parameters by Country



display lower estimates (with a couple of exceptions). Economies in the South of Europe show evidence for higher levels of fixed distortions.

Certain features of the estimates reported in Table 3.4 are predictable given the nature of the target moments used to estimate the model. Firstly, some of the countries in our sample have quite a low variance of investment over the sample period. This suggests a role for adjustment costs. According to Asker et al. (2014), quadratic adjustment costs tend to induce strong serial correlation in investment, and this is borne out by the countries with lower autocorrelation of investment having lower estimates for adjustment costs. Secondly, the reasonable correlation between investment and lagged productivity suggests that firms do not respond immediately to shocks. This would give an indication of the reasonably large parameter estimates for the uncertainty component.

One general conclusion that emerges is that estimates for adjustment costs and uncertainty are heterogeneous within geographic regions, and that neighbouring economies with comparable industrial compositions can generate different estimates. For the case of transitory distortions, and in particular permanent distortions, we can see evidence for regional comparability of estimates. For example, Northern and Western Europe show lower levels for permanent distortions, relative to Southern Europe.

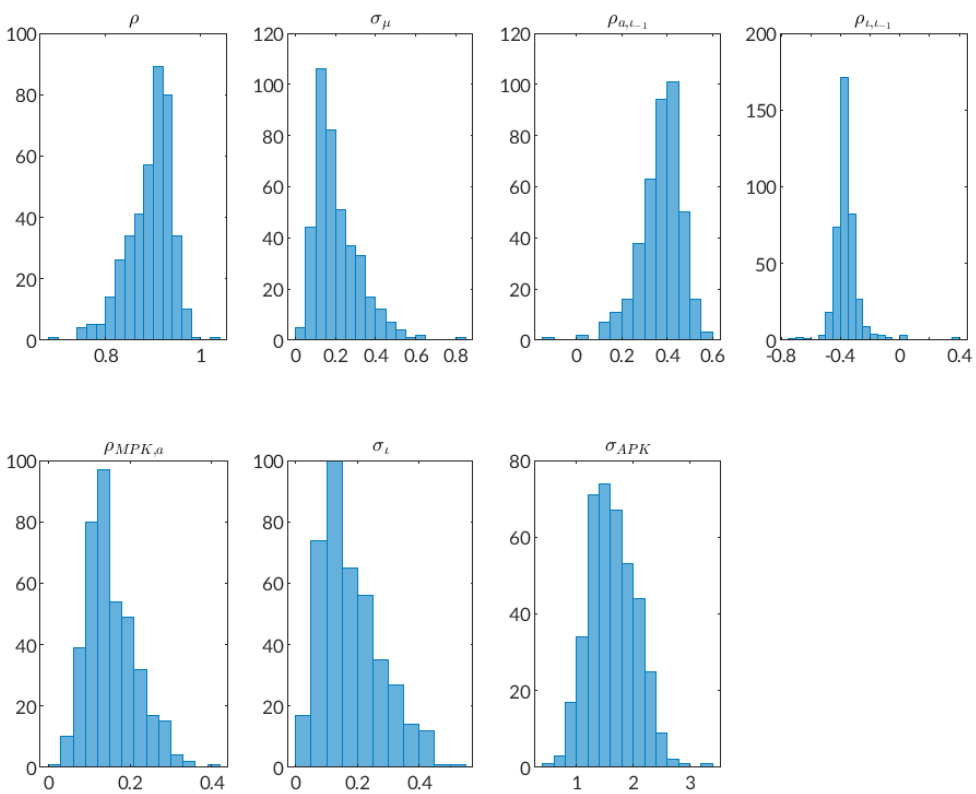
3.5.2 Industry-Level Estimates

While our country-level estimates are suggestive regarding the broad features giving rise to factor product dispersion across European economies, they treat the manufacturing sector in each case as an aggregate. An open question is the extent to which our estimates vary across the more narrow industries within the respective manufacturing sectors. We also estimate the factors contributing to *arpk* dispersion at the industry level, by computing target moment for each NACE 2-digit industry within the manufacturing sector, before re-estimating the model. This avenue was not pursued in the study of DV. We therefore document novel estimates of industry-level heterogeneity.

Figure 3.5 shows density plots of each of the target moments across countries and industries. The distribution of *arpk* dispersion across countries and industries is broadly normally distributed, but it is clear that some industries display higher levels of misallocation than others. By applying the framework of DV across industries, we aim to shed light on the sources of such heterogeneity.

Figure 3.6 shows that distribution of each estimated parameter at the country-industry level. Estimates of the adjustment costs parameter are positively skewed with a long right tail, indicating that the estimate for average adjustment costs are driven by a few country-industry pairs. The estimates for the uncertainty parameter at the country-industry level are somewhat negatively skewed, but with a notable mass on the left side of the distribution, in particular around zero. This suggests that the uncertainty parameter is an important driver of overall misallocation, but

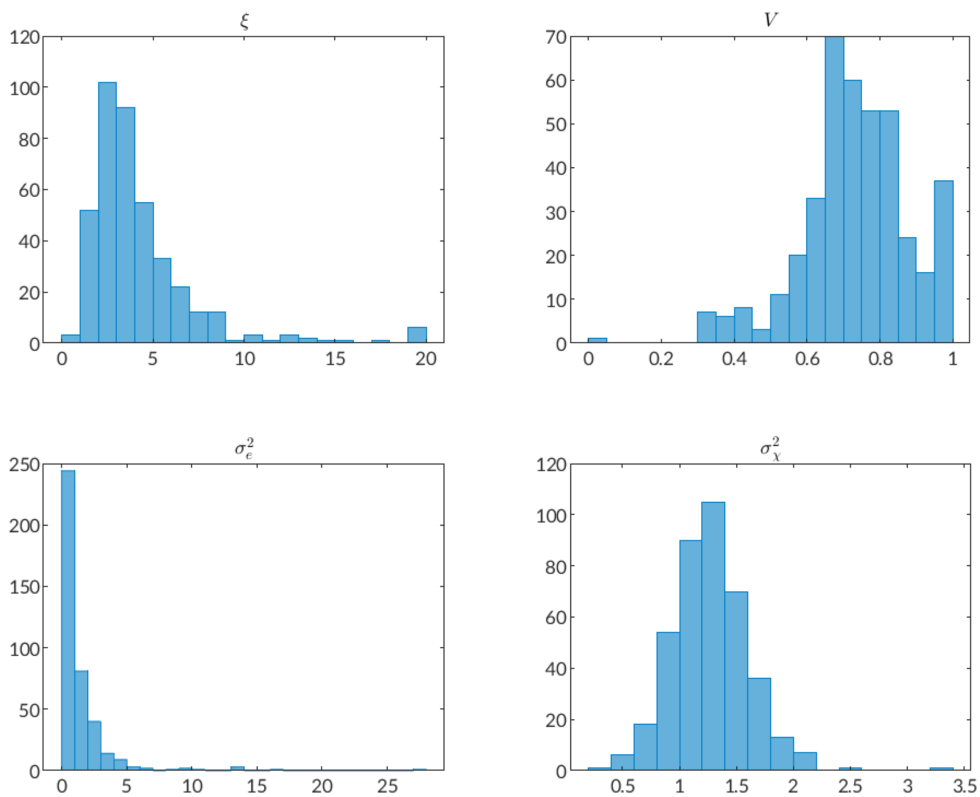
Figure 3.5: Target Moments Across Sectors and Countries



Notes: Figure shows histograms representing target moments computed from firm-level data from the manufacturing sector across 19 European economies. Moments are computed at the industry level, and pooled across countries.

that for some sectors it may make only a minimal contribution. Turning to the components of the distortion, τ, it is clear that for the majority of the sectors examined idiosyncratic firm specific distortions play a negligible role, with most of the mass of the distribution hovering around zero. The parameter for permanent distortions however is more normally distributed at the country-industry level.

Figure 3.6: Parameter Estimates Across Sectors and Countries



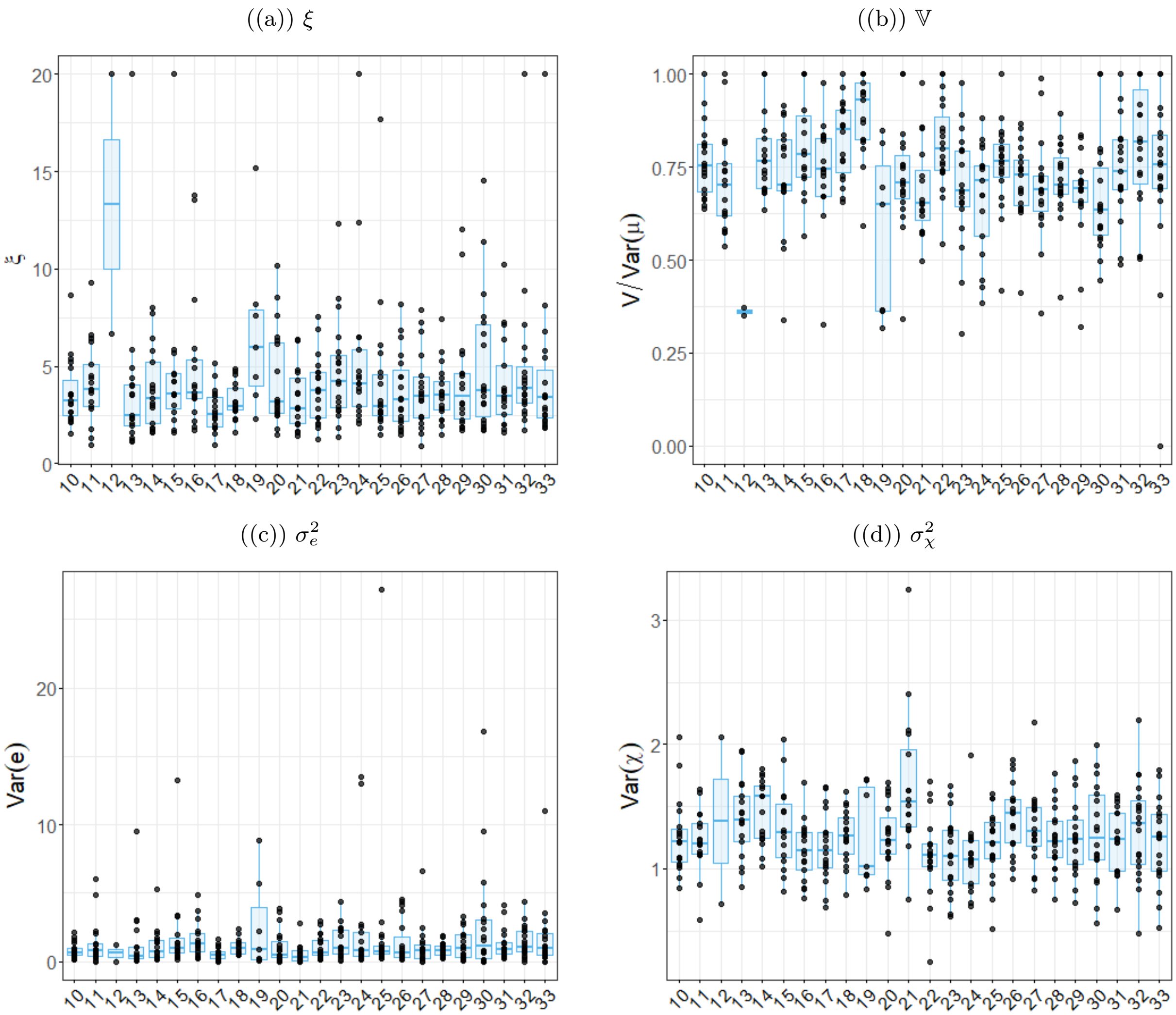
Notes: Figure shows histograms representing estimated parameters across individual industries, pooled across 19 European economies.

Importantly, we find that much of the variation across country-industry pairs can vary across European economies, even within 2-digit NACE category. In Figure 3.6 we display, within each 2-digit NACE category, the dispersion in estimates across countries. There are many cases for which individual countries display estimates that are markedly removed from the median across cases. We view this result as helpful from a policy perspective, since it is unclear, for example, why adjustment costs in the manufacture of wood products are higher in Spain, relative to Germany.

To demonstrate how our approach could inform potential policy choices, we perform a simulation exercise. Specifically, we take estimates of adjustment costs from Spain and Germany. As can be seen from Panel (a) of Figure 3.7(a), Spanish estimates are higher than German ones across every manufacturing industry, not just for the aggregate sector. We then compute the contribution to arpk dispersion for the German and Spanish cases, as displayed in Panel (b). We also compute an estimated contribution for the case when Spanish adjustment costs are set to German levels, and find a sizeable reduction in the misallocation costs for this case. Although adjustment costs are frequently treated as "efficient" distortions in the literature, in the sense that they are an intrinsic feature of any policy environment, our approach suggests that such determinants could potentially be used to reduce misallocation levels within Europe.

In order to understand this heterogeneity, in the next section, we investigate what factors at the country industry level are correlated with variation in these parameters.

Figure 3.7: Country-Sector Estimates by Country



((a)) ξ

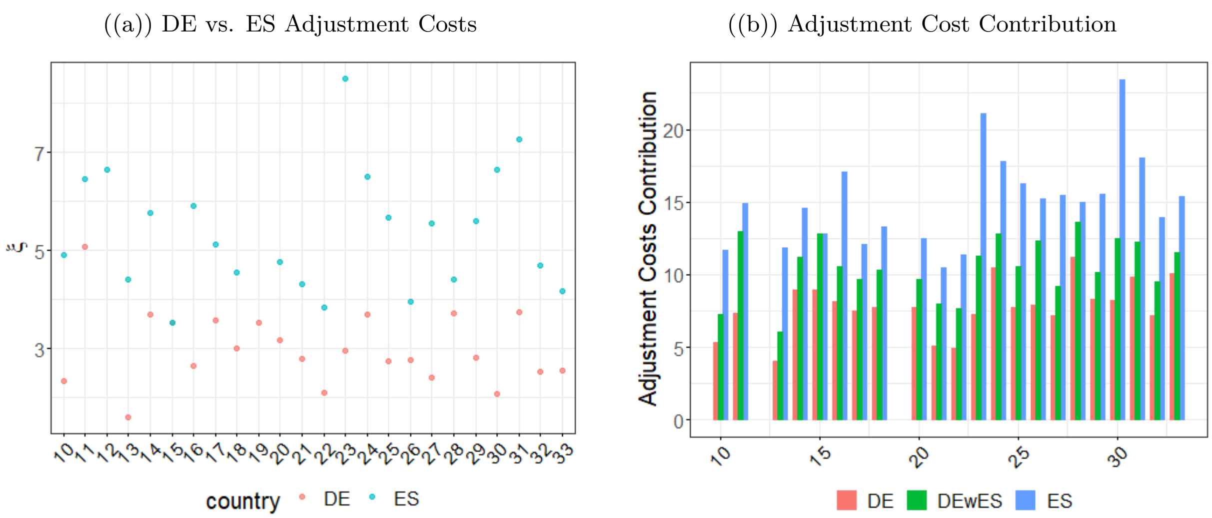
((b)) $\mathbb{V}$

((c)) σ_e^2

((d)) σ_χ^2

Notes: Figure displays the relationship between country-level parameter estimates and moments.

Figure 3.8: Reduction of Spanish Adjustment Costs to German Levels



Notes: Figure displays results from setting Spanish adjustment costs to German values, on a sub-industry by sub-industry basis.

3.6 Which Factors Predict Distortions?

At this stage our analysis points to the following conclusions: 1) there is meaningful dispersion in *arpk* across a sample of European countries; 2) that "efficient" sources do not account for the whole picture, i.e. when explicitly accounting for adjustment costs and firm level uncertainty, we still find meaningful contributions of the components of the wedge τ to overall dispersion in *arpk* both across countries and across countries and industries.

But what macroeconomic features of these countries and sectors in turn predict these results? To investigate this, we turn to the CompNet dataset. These data contain aggregated firm-level information at the country-sector level, with a richer set of variables than is available from the ORBIS dataset. As discussed in Section 3.3.2, CompNet contains data sub-divided into six categories: competitiveness, productivity, labour, trade, finance, and a residual category termed "other". These data are presented as aggregate means at the country-industry level, but the variance and higher order moments are also included.

This rich dataset allows us to investigate which factors lead to variation in the country/sector level parameter estimates displayed in Figure 3.6.

3.6.1 Estimation Strategy

Our estimation strategy is simple, we regress the parameter estimates for the components of misallocation (adjustment costs, uncertainty and the components of the wedge) for each country and industry on a set of potential predictors from CompNet.

The set of predictors are chosen based on the literature. We regress each of the parameters on country $\times$ sector measures of labour costs, investment ratios, firm demographic variables, a measure of firm financial constraints, and the wage share of sector i in country j. The results are presented in Table 3.2.

Table 3.2: OLS Regression Results for Sectoral Misallocation Components

VARIABLES	(1) xi	(2) vsig2u	(3) sig2e	(4) sig2chi
Growth rate (from t-1): Ratio: labour cost per employee_mn	-2.573	1.548***	27.75**	-1.473
	(10.54)	(0.568)	(13.02)	(0.982)
Growth rate (from t-1): labor = number of employees _mn	-48.53***	0.0224	-37.18**	2.137*
	(13.69)	(0.738)	(16.91)	(1.275)
Ratio: investment (change in nk + depr) as fraction of nk(t-1)_mn	1.638**	0.0108	0.601	0.111
	(0.748)	(0.0403)	(0.924)	(0.0697)
Age of firm in years_mn	-0.242*	0.0108	-0.165	0.0117
	(0.135)	(0.00729)	(0.167)	(0.0126)
D = 1, if firm is financially constrained_mn	-4.623	-0.627	-7.920	1.855*
	(10.51)	(0.567)	(12.98)	(0.979)
nominal labor costs_mn	-2.63e-05	-2.07e-05**	-0.000229	1.05e-05
	(0.000178)	(9.61e-06)	(0.000220)	(1.66e-05)
Ratio: wageshare: nom. labor cost / nom. value-added_mn	3.782	0.288	9.824*	-0.197
	(4.532)	(0.244)	(5.599)	(0.422)
Firm's labor market power: rev-based CD, sec, WD_mn	0.0736	0.00700*	0.0582	-0.00884
	(0.0664)	(0.00358)	(0.0820)	(0.00619)
Ratio: Unit labor costs: nom. labor cost / real value-added_mn	-4.898	0.147	-3.255	0.420
	(3.134)	(0.169)	(3.872)	(0.292)
Constant	8.909**	0.376**	-1.600	0.931***
	(3.517)	(0.190)	(4.345)	(0.328)
Observations	155	155	155	155
R-squared	0.583	0.491	0.306	0.787

Standard errors in parentheses

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

In Column 1, we find preliminary evidence of a negative relationship between adjustment costs and firm demographics, particularly firm size and age. Column 2 shows that labour market power and the growth rate of labour costs help explain the variation in the uncertainty measure across countries and sectors. In Column 3, sectoral wages appear to account for some of the variation in transitory distortions, though the negative coefficient on the growth rate of employees suggests that the effect is driven by wage costs per worker rather than total wage costs. Finally, Column 4 indicates a role for financial constraints and employment growth in explaining the variation in permanent distortions.

3.6.2 Lasso Estimation

In section 3.6.1 we choose a set of predictor variables based on theory. However, another approach would be to use the richness of the data in CompNet to see which variables predict the distortions. However, CompNet contains many potential predictors (>300 when the estimations include the variance of each of the predictors) and our parameter estimates from ORBIS give comparatively fewer observations. To address this, we adopt the "elastic net" least absolute shrinkage and selection operator (LASSO) from Zou and Hastie (2005), and solve,

$$\min_{\gamma_Y} \sum_c \sum_i \left(y_{ci} - \gamma^T X_{ci}\right)^2 + \lambda \left[\alpha \left\|\gamma\right\|_1 + (1-\alpha) \left\|\gamma\right\|_2^2\right] \tag{3.3}$$

for some $\lambda > 0$ and $\alpha \in [0, 1]$. For country c and industry i, y_{ci} denotes a dependent variable of interest and X_{ci} is an $m \times 1$ vector of potential explanatory variables. In our context y_{ci} are estimated parameters at the industry-country level, and X_{ci} represents industry-country information from CompNet. We set $\alpha = 0.99$.

It is well known that the LASSO estimator can run into problems when estimating with highly correlated independent variables, the algorithm can select parameters in a somewhat arbitrary manner (Taddy, 2017). In our CompNet dataset, we include both the mean and the standard deviation of all our potential explanatory variables. Not only this, the variables within each of the six categories are in a lot of cases highly correlated.

To account for this, we summarise our the results from our LASSO estimation using a non-parametric bootstrap. We draw with replacement from our dataset 500 times, and store the estimated parameters. We compute the adjusted R^2 by re-estimating our prediction equation via OLS conditional on the subset of variables that were assigned non-zero coefficients by the LASSO algorithm.

Table 3.3 reports the bootstrapped median Adjusted R^2 values from post-LASSO OLS regressions of the country-industry parameter estimates for the factors affecting *arpk* dispersion on the categories of variables selected by the LASSO estimation.

We have four separate elastic net regressions, for each of the four parameters on the parameters contributing to misallocation. For parsimony, we present the results in the following way. The values shown in Table 3.3 represent the percentage point deviations in the adjusted R^2 as a result of omitting the variables in that category. The more significant the deviation, the more explanatory power that is lost by omitting those variables and hence the greater importance we can assign in terms of explaining the variation in the parameters contributing to *arpk* dispersion. We use these results as a guide to investigate which variables from those categories have the highest selection probability in the baseline model (including all explanatory variables). We can then in turn report the coefficients on those variables and the relevant interpretation.[5].

With respect to the distortions, the main message is that the financial and productivity variables have the greatest explanatory power, though labour market variables have some explanatory power for the transitory distortions. For adjustment costs, productivity variables again generate the largest percentage point change in the adjusted R^2 when omitted from the model. For the case of uncertainty, each of the groups of independent variables play a role at explaining variation in our parameter estimates. However, we again find that factors relating to industry-level productivity play a role at explaining firm-level uncertainty.

[5] The full set of results is available on request

Table 3.3: LASSO Category Analysis

	Permanent	Transitory	Uncertainty	Adjustment Costs
Baseline R^2	*93.9*	*65.7*	*78.6*	*64.3*
Competitiveness	-0.4	-1.0	-1.1	-0.2
Financial	-9.4	-3.6	-2.4	-1.6
Labour	-0.3	-3.5	-3.3	-0.9
Productivity	-2.7	-5.8	-4.3	-5.7

Notes: Figures are expressed as the percentage point deviation from the baseline R^2.

3.7 Conclusion

Several papers have shown that misallocation of factor inputs, measured by dispersion in the marginal revenue product of those inputs, are one of the factors behind slow productivity growth. In Europe, the literature has shown that misallocation of capital flows has been one of the main sources of the dispersion in the marginal revenue product of capital, particularly in southern countries.

Our paper sheds important light on both the *sources* of capital misallocation in Europe and macroeconomic features at the country-industry level which are correlated with those sources. We find that a large proportion of the observed dispersion stems from permanent firm-specific factors. This is particularly true in the periphery countries. We also find an important role adjustment costs and uncertainty at the country sector level, and a more limited role for idiosyncratic firm-specific distortions. We additionally find that industry-level characteristics relating to financial variables and productivity have an important role in explaining permanent distortions.

The findings in this paper shed light on the factors influencing capital misallocation in Europe. By better understanding these relationships, policymakers can identify the impediments to productivity growth and output expansion. This is of particular importance in the eurozone common currency area, where divergences in output growth have been substantial in recent decades. The findings have implications for designing policies aimed at enhancing productivity and promoting output growth in the region.

Appendix

3.A Additional Tables

Table 3.4: Estimated Moments from ORBIS Data (Differences)

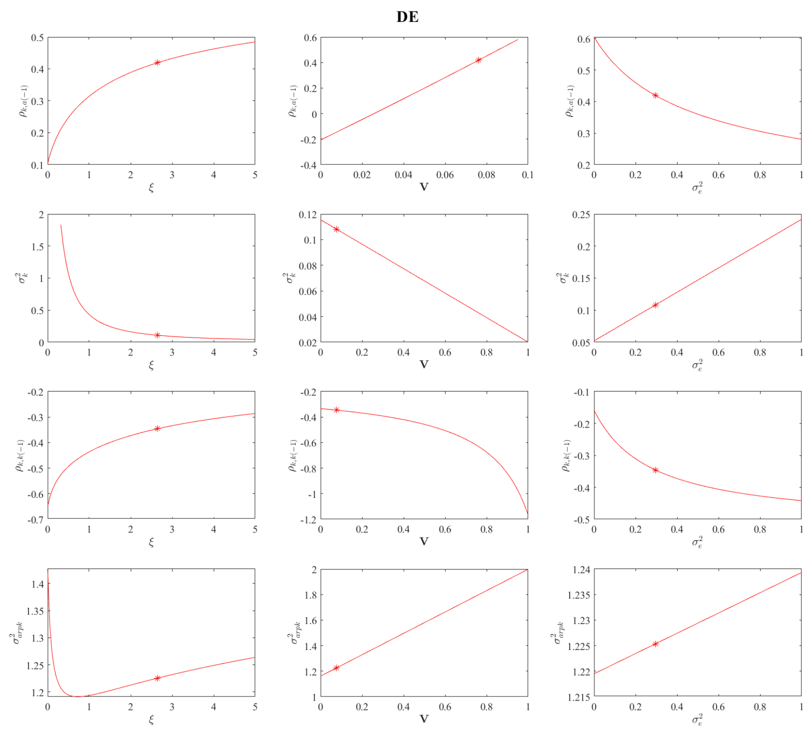
Country	α	ρ	σ_μ	$\rho_{a,\iota_{-1}}$	$\rho_{\iota,\iota_{-1}}$	$\rho_{MPK,a}$	σ_ι	σ_{APK}
AT	0.62	0.90	0.13	0.38	-0.34	0.71	0.09	1.27
BE	0.62	0.93	0.13	0.42	-0.35	0.74	0.12	1.38
DE	0.62	0.91	0.10	0.42	-0.35	0.75	0.11	1.23
EE	0.62	0.85	0.30	0.37	-0.38	0.75	0.30	1.50
ES	0.62	0.92	0.17	0.35	-0.37	0.76	0.12	1.65
FI	0.62	0.90	0.19	0.35	-0.41	0.72	0.15	1.34
FR	0.62	0.90	0.10	0.43	-0.38	0.70	0.14	0.84
GR	0.62	0.91	0.13	0.27	-0.36	0.82	0.06	1.44
HR	0.62	0.83	0.30	0.39	-0.37	0.76	0.36	1.88
IT	0.62	0.89	0.15	0.37	-0.36	0.81	0.13	1.47
LT	0.62	0.85	0.16	0.47	-0.36	0.70	0.22	1.09
LV	0.62	0.81	0.41	0.34	-0.36	0.78	0.38	2.03
NL	0.62	0.92	0.18	0.18	-0.40	0.79	0.14	1.72
PT	0.62	0.87	0.18	0.40	-0.38	0.75	0.21	1.42
RO	0.62	0.86	0.37	0.32	-0.38	0.77	0.22	2.03
SE	0.62	0.92	0.23	0.44	-0.40	0.74	0.25	1.97
SI	0.62	0.87	0.20	0.39	-0.39	0.73	0.22	1.60
SK	0.62	0.85	0.28	0.41	-0.40	0.75	0.32	1.54

Table 3.5: Parameter Estimates

Country	ξ	V	σ_e^2	σ_χ^2	log Error
AT	3.789	0.696	0.478	1.033	-27.740
BE	3.558	0.753	0.603	1.133	-27.305
DE	2.643	0.746	0.296	1.054	-28.174
EE	2.609	0.739	0.919	1.030	-25.892
ES	4.905	0.703	1.236	1.307	-29.434
FI	5.404	0.800	2.212	0.931	-28.436
FR	2.250	0.810	0.325	0.678	-26.326
GR	6.842	0.575	1.146	1.154	-29.640
HR	1.801	0.747	0.499	1.459	-25.195
IT	3.337	0.716	0.613	1.203	-28.984
LT	1.538	0.815	0.214	0.874	-26.479
LV	2.172	0.693	0.731	1.455	-24.866
NL	5.785	0.498	2.196	1.355	-30.012
PT	2.393	0.770	0.541	1.140	-26.334
RO	4.655	0.681	2.068	1.352	-27.656
SE	3.596	0.868	1.557	1.515	-27.637
SI	2.859	0.796	0.889	1.249	-26.630
SK	2.533	0.812	1.005	1.078	-25.914

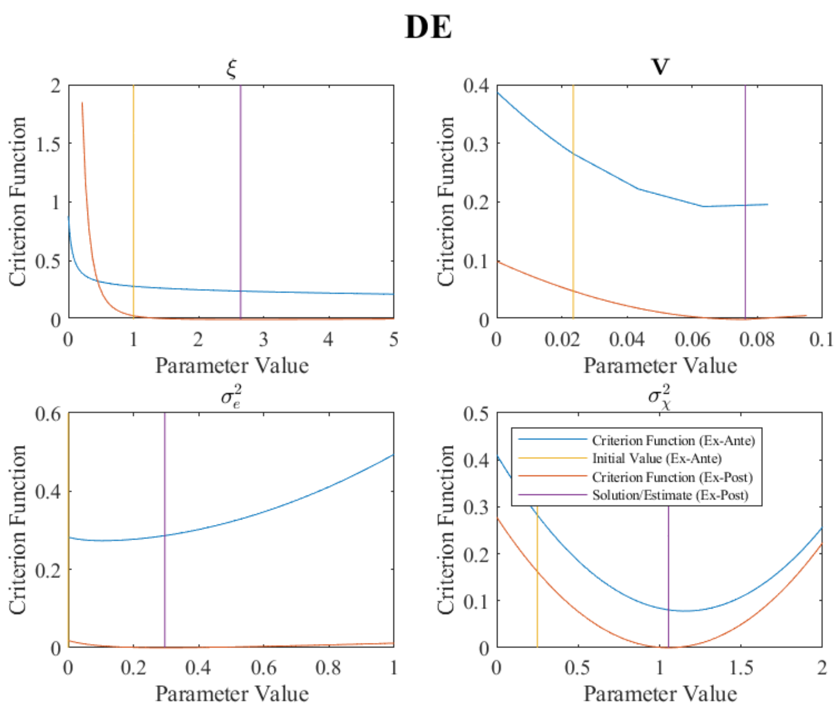
3.B Additional Figures

Figure 3.9: Simulated Moments Across The Parameter Space - German Example



Notes: Figure shows predicted moments as individual parameters are varied.

Figure 3.10: Parameter Estimates Across Sectors and Countries - German Example



Notes: Figure criterion function around SMM estimates. The criterion function around the initial values is also displayed.

3.C Data Cleaning

Table 3.6: Comparison of the ORBIS Size-Distribution with Eurostat Data (2018) – Operating Revenue

Size Class	Dataset	AT	BE	DE	EE	ES	FI	FR	GR	LU	IE	IT	LT	LV	NL	SI	SK	PT
0–9	ORBIS	1	2	2	10	5	3	1	5	.	1	6	1	7	2	7	2	5
0–9	SBS	3	4	2	8	6	4	4	9	0	3	8	3	6	5	8	6	7
10–19	ORBIS	1	2	3	7	5	4	1	8	.	1	10	2	6	0	6	2	6
10–19	SBS	2	2	2	6	4	3	2	5	0	0	8	3	5	3	5	2	6
20–49	ORBIS	5	7	6	18	12	11	5	18	.	8	16	10	15	9	11	5	13
20–49	SBS	5	6	4	13	9	6	4	8	5	0	12	8	13	7	10	5	12
50–249	ORBIS	20	22	18	40	26	19	17	39	.	16	31	45	42	40	25	16	32
50–249	SBS	19	15	12	43	20	19	11	19	21	0	25	29	39	26	22	16	32
250+	ORBIS	73	67	72	25	51	63	76	31	.	74	36	42	30	50	51	75	44
250+	SBS	70	72	80	30	61	68	78	58	71	0	46	57	36	59	54	72	43

Table 3.7: Comparison of the ORBIS Size-Distribution with Eurostat Data (2018) – Employment

Size Class	Dataset	AT	BE	DE	EE	ES	FI	FR	GR	LU	IE	IT	LT	LV	NL	SI	SK	PT
0–9	ORBIS	1	1	1	13	11	7	1	5	.	1	10	2	13	0	10	4	11
0–9	SBS	8	11	6	13	17	10	12	32	0	11	22	12	16	15	16	20	17
10–19	ORBIS	2	2	5	10	11	7	2	11	.	1	14	4	10	0	7	4	11
10–19	SBS	5	5	6	8	9	7	5	10	0	0	14	7	9	8	7	4	10
20–49	ORBIS	7	8	12	21	19	13	7	23	.	3	21	12	19	2	11	9	20
20–49	SBS	9	11	8	16	15	11	8	13	9	0	15	13	16	13	10	8	18
50–249	ORBIS	20	33	22	39	29	26	26	39	.	22	30	42	41	34	28	27	35
50–249	SBS	22	23	20	40	23	24	16	21	27	0	22	32	37	32	25	22	31
250+	ORBIS	70	56	61	17	31	48	63	22	.	73	26	40	18	64	44	55	24
250+	SBS	55	50	60	24	37	49	60	24	56	0	27	36	22	32	43	46	23

3.D The David and Venkateswaran (2019) Framework

We use the model of David and Venkateswaran (2019), which in turn is an extension of the model of monopolistic competition with heterogeneous firms used in Hsieh and Klenow (2009). We consider a discrete time, infinite horizon economy populated by a representative household. The household inelastically supplies a fixed quantity of labour N and has preferences over consumption of a final good. The household discounts time at a rate β.

Production in the economy is carried out by a continuum of firms of fixed measure one, indexed by i. The produce intermediate goods using capital and labour according to

$$Y_{it} = K_{it}^{\hat{\alpha}_1} N_{it}^{\hat{\alpha}_2}, \quad \hat{\alpha}_1 + \hat{\alpha_2} \leq 1. \tag{4}$$

Intermediate goods are bundled to produce the single final good using a standard constant elasticity of substitution (CES) aggregator

$$Y_t = \left(\int \hat{A}_{it} Y^{\frac{\theta-1}{\theta}} di \right)^{\frac{\theta}{\theta-1}}, \tag{5}$$

where $\theta \in (1, \infty)$ is the elasticity of substitution between intermediate goods and $\hat{A}_{it}$ represents a firm specific idiosyncratic component in production/demand. This idiosyncratic productivity shock is the only source of risk in the economy.

The final good is produced under perfect competition, frictionlessly, by a representative firm. This yields a standard demand function for intermediate good i

$$Y_{it} = P_{it}^{-\theta} \hat{A}_{it}^{\theta} Y_t \implies P_{it} = \left(\frac{Y_{it}}{Y_t} \right)^{-\frac{1}{\theta}} \hat{A}_{it}, \tag{6}$$

where P_{it} denotes the relative price of good i in terms of the final good, which serves as the numeraire.

Revenues for firm i at time t are

$$P_{it} Y_{it} = Y_t^{\frac{1}{\theta}} \hat{A}_{it} K_{it}^{\alpha_1} N_{it}^{\alpha_2}, \tag{7}$$

where $\alpha_j = \left(1 - \frac{1}{\theta}\right) \hat{\alpha}_j, \quad j = 1, 2.$

As such, $\hat{A}_{it}$ can be interpreted as either a firm-specific shifter of quality/demand or productive efficiency.

Firms hire labour period by period under full information at a competitive wage W_{it}. At the end of each period, firms choose capital for the following period. Investment is subject to capital adjustment costs, given by

$$\Phi(K_{it+1}, K_{it}) = \frac{\hat{\xi}}{2}\left(\frac{K_{it+1}}{K_{it}} - (1-\delta)\right)^2 K_{it}, \tag{8}$$

where $\hat{\xi}$ controls the severity of the adjustment costs and δ represents the rate of depreciation.

Following Hsieh-Klenow (2009), the model introduces other factors affecting investment decisions as firm-specific proportional "taxes" on the flow cost of capital. These taxes are denoted $T^K_{i,t+1}$. Using the terminology from Hsieh-Klenow, these are referred to as distortions and/or wedges in the analysis. The wedge affects the firms choice of capital in the next period $K_{i,t+1}$.

The firms problem in a stationary equilibrium can be represented by

$$\begin{aligned}\mathcal{V}(K_{it}, \mathcal{I}_{it}) = \max_{N_{it}, K_{it+1}} \mathbb{E}_{it}\Big[&Y^{\frac{1}{\theta}} \hat{A}_{it} K_{it}^{\alpha_1} N_{it}^{\alpha_2} - W N_{it} \\ &- T^K_{it+1} K_{it+1}(1-\beta(1-\delta)) - \Phi(K_{it+1}, K_{it})\Big] \\ &+ \beta \mathbb{E}_{it}[\mathcal{V}(K_{it+1}, \mathcal{I}_{it+1})].\end{aligned} \tag{9}$$

where $\mathbb{E}_{it}[\cdot]$ denotes expectations conditional on $\mathcal{I}_{it}$, the firms information set a the time that it chooses investment for next period K_{it+1}. The wedge $T^K_{it+1} K_{it+1}$ affects both the capital decision and the capital-labour ratio.

After maximising over labour N_{it}, this becomes

$$\begin{aligned}\mathcal{V}(K_{it}, \mathcal{I}_{it}) = \max_{K_{it+1}} \mathbb{E}_{it}\Big[&G A_{it} K_{it}^{\alpha} - T^K_{it+1} K_{it+1}(1-\beta(1-\delta)) - \Phi(K_{it+1}, K_{it})\Big] \\ &+ \beta \mathbb{E}_{it}[\mathcal{V}(K_{it+1}, \mathcal{I}_{it+1})].\end{aligned} \tag{10}$$

where $\alpha \equiv \frac{\alpha_1}{1-\alpha_2}$ is the curvature of operating profits (value added less labour expenses) and $A_{it} \equiv \hat{A}_{it}^{\frac{1}{1-\alpha_2}}$ is the firm specific profitability of capital, which David and Venkateswaran call "productivity" and the term $G \equiv (1-\alpha_2)\left(\frac{\alpha_2}{W}\right)^{\frac{\alpha_2}{1-\alpha_2}} Y^{\frac{1}{\theta}\frac{1}{1-\alpha_2}}$ is a constant that captures the effects of the aggregate variables.

The stationary equilibrium in the model is defined as a set of value and policy functions for the firm, $\mathcal{V}(K_{it}, \mathcal{I}_{it})$, $N_{it}(K_{it}, \mathcal{I}_{it})$ and $K_{it+1}(K_{it}, \mathcal{I}_{it})$; a wage W; and a joint distribution over

$(K_{it}, \mathcal{I}_{it})$ such that taking wages as given and the law of motion for Investment $\mathcal{I}_{it}$. The value and policy functions solve the firm's optimisation problem, the labour market clears and the joint distribution remains constant over time.

The model is solved using perturbation methods. Following David and Venkateswaran (2017), the firms optimality conditionas and laws of motion are log-linearised around $A_{it} = \bar{A}$ (the unconditional average level of productivity) and setting $T_K = 1$ (i.e. the case with no distortions), the model yields a log-linearised Euler equation

$$k_{it+1}((1+\beta)\xi + 1 - \alpha) = \mathbb{E}_{it}[a_{it+1} + \tau_{it+1}] + \beta\xi\mathbb{E}_{it}[k_{it+2}] + \xi k_{it}, \tag{11}$$

where ξ and τ_{it+1} are re-scaled versions of the adjustment cost parameter and the distortion/wedge, respectively.

Productivity A_{it} is assumed to follow an AR(1) process in logs with normally distributed iid innovations, i.e.$a_{it} = \rho a_{it-1} + \mu_{it}, \quad \mu_{it} \sim \mathcal{N}(0, \sigma_\mu^2)$, where rho is the persistence and σ_μ^2 is the variance of the innovations.

The distortion τ_{it} takes the form

$$\tau_{it} = \gamma a_{it} + \epsilon_{it} + \chi_i, \quad \epsilon_{it} \sim \mathcal{N}(0, \sigma_\epsilon^2), \quad \chi_i \sim \mathcal{N}(0, \sigma_\chi^2), \tag{12}$$

where the parameter γ controls the extent to which τ_{it} co-moves with productivity. If $\gamma < 0$ the distortion encourages investment by firms with higher productivity and discourages investment by firms with lower productivity. The opposite is true if $\gamma > 0$. The remaining components of τ_{it} are both uncorrelated with a_{it}. The term ξ_{it} is permanent while ϵ_{it} is i.i.d over time. Thus, the severity of factors is summarised by three parameters; γ, σ_ϵ^2 which is the volatility of the i.i.d shocks to τ_{it} and σ_χ^2, which is the cross-sectional variation in the fixed component.

The firms information set at the time of choosing next periods capital is denoted by $\mathcal{I}_{it}$. This inccludes the entire history of productivity realisations through to period t. i.e. $\{a_{it-s}\}_{s=0}^{\infty}$. Since this is assumed to be AR(1), this can be summarised by the most recent observation, a_{it}.

The firm also observes a noisy signal of next periods productivity innovation

$$s_{it+1} = \mu_{it+1} + e_{it+1}, \quad e_{it+1} \sim \mathcal{N}(0, \sigma_e^2), \tag{13}$$

where e_{it+1} is an i.i.d, mean zero and normally distributed noise term. The firms also perfectly observe the uncorrelated transitory component of distortions at the time of choosing period t investment. Firms also observe the fixed component of the distortion, χ_i. They do not see the correlated component, but are aware of its structure, i.e. they know γ. As such, the firms information set is given by

$$\mathcal{I}_{it} = (a_{it}, s_{it+1}, \epsilon_{it+1}, \chi_i). \tag{14}$$

A direct application of Bayes' rule yields the conditional expectation of productivity

$$\begin{aligned} a_{it+1} \mid \mathcal{I}_{it} \sim & \mathcal{N}(\mathbb{E}_{it}[a_{it+1}], \mathbb{V}) \\ \mathbb{E}_{it}[a_{it+1}] \sim & \rho a_{it} + \frac{\mathbb{V}}{\sigma_e^2} s_{it+1}, \quad \mathbb{V} = \left(\frac{1}{\sigma_\mu^2} + \frac{1}{\sigma_e^2} \right)^{-1}. \end{aligned} \tag{15}$$

In the absence of news, i.e. $\sigma_e^2 = \infty$ we have that $\mathbb{V} = \sigma_\mu^2$. This corresponds to a standard one period time to build assumption. Alternatively $\sigma_e^2 = 0$ implies that $\mathbb{V} = \sigma_\mu^2$ so the firm is perfectly informed about next periods productivity a_{it+1}.

The Euler equation in 9 can be solved forward to obtain the law of motion for capital

$$k_{it+1} = \psi_1 k_{it} + \psi_2 (1+\gamma) \mathbb{E}_{it}[a_{it+1}] + \psi_3 \epsilon_{it+1} + \psi_4 \chi_i, \tag{16}$$

where

$$\begin{aligned} \xi(\beta\psi_1^2 + 1) = \psi_1((1+\beta)\xi + 1 - \alpha) \\ \psi_2 = \frac{\psi_1}{\xi(1-\beta\rho\psi_1)}, \quad \psi_3 = \frac{\psi_1}{\xi}, \quad \psi_4 = \frac{1-\psi_1}{1-\alpha}. \end{aligned} \tag{17}$$

The coefficients ψ_1-ψ_4 depend only on production (and preference) parameters, including the adjustment cost, and are independent of assumptions about information and distortions.The coefficient ψ_1 is increasing and ψ_2-ψ_4 are decreasing in the severity of adjustment costs. if there is no adjustment costs, (i.e. $\xi = 0$), $\psi_1 = 0$ and $\psi_2 = \psi_3 = \psi_4 = \frac{1}{1-\alpha}$. On the other hand, if $\xi \to \infty$, $\psi_1 \to 1$ and$\psi_2 - \psi_4$ vanish. As adjustment costs become large, the firm's choice of capital becomes more autocorrelated and less responsive to productivity and distortions.

Aggregate output can be expressed as

$$\log Y \equiv y = a + \hat{\alpha}_1 k + \hat{\alpha}_2 n, \tag{18}$$

where k and n denote the logs of the aggregate capital stock and labour inputs, respectively. Aggregate TFP, denoted by a, is given by

$$a = a^* - \frac{(\theta\hat{\alpha}_1 + \hat{\alpha}_2)\hat{\alpha}_1}{2}\sigma^2_{arpk}, \quad \frac{da}{d\sigma^2_{arpk}} = -\frac{(\theta\hat{\alpha}_1 + \hat{\alpha}_2)\hat{\alpha}_1}{2}, \tag{19}$$

where a^* is aggregate TFP if static capital products ($arpk_{it}$) are equalised across firms and σ^2_{arpk} is the cross sectional dispersion in (the log of) the static average product of capital ($arpk_{it} = p_{it}y_{it} - k_{it}$).

Chapter 4

Macroprudential Policies and The Rise of Non-Bank Lending: Evidence and Implications for Monetary Policy

[1]

4.1 Introduction

In the years since the global financial crisis, European policymakers have grappled with the delicate balance of promoting financial stability while also fostering economic and price stability. To achieve these dual aims, macroprudential authorities implemented policies designed to curb excessive credit growth and preserve financial stability (Cerutti et al., 2017), while central banks in the Euro-area set monetary policy at or below the zero-lower-bound, loosening financial conditions to spur demand and maintain price stability.

During the same period, Europe has witnessed a substantial expansion of non-bank financial intermediaries (NBFIs), particularly financial vehicle corporations (FVCs), which now play an

[1] The opinions expressed in this paper are those of the author and do not represent the views of the Central Bank of Ireland or the European System of Central Banks. I thank Agustín Bénétrix, Cian Ruane and Matija Lozej for helpful comments on earlier drafts of the paper. I thank Arya Pillai and colleagues in the Statistics Division of the Central Bank of Ireland for helpful guidance with the data. All remaining errors are my own.

increasingly prominent role in the financial landscape. FVCs are entities that handle securitisation transactions, facilitating the transfer of risk away from originating entities (e.g. Traditional Banks).

This transfer of risk can pose problems. Firstly, this transfers risk to other parts of the financial system, creating “complex interconnections that are not well understood” (International Monetary Fund, 2023). Secondly, banks that originate the loans and sponsor these entities become vulnerable to the risk of needing to provide these entities financial support in times of stress (“step-in” risk). In this regard, policymakers have highlighted that ”gaps in regulatory frameworks for NBFIs from a financial stability perspective” still exist (Carstens, 2021).

These facts prompt an important research question: Are macroprudential policies, designed to stabilise the financial system, inadvertently encouraging a shift of credit activity into less regulated and potentially riskier segments of the financial system? This phenomenon, referred to here as “cross-sectoral arbitrage,” represents a form of regulatory arbitrage of the form outlined in Acharya et al. (2013), Acharya et al. (2024) and theorised by Farhi and Tirole (2017) and Plantin (2014). It has also been highlighted in speeches by policymakers involved in financial regulation (Bank, 2017).[2]

In this paper, I leverage the variation in the timing of macroprudential policy implementation across a panel of European countries from 2009 to 2021 to identify the impact of a change in macroprudential policy on FVC loan claims. Using data on FVC assets published by the ECB and macroprudential policy information from the IMF’s Integrated Macroprudential Policy database (iMaPP), I find that a tightening of macroprudential regulations imposed on traditional banks is associated with an increase in the growth rate of FVC loan claims in Euro area member countries. I show the effect peaks after two quarters but remains statistically significant for three quarters. This finding supports the ’cross-sectoral arbitrage’ hypothesis, suggesting that regulatory constraints on traditional banks may lead to a diversion of credit activity towards the non-bank sector.

[2] The term ”regulatory arbitrage” is sometimes employed in other contexts to refer to entities moving across jurisdictions to attain more favourable regulatory frameworks. However, this paper only addresses the phenomenon of banks transferring loans to non-bank entities to circumvent domestic regulatory constraints, specifically macroprudential policies, distinct from the broader interpretations of the term.

I make two additional findings in this regard. First, using a quantile regression approach, I show that this effect is driven by the top two quantiles of the distribution of FVC loan growth rates across countries and periods. The intuition for this result is that the arbitrage channel may be stronger in countries and periods where FVC loan growth is already established. Second, I find that "loan-targeted" macro prudential policies are not a statistically significant driver of this effect. The intuition for this finding is that macro prudential policies that target systemic risk (e.g. policies targeting bank capital and the use of bank profits), are the main driver of the result.

These dynamics pose an important policy question: if macro prudential measures divert lending from traditional banks to FVCs, do these entities respond in the same way as traditional banks to monetary policy shocks, i.e. the "the bank lending channel" (Kashyap and Stein, 2000)? Using Euro area monetary policy shocks from Jarociński and Karadi (2020), I find that, contrary to the traditional bank lending channel narrative, a contractionary monetary policy shock is associated with an increase in the growth of FVC loans. This evidence suggests that the expansion of FVCs, spurred by macro prudential tightening, may alter the transmission of monetary policy to the broader financial system. Understanding these dynamics is important not only for preserving financial stability but also for anticipating the future transmission of shocks.

This paper makes a number of key contributions to the literature. Firstly, to the authors knowledge, it is the first to document a link between tightening macroprudential policy and non-bank financial intermediation growth in Europe. Second, I show evidence that the effect is driven by macroprudential policies designed to target systemic risk as opposed to "loan-targeted" measures. Third, I show that FVCs appear to increase their loan claims in response to monetary policy shocks, contrary to the predictions of the Bank lending channel but in line with similar findings from non-banks in the US. These findings underscore the importance of macroprudential and monetary policy authorities working together.

This paper is related to several strands of literature. There is a growing body of research that seeks to understand the effects of macro prudential policies across countries. Claessens (2014) show that macroprudential policies are designed to safeguard financial stability by regulating financial institutions to prevent systemic risks. These policies include capital requirements, countercyclical buffers, and liquidity constraints, which aim to enhance the resilience of the banking sector (Claessens, 2014). Alam et al. (2024) develop the IMF's integrated macroprudential policy (iMAPP) database to investigate the impact of macroprudential policies on credit, GDP, and other macroeconomic variables. While this literature finds positive effects of macro prudential policies on the outcomes they were designed to target, a new strand of literature seeks to understand whether there are potential unintended effects. For example, Galati and Moessner (2018) find that macroprudential policies could lead to regulatory arbitrage by encouraging lending through foreign affiliates. In the US, Buchak et al. (2018) suggest that the imposition of macroprudential policies on the traditional banking sector might encourage the migration of credit activity to less-regulated non-banks (Buchak et al., 2018). The channels underpinning these effects are theorised in Farhi and Tirole (2017) and Plantin (2014).

This paper is also related to the literature on the effect of monetary policy on non-banks. The relationship between monetary policy and non-bank financial intermediaries is less explored than that with traditional banks. The conventional view, articulated by Bernanke and Gertler (1995) and Kashyap and Stein (2000), emphasises the pivotal role of banks in transmitting monetary policy to the real economy. However, recent studies suggest that non-bank financial intermediaries might respond differently to monetary policy changes. In the U.S., for instance, Elliott et al. (2022) observe that non-bank financial institutions may increase their lending in response to monetary tightening, driven by higher returns on their investment portfolios. This behaviour contrasts with traditional banks, which typically reduce lending in response to higher interest rates due to increased funding costs and risk aversion. In the US, policymakers have argued that monetary policy "gets in all of the cracks" of the financial system, suggesting that NBFIs should react similarly to traditional banks in response to a monetary policy tightening. The hypothesis is that as traditional banks face tighter regulatory constraints, non-bank intermediaries—subject to less rigorous oversight—may expand their lending activities to compensate for the reduced capacity of banks.

These findings are important for several reasons. First, they suggests that while macro prudential policies may enhance the resilience of the banking sector, they could inadvertently shift credit activities into less regulated areas, potentially heightening systemic risk. Second, the findings reveal that NBFIs may respond differently to monetary policy shocks compared to traditional banks. Specifically, some NBFIs expand their lending in response to monetary tightening, a behaviour that challenges the conventional understanding of the monetary policy transmission mechanism. This indicates that the increasing prominence of NBFIs could complicate the central bank's ability to manage the economy effectively through traditional monetary policy tools. Lastly, these results underscore the evolving significance of NBFIs within the financial system and highlight the need for policymakers to consider the broader financial system when designing regulatory and monetary policies to ensure that stability is maintained across all sectors, not just within the traditional banking domain.

The remainder of this paper is organised as follows: Section 4.2 describes the data and presents stylised facts on the growth in non-bank lending. Section 4.3 presents the evidence on the spillover of macroprudential policies, while section 4.4 explores the impact of monetary policy shocks on nonbanks. Finally, Section 4.5 concludes with suggestions for future research.

4.2 Data and Stylised Facts

4.2.1 Financial Vehicle Corporations

Financial Vehicle Corporations (FVCs) are special-purpose entities (SPE), who engage in securitisation. FVCs are established by sponsors, and acquire assets from originators which are the entity that originally issued the loans. The primary types of securitised loans on the balance sheet of FVCs are outlined in table 4.1[3]. This involves the transformation of illiquid assets, such as loans and mortgages, into liquid securities that are subsequently sold to investors (Acharya et al., 2013). Through this mechanism, FVCs undertake maturity transformation, whereby they acquire medium- to long-term assets and finance them through the issuance of short-term securities. This structure inherently creates a maturity mismatch, necessitating that FVCs consistently roll over their short-term liabilities by issuing new securities as existing ones mature.

[3] See Golden and Hughes (2018) for a full description of business models

Table 4.1: Main types of securitised loans on Euro-area FVC Balance Sheets

Vehicle Type	**Description**
RMBS	Loan-based securities secured upon residential property.
CMBS	Loan-based securities secured upon commercial property.
Consumer ABS	Loan-based securities secured upon consumer products; debtors are individuals.
Corporate ABS	Loan-based securities secured upon assets; debtors are corporations.

Source: European Systemic Risk Board (2024)

According to European Systemic Risk Board (2024), securitised loans are the largest portion of FVC portfolios in the Euro-area itself, and more than 90% of these loans were originated within the Euro-area . FVC's have a "pronounced engagement" in risky activities such as credit intermediation, maturity transformation and liquidity transformation. Data show that these entities are highly leveraged and exhibit high levels of interconnectedness with Euro-area MFIs.[4]

For these reasons, FVCs can expose the Banking sector to considerable risks. In the event that the FVC faces difficulties in refinancing its maturing liabilities, whether due to market disruptions or a decline in asset values, the sponsor may be required to extend financial support. This could involve an explicit contractual obligation, or "step-in risk" where the sponsor provides financial support beyond, or in the absence of, a direct obligation.

Data on FVCs in Europe

Financial Vehicle Statistics for the euro-area are published quarterly by the ECB. They present the aggregated balance sheets of of euro-area resident FVCs and are available from the fourth quarter of 2009. The dataset contains the assets and liabilities of the firms, covering end of quarter outstanding amounts and financial transactions (*ECB* n.d.). Outstanding amounts refer to end-of-period stocks, i.e. the stock of loans outstanding at the end of the quarter. Transactions, or flows, refer to the net acquisition (incurrence) of a particular asset (liability) during the reference period.

[4]Leverage measured as the sum of loans received and debt securities issued divided by total assets greater than 80%

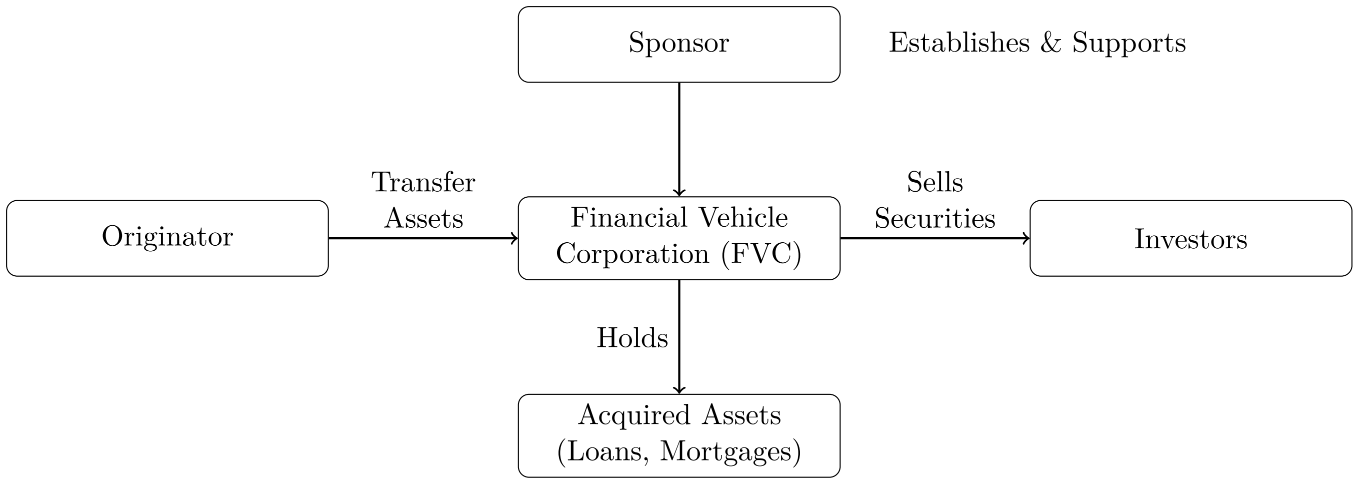


Figure 4.1: Operational Structure of a Financial Vehicle Corporation

Note: Based on descriptions from Golden and Hughes (2018)

For the purposes of this analysis, I analyse changes loan claims on the balance sheets of FVCs. However, changes in outstanding stocks of loans cannot be used to conduct this analysis. This is because changes in the outstanding stocks are also affected by reclassifications, other revaluations, exchange rate variations and other changes. Data on the flows/transactions give us the period to period change in the stock adjusted for these factors.

To address this, I calculate the year-on-year growth rates of FVC assets using "notional stocks". Notional stocks are calculated by taking the outstanding stock at the end of the first period of the series, and iteratively adding each subsequent period's transaction to the stock in order to calculate the series.

Specifically, the notional stocks are calculated using the following iterative process:

$$\text{Notional Stocks}_t = \begin{cases} \text{Outstanding Stocks}_t & \text{if } t = 1, \\ \text{Notional Stocks}_{t-1} + \text{Transactions}_t & \text{if } t > 1. \end{cases}$$

Notional Stocks are referred to as *FVC Loans* hereafter. In the case of the FVC dataset, the first period, i.e. 2009Q4, the notional stocks are set equal to the observed outstanding stocks. In the second period For all subsequent periods ($t > 1$), the notional stocks are computed by adding the transactions of the current period to the notional stocks from the previous period.

This recursive method ensures that the notional stocks at each period are consistently updated to reflect the cumulative effect of transactions over time.

The growth of FVCs in Europe has seen a significant upward trend over the past decade. FVCs, which are special-purpose entities used primarily for securitisation activities, have expanded in response to changes in the regulatory environment and market demand for structured finance products. European Central Bank (ECB) reports that the total assets of FVCs in the Euro area increased from approximately €1.5 trillion in 2013 to over €2.2 trillion by 2023, reflecting a compounded annual growth rate (CAGR) of around 4% *ECB* (n.d.).

Figure 4.2 shows the development of the main measure of FVC Loans used in this analysis, namely FVC loan and deposit claims. The measure is indexed to 2010Q1 for each country in the sample, and the line shows the median development of the index over time while the shaded area shows the 16th and 84th percentiles. As discussed in Lane and Milesi-Ferretti (2018), certain Euro area countries with large financial centres have seen significant growth in FVC Loans over the period, while other countries have seen more muted growth and even negative growth over the decade. These features account for the reasonably wide range for the index.

4.2.2 Macroprudential Policies

Data on macroprudential policy comes from the IMF's Integrated Macroprudential Policy database (iMaPP). This database integrates information from five major existing databases on macroprudential policy and augments this with further information from the IMFs annual macroprudential policy survey, authorities' official announcements, as well as official information from the BIS, FSB and the IMF (Alam et al., 2024). The database provides a comprehensive overview of 17 different categories of macroprudential policies, covering 134 countries and data are available from 1990 onwards.

The iMaPP includes dummy-type indicators for each of the 17 different macroprudential policy classifications in the database. These indices indicate the direction of policy actions (tightening or loosening) macroprudential policy instruments and their subcategories. These indices take a

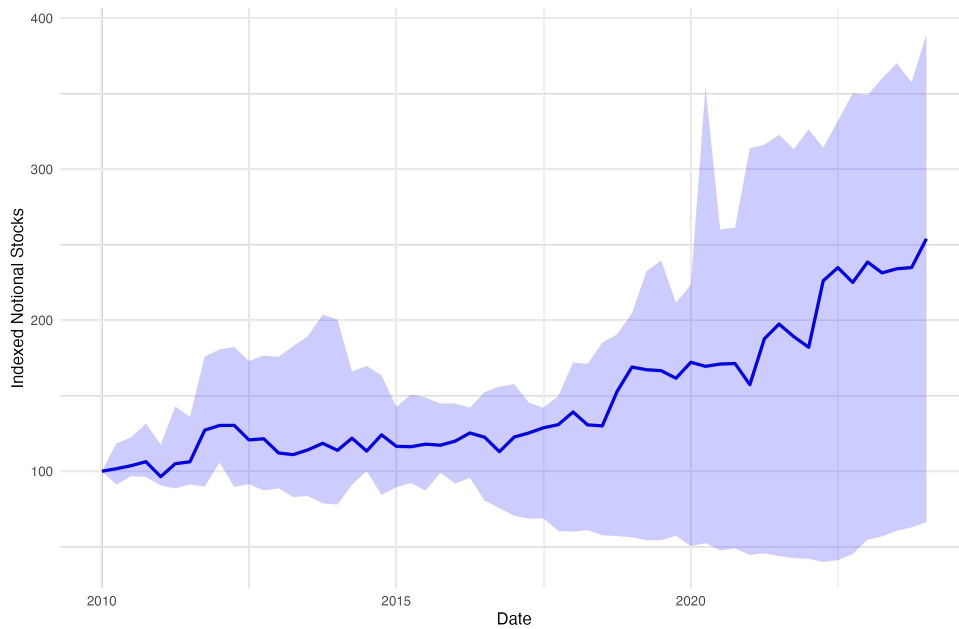


Figure 4.2: Indexed Notional Stocks Over Time (Base: 2010Q1 = 100)

Source: European Central Bank
Notes: Shaded area represents the range of growth rates in the sample.

value of 1 for tightening actions, -1 for loosening actions, and 0 for no change. They are provided at a monthly frequency.

The use of the dummy indices provides several advantages. By focusing on policy actions and their directions, these indices synthesise information across various policies. While information on the intensity of all policy instruments would be preferable, it is impractical due to the diverse nature of these instruments (Alam et al., 2024). Many tools are implemented differently across countries, with varying definitions of regulated variables, making numerical comparisons difficult. Dummy indicators, therefore, serve as a valuable means to characterise the application of macroprudential policies and to estimate their effects per policy action.

In Figure 4.3, I show the cumulative sum of this measure over the years immediately preceding the financial crisis until the end of 2021.

For the purposes of this paper, I use the two main composite indices from the database. The first, denoted iMaPP index, is the sum of the dummies for all of the 17 categories in the database.

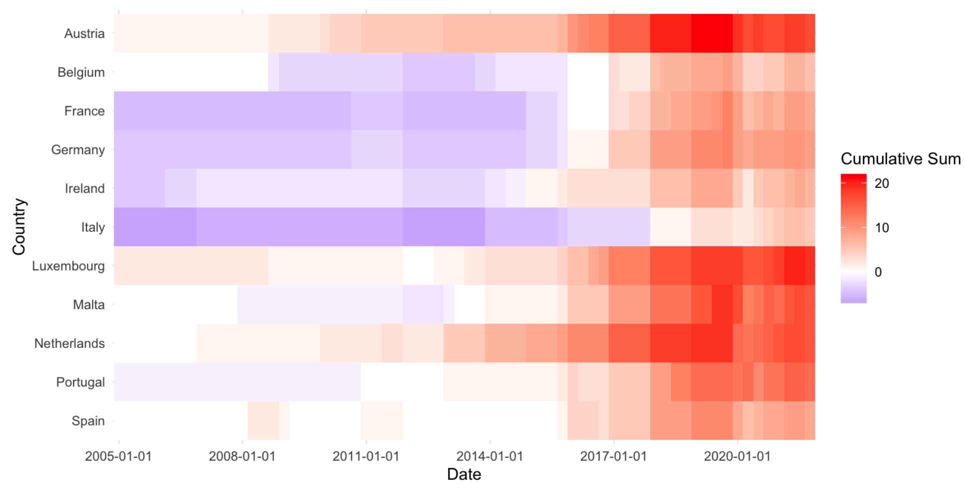


Figure 4.3: Cumulative sum of net macroprudential policy tightening 2005-2021

Source: IMF Integrated Macroprudential Database (iMaPP)
Notes: Plot represents the cumulative sum of the net macroprudential policy measures taken between 1990 and 2021. The measure represents the cumulative sum of the net number of tightening actions of any macroprudential policy

To account for the fact that macroprudential policy affects the economy with a lag, the index is cumulated over the past four quarters (and divided by four).

The second is what Alam et al. (2024) refer to as "loan targeted" policies. These policies include both demand-side and supply-side measures:

- **Demand-side tools**: These include Loan-to-Value (LTV) limits and Debt-Service-to-Income (DSTI) limits, which directly constrain household borrowing by limiting credit against collateral or relative to income.

- **Supply-side tools**: These measures influence the supply of credit by imposing constraints on lenders, such as restrictions on bank credit growth, loan loss provisioning requirements, and loan restrictions like caps on foreign currency loans or loan-to-deposit ratios.

I use the sum of the dummies for both supply and demand side tools to generate the measure of "loan targeted" policies. Similar to the overall measure, the index is cumulated over the past four quarters and divided by four to account for potential lagged effects. In Alam et al. (2024), these loan-targeted measures significantly affect household credit growth, especially in emerging markets, where demand-side tools like LTV and DSTI limits reduce borrowing capacity directly, and supply-side tools impose broader constraints on credit availability.

Macroprudential policy represents an additional set of regulations on the traditional banking sector. For instance, macroprudential policy seeks to enhance financial stability by mitigating systemic risks and preventing economic disruptions. This is in addition to already existing national and international regulatory frameworks which govern the activities of the traditional banking sector, covering things like capital adequacy, liqudity and leverage (on Banking Supervision, 2017).

The rationale for macroprudential policies is based on the finding by Mian et al. (2017) that higher household leverage has historically been associated with busts, as well as business cycle downturns. Policies which limit credit to households, in turn, limit the feedback loop between bank credit and fluctuations in real assets such as house prices.

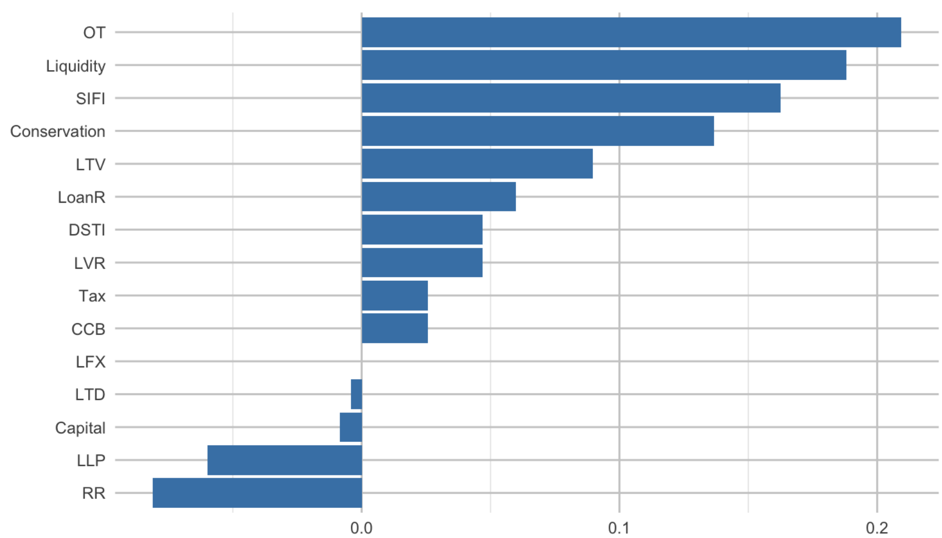


Figure 4.4: Average net tightening/loosening per year by Instrument: 2009-2021

Source:IMF Integrated Macroprudential Database (iMaPP)
Notes: The measure represents the average net tightening/loosening of macroprudential policies for each instrument across all countries in the sample.

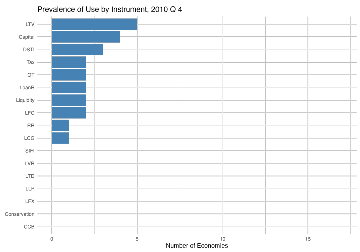
The iMaPP database allows for a comprehensive decomposition of what type of macroprudential policy actions were taken in the Eurozone over my sample period (2009 to 2021). Figure 4.4

illustrates the average net tightening/loosening per year categorised into specific instruments using the 17 categories outlined in Alam et al. (2024). Recall that the database records a +1(-1) for a tightening (loosening) action and 0 for a month where no action was taken. Looking at Figure 4.4 the ”Other” category is the most tightened on average over the period. According to the database, the “Other” category encompasses “macroprudential measures not captured in the above categories—e.g., stress testing, restrictions on profit distribution, and structural measures (e.g., limits on exposures between financial institutions)”. The prevalence of this residual category indicates a significant reliance on measures aimed at reducing systemic risk. Measures focused on liquidity rank second in terms of most-tightened on average. Measures targeting Systemically Important Financial Institutions (SIFIs), including capital and liquidity surcharges, also feature prominently, reflecting the heightened awareness of systemic risks posed by these entities. Interestingly, instruments like reserve requirements (RR) show a negative average frequency, suggesting a net relaxation over the period.

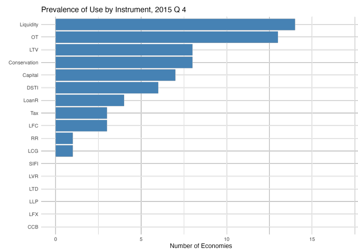
Figure 4.5 shows the prevalence of each type of policy instrument across the countries for the fourth quarters of 2010, 2015 and 2021. Clearly, while it is less frequently altered (as shown in Figure 4.4) “Loan to Value” policies are quite prevalent across all three selected periods in Figure 4.5. However, over the course of the 2010s, liquidity and other policies became more prevalent. The prevalence of the “other” category in 2021Q4 is a result of the very large surge in macroprudential policy announcements as a result of the Covid-19 pandemic. The surge in these macroprudential measures during the COVID-19 pandemic was driven by the need to ensure financial stability in the face of severe economic stress, preserve capital within financial institutions, mitigate systemic risks, and adapt to the evolving nature of the crisis.

Given the prominence of the “other” category, I utilise the textual information on Macroprudential policy announcements in the iMaPP database to generate a word cloud of these policies over the sample period.[5] Figure 4.6 provides a useful visualisation of the themes of these policies. The wordcloud highlights terms such as “institutions”, “recommendation”, “significant”, “dividend” and “distributions”, indicating a strong focus on regulating financial institutions’ behaviour, particularly concerning capital distributions and shareholder payments. These policies

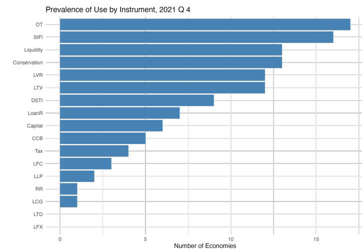
[5] Wordcloud generated using the “Topic modelling” package in RStudio



((a)) 2010 Q4



((b)) 2015 Q4



((c)) 2021 Q4

Figure 4.5: Prevalence of Use by Instrument in the Eurozone (Comparison across 2010 Q4, 2015 Q4, 2021 Q4)

Source:IMF Integrated Macroprudential Database (iMaPP)
Notes: The measure represents the prevalence of each instrument across countries in the three selected period.

became particularly important in the wake of the Covid-19 pandemic. For example, in December 2020 - the ECB recommended banks under its direct supervision (that is, significant institutions (SIs)) to refrain from making dividend distributions and performing share buy-backs aimed at remunerating shareholders during the period of the COVID-19-related economic shock, at least until September 30, 2021. Many of these policies aimed to enhance financial stability by ensuring banks retained sufficient capital.

4.3 Macroprudential Spillovers

This section outlines a theoretical framework explaining how the tightening of macro prudential policy may lead to an increase in loan claims by financial vehicle corporations (FVCs). Following this, I present the findings from the econometric analysis.

4.3.1 Conceptual Framework: Regulatory Arbitrage and the Growth of FVCs

Farhi and Tirole, 2017 and Plantin, 2014 lay theoretical frameworks underpinning the empirical analysis in this paper. These theoretical foundations suggest that a form of regulatory arbitrage is one of the drivers explain the impact of macroprudential policies on the growth in loans held

Figure 4.6: Textual analysis of macroprudential policies classified as "other" by the iMaPP database

Source: IMF Integrated Macroprudential Database (iMaPP)
Notes: The iMaPP database provides a textual desciption of each policy measure taken. This chart takes the most frequently used words in these descriptions, after filtering stopwords.

by Financial Vehicle Corporations (FVCs) in Europe. Under this hypothesis, traditional banks are subject to increasingly stringent macroprudential regulations, aimed at reducing systemic risk. These regulations raise the cost of compliance for banks, prompting financial institutions to seek alternative channels to maintain profitability. In this paper, this cost of compliance is empirically captured by the macroprudential policy stance (MaPP_{it-1}) in the baseline regression model.

FVCs, operating outside the stringent regulatory perimeter of traditional banks, provide an avenue for banks to offload risks through securitisation while avoiding the costs associated with holding assets on their balance sheets. According to Plantin, 2014, when banks face tighter capital requirements, they often use FVCs and other shadow banking entities to continue issuing money-like liabilities through securitised products. This practice allows them to bypass direct regulatory oversight while still maintaining leverage.

To formalise this mechanism, one can adopt a modified version of the utility function in Farhi and Tirole, 2017, U, where the utility of a financial institution is a function of expected profits π and the regulatory cost $C(R)$, with R representing the regulatory burden:

$$U = \pi - C(R)$$

As macroprudential policies increase, the regulatory burden on traditional banks R_b, the cost of compliance $C(R_b)$ rises, leading banks to shift their activities to FVCs, where the regulatory burden R_{fvc} is lower. In the empirical analysis that follows, this shift is captured empirically through the FVC loans variable, as the theoretical model predicts that:

$$\frac{dL_{fvc}}{dR_b} > 0$$

In the empirical framework, the macroprudential policy variable MaPP_{it-1} corresponds to the regulatory burden R_b faced by traditional banks, and the dependent variable $\Delta_4 FVC_Loans_{it}$ represents the annual growth in FVC loans. I expect to observe a positive relationship between these two variables, consistent with the mechanism of regulatory arbitrage.

Farhi and Tirole, 2017 and Plantin, 2014 also highlight how regulatory arbitrage can amplify systemic risk through the interconnectedness of banks and nonbank financial entities. Although FVCs are less regulated, they maintain significant ties with traditional banks through credit markets and securitisation activities. This interconnectedness creates channels through which risks originating in FVCs can spill over into the banking system, particularly during periods of financial stress. Plantin (2014) shows how FVCs contribute to overall financial instability by increasing the effective leverage of the financial system, even as traditional banks face tighter capital requirements. As FVCs issue securitised products backed by bank-originated loans, they help banks maintain leverage while circumventing some regulatory requirements. This practice can lead to an overall increase in the exposure of both regulated and unregulated institutions to liquidity and credit risks.

Acharya et al., 2024 present a related but novel interpretation of these developments. They show that the relationship between banks and non-bank financial intermediaries (NBFIs) has transformed over time rather than risk simply migrating from banks to NBFIs. According to this "transformation view", Banks remain liquidity providers to NBFIs and the two sectors are highly interdependent, with risks shifting between them. If this is the case, regulation focussing on the traditional bank sector does not eliminate risks but shifts and amplifies them across sectors.

In the empirical analysis that follows, I hypothesise that macroprudential policies targeted at banks, while reducing risk in the regulated sector, may inadvertently contribute to systemic risk. Growth in FVC loan claims strengthens the interconnectedness between regulated and unregulated sectors, amplifying systemic vulnerabilities.

4.3.2 Pairwise correlations

Table 4.2 reports simple pairwise correlations between measures of macroprudential policy taken from the IMF's macroprudential policy database (Alam et al., 2024) and FVC loan claims from my panel of European countries.

To account for lagged responses of FVC loan claims to tightening of macroprudential policies, I particularly focus on the relationship between *FVCLoans*, and the lagged 4-quarter average of the overall macroprudential policy measure ($MaPP_{t-1}$).

Table 4.2 shows that FVC loan growth exhibits a modest but statistically significant positive correlation with the lagged measure of macroprudential policy stringency ($MaPP_{t-1}$) . This is consistent with the theoretical prediction that as regulatory costs increase, financial institutions reallocate lending activities to FVCs, leading to increased FVC loan growth.

By contrast, the correlation between these FVC loan claims and the simple lag of macroprudential policy (*L1_MaPP*) is smaller and not statistically significant. This suggests that the effects of macro prudential policies on FVC loan volumes develop over time, rather than contemporaneously, which is consistent with the dynamic adjustment process highlighted in the conceptual framework.

Alam et al., 2024 demonstrate that, within advanced economies, the impact of macroprudential policy on credit growth in the traditional banking sector is primarily driven by ”loan-targeted” measures, which exhibit a statistically significant effect on credit expansion. Using the simple pairwise analysis displayed in table 4.2, this does not appear to be the case when considering FVC loans.

Table 4.2: Correlation of lagged macro prudential policy changes with FVC Loan Claims

	L1_MaPP	L1_MaPP_4q_avg	L1_lt_4qavg
FVCLoans	0.04	0.10*	0.03

4.3.3 Baseline Specification with Time and Country Fixed Effects

I employ a robust empirical framework to assess the effect of macroprudential policy on FVC loans using a panel of ten European countries who report detailed data on FVCs. The primary dependent variable, measured as the year-over-year change in $\Delta_4 FVC\_Loans_{it}$, is winsorised at the 1st and 99th percentile to mitigate the influence of outliers.[6]

Drawing upon the empirical specification in Alam et al. (2024), I implement a panel regression model specified as follows:

$$\Delta_4 FVC\_Loans_{it} = \alpha_i + \beta_1 \Delta_4 FVC\_Loans_{it-1} + \beta_2 \mathrm{MaPP}_{it-1} + \gamma \mathbf{X}_{it-1} + \gamma_t + \epsilon_{it}, \tag{4.1}$$

where the dependent variable, $\Delta_4 FVC\_Loans_{it}$, represents the annual change in notional stocks for country i at time t. MaPP_{it-1}, captures the macroprudential policy stance using the measure described in section 4.2.2. $\mathbf{X}_{it-1}$ is a vector of controls. In the baseline specification, I control for total credit in the economy to account for overall credit market conditions and GDP to account for country level demand conditions. Country fixed effects (α_i) and time fixed effects (γ_t) are included in the model to control for unobserved heterogeneity and common shocks. Country fixed effects capture time-invariant characteristics that might influence both the dependent and independent variables, while time fixed effects account for shocks that are common to all countries

[6] Results are robust to using the non-winsorised data.

within a given period. Estimation is conducted using robust standard errors clustered at the country level.

Identification of macroprudential policy effects in based on a simple timing assumption macroprudential policy does not affect FVC loans within the same quarter. This is a strong assumption, and the estimated coefficient on MaPP_{it-1} would be subject to the attenuation bias if the timing assumption did not hold. This approach is consistent with the typical identification strategies used in this literature, for example Alam et al. (2024).

Potential endogeneity between the macroprudential policy stance (MaPP_{it-1}) and FVC loans presents a challenge in this specification. Reverse causality may arise if changes in FVC loans influence contemporaneous policy decisions, while omitted variable bias could occur if unobserved factors jointly affect both MaPP_{it-1} and $\Delta_4 FVC\_Loans_{it}$.

I employ several strategies to mitigate these endogeneity concerns. First, the main variable of interest, MaPP_{it-1}, is lagged by one quarter in the specification. This reduces the risk of reverse causality since it ensures that MaPP_{it-1} reflects policy actions prior to the observed changes in lending.

Second, as outlined in section 4.2.2, MaPP_{it-1} is constructed as a cumulative measure, averaging over the past four quarters and dividing by four. This cumulative approach accounts for the the delayed impact of macroprudential policies, addressing the possibility of delayed responses in lending behaviour.

The results are displayed in Table 4.3. In column one I present the specification with only the lagged dependent variable and the time and country fixed effects as controls. Then I add the credit and GDP controls in column two and three, respectively. Across all specifications, a one unit change in the macroprudential policy stance is, *ceteris paribus*, associated with a four percentage point increase in the growth rate of FVC loans in my sample. The coefficient on macroprudential policy $\hat{\beta}_2$ is statistically significant at the 10% level once the control for credit market conditions overall is added.

There are some caveats to this finding. First, the design of the macroprudential policy variable does not allow me to assess how differences in the intensity of the policy change in a given

Table 4.3: Baseline Specification with Time and Country Fixed Effects

VARIABLES	(1) FVC_loans	(2) FVC_loans	(3) FVC_loans
FVC_loans_{t-1}	0.678***	0.678***	0.677***
	(0.0470)	(0.0469)	(0.0523)
MaPP_{it-1}	4.129	4.288	4.303*
	(2.448)	(2.427)	(2.253)
$total\_credit_{t-1}$		-0.197	-0.221
		(0.204)	(0.220)
GDP_{t-1}			0.230
			(0.271)
Constant	2.461	3.554	3.003
	(4.451)	(4.296)	(4.025)
Observations	428	428	428
R-squared	0.527	0.528	0.529
Number of ID	10	10	10
Country Fixed Effects	YES	YES	YES
Time Fixed Effects	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

quarter may affect the result. The dummy variable structure of the main measure in the iMaPP database treats all policy actions the same, regardless of the magnitude of the change. As a result, more aggressive policy interventions may have larger or more persistent effects than smaller adjustments, but these distinctions are not captured in the current specification. However, the benefit of this structure is that it allows for better comparability across countries when considering many different macroprudential policies. I deal with some further caveats in the robustness section 4.3.4

Assessing dynamic effects using local projections

In assessing the affect of a change in the stringency of macroprudential policy on FVC loans, one is also interested in assessing the dynamics of the effect. To investigate this, I employ a local projections methodology, which allows for the estimation of impulse response functions that assess the evolution of FVC loans following a macroprudential policy change Jordà (2005).

The local projections approach involves estimating a sequence of regressions for each future horizon h, which take the form:

$$\Delta_4 FVC\_Loans_{i,t+h} = \alpha_i + \beta_{1,h}\Delta_4 FVC\_Loans_{it-1} + \beta_{2,h}\mathrm{MaPP}_{it-1} + \gamma_h \mathbf{X}_{it-1} + \gamma_{t+h} + \epsilon_{i,t+h}, \quad (4.2)$$

where $\beta_{2,h}$ reflects the impact of a macroprudential policy shock on FVC loans at horizon h.

Unlike vector autoregressions (VARs), which require strong assumptions about the data-generating process, local projections estimate the response at each horizon directly from the data, thereby accommodating potential nonlinearities and nonstationarities in the underlying series. Moreover, by incorporating time and country fixed effects, this approach allows me to continue to control for unobserved heterogeneity, which could bias the estimated effects of policy tightening.

Figure 4.7 displays the impulse response, showing how FVC loans reacts over six quarters following a shock to the macroprudential policy variable. The results indicate a significant and sustained increase in FVC loans over three to four quarters following the shock, reinforcing the conclusions drawn from the baseline model.

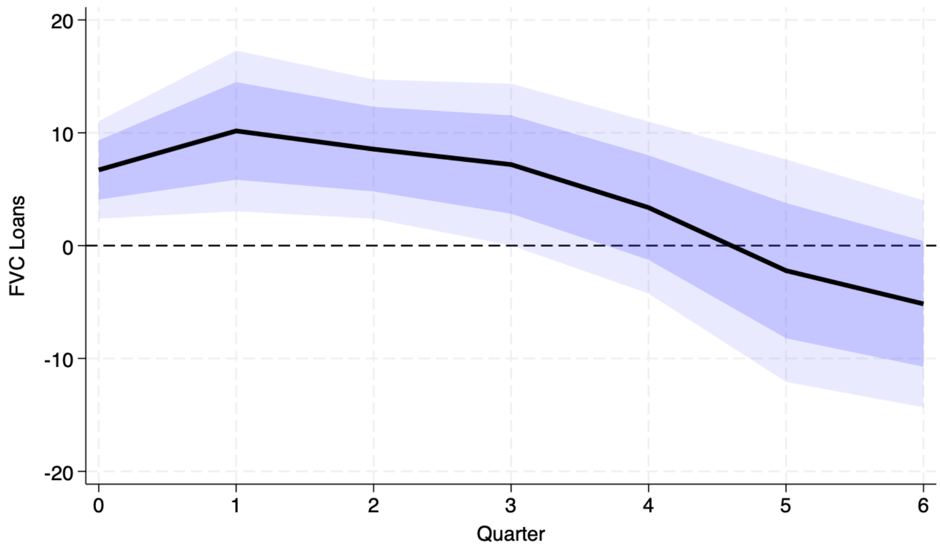


Figure 4.7: Local Projection: Impact of Macroprudential Tightening on FVC loans

Notes: Darker shaded area represents the one standard deviation interval while lighter blue shaded area represents the 95% confidence interval.

4.3.4 Robustness checks

To ensure the robustness of my baseline findings on the effect of macroprudential tightening I begin by adding a measure of international financial integration (IFI) to the regression analysis. The IFI captures the degree of a country's integration into global financial markets and could potentially affect both macroprudential policy effectiveness and lending dynamics. This is to address the concern that the the effect of tightening on FVC loan growth may be dampened by controlling for a measure of financial openness. Column 1 of Table 4.7 shows that while the coefficient on IFI is negative, it is not statistically significant and adding this control does not meaningfully change the magnitude or significance of $Mapp$, the main variable of interest.

Next, I investigate whether the effect of macroprudential tightening on FVC loan growth is conditioned by the rate of total credit growth. To do this, I introduce an interaction term between macroprudential tightening and total credit growth. Column 2 of Table 4.7 shows that the coefficient on $MaPP_{t-1}$ increases slightly, but remains statistically significant. Meanwhile, the coefficient on the interaction term is negative and statistically significant. This indicates that the positive effect of macroprudential tightening on FVC loan growth diminishes as total credit growth increases. A possible intuition for this result is that during periods of high overall credit growth in the economy, the incentive for financial institutions to shift lending to FVCs in response to tighter macroprudential policies is reduced.

In addition to estimating standard errors clustered at the country level, I estimate the model using Driscoll and Kraay (1998) standard errors (DKSE). While clustering allows for dependence within countries, it assumes independence across countries. Column 3 of Table 4.7 shows that the results of the baseline model are robust to estimating the model with DKSE.

In order to reduce the effect of outliers in the main specification, I winsorise the measure of FVC loans at the 1st and 99th percentiles. Column 4 of Table 4.7 shows that the results of the baseline specification are robust to estimating the model using the non-winsorised dependent variable.

To test for attenuation bias arising from the timing assumption used for identification in the baseline specification, I reestimate the model using the contemporaneous macroprudential policy variable (MaPP_{it}) and controls. Column 5 of Table 4.7 shows that the estimated coefficient is larger, indicating some attenuation bias in the main result. However, the use of the lagged variable in the baseline specification (MaPP_{it-1}) is for identification, specifically addressing potential reverse causality. While although the non-lagged specification suggests some bias, the timing assumption strengthens the causal interpretation and aligns with standard practices in the literature.

Lastly, the baseline estimation does not allow for macroprudential policy tightening in other countries in the sample to affect FVC loans. There may however be the potential that the growth in FVC loans in one country is affected by tightening in a second country. To address this, I control for the average tightening/loosening of the macroprudential policy measure in all other countries in the sample. Column 6 of table 4.7 shows that the coefficient on the domestic macroprudential tightening variable remains positive and significant. The coefficient on the average foreign macroprudential tightening is negative but not statistically significant. International spillover effects do not appear to drive the main result.

4.3.5 Extensions

Loan-Targeted Macroprudential Policies

In their investigation on the effect of macroprudential policy on total credit, Alam et al., 2024 find that "loan-targeted" policies have a significant impact in advanced economies. The loan targeted instruments in the database are outlined in Table 4.4.

Table 4.4: Overview of Loan-targeted Measures in the Model

Category	**Instruments/Measures**
Demand Instruments	Loan-to-value ratio limits (LTV), Debt-service-to-income ratio limits (DSTI)
Supply-loans Measures	Credit growth limits (LCG), Loan loss provisions (LLP), Loan restrictions (LoanR), Loan-to-deposit ratio limits, Foreign currency loan limits

Source: Alam *et al* (2024).
Notes: Table shows list of measures categorised as Loan-targeted in the iMaPP database.

To investigate the effect of these instruments on non-bank lending. I estimate Equation 4.1, but replacing the $iMaPP$ measure with the loan-targeted measure. The results are displayed in Table 4.5. While the coefficient is positive, I find no statistically significant effect of the loan targeted measures on the growth rate of FVC loans This result suggests that other-macroprudential measures, such those affecting capital (e.g. countercyclical capital buffers), are more important.

Several factors might explain the difference in these results. Firstly, the summary measure of macroprudential policies includes measures such as capital requirements and leverage caps. When traditional banks are subject to these requirements, they may reduce their lending in order to manage their balance sheets. Or, they may use FVCs to securitise the loans in order to reduce regulatory capital requirements while retaining a significant portion of the risk, as documented by Acharya et al. (2013).

Table 4.5: Specification with Loan-Targeted policies

VARIABLES	(1) FVC_loans	(2) FVC_loans	(3) FVC_loans	(4) FVC_loans
FVC_loans_{t-1}	0.684***	0.683***	0.684***	0.682***
	(0.0489)	(0.0489)	(0.0517)	(0.0539)
Loan Targeted$_{t-1}$	2.311	2.376	2.567	2.313
	(3.361)	(3.317)	(2.969)	(2.573)
IFI_{t-1}		-0.0149	-0.0144	-0.0124
		(0.0146)	(0.0142)	(0.0138)
$total\_credit_{t-1}$			-0.172	-0.201
			(0.205)	(0.222)
GDP_{t-1}				0.269
				(0.262)
Constant	2.820	3.312	3.629	2.979
	(4.530)	(4.293)	(4.316)	(4.045)
Observations	428	428	428	428
R-squared	0.525	0.525	0.526	0.526
Number of ID	10	10	10	10
Country Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Does the effect of macro prudential policy differ across quantiles of FVC Loan growth?

The baseline results in Section 4.3.3 present the conditional mean effect of macroprudential policy tightening on FVC loans. However, the effects of macroprudential policies may vary across the distribution of FVC loan growth. For instance, countries experiencing high levels of FVC loans (indicative of a well-developed non-bank financial sector) may see a larger effect from macro prudential policy changes. Focusing on mean effects alone could mask important heterogeneity.

To investigate this, I employ a quantile regression, which allows the impact of $MaPP$ to be estimated across different quantiles of the conditional distribution of FVC loan growth. Quantile regression, as introduced by Koenker and Bassett (1978), is well-suited for capturing heterogeneous effects across the distribution, allowing for a more nuanced analysis of policy impacts. I estimate the model using Bayesian methods, as introduced by Yu and Moyeed, 2001. This offers distinct advantages in this context. First, they facilitate the incorporation of prior information, helping to stabilise estimates in small samples. Second, Bayesian credible intervals provide a more informative measure of the uncertainty surrounding the estimates compared to ordinary least squares.

Let $\Delta_4 FVC\_Loans_{it,\tau}$ denote the τ-th quantile of the annual change in Financial Vehicle Corporation (FVC) lending for country i at time t. The quantile regression takes the following form:

$$\begin{aligned} \Delta_4 FVC\_Loans_{it,\tau} &= \alpha_{i,\tau} + \beta_{1,\tau}\Delta_4 FVC\_Loans_{it-1} \\ &\quad + \beta_{2,\tau}\text{MaPP}_{it-1} + \gamma_\tau \mathbf{X}_{it-1} + \epsilon_{it,\tau}, \\ \epsilon_{it,\tau} &\sim \text{ALD}(0, \sigma_\tau, \tau) \end{aligned} \tag{4.3}$$

where $\alpha_{i,\tau}$ is the country-specific intercept for quantile τ, $\Delta_4 FVC\_Loans_{it-1}$ is the lagged dependent variable (annual change in FVC loans), MaPP_{it-1} is the lagged macroprudential policy stance, and $\mathbf{X}_{it-1}$ is a vector of other covariates, including macroeconomic and financial variables, lagged by one period. The error term $\epsilon_{it,\tau} \sim \text{ALD}(0, \sigma_\tau, \tau)$ follows an asymmetric Laplace distribution (ALD) with location 0, scale σ_τ, and skewness controlled by the quantile τ. The ALD is used due to its connection with the quantile loss function, aligning with the objective of quantile regression by directly modelling the τ-th quantile of the conditional distribution, minimising asymmetrically weighted absolute residuals Yu and Moyeed, 2001.

Given the relatively small sample size, I use informative priors based on the results from the main panel specification. Specifically, I place a normal prior on the coefficient of the lagged macro prudential variable $Mapp_{it-1}$, i.e., $\beta_2\tau, j \sim \text{Normal}(4, 2)$. This prior is informed by the results from the panel model in 4.3.3. The choice of prior allows the posterior estimates to be influenced by the data, while acknowledging knowledge about the parameter from the panel analysis.

The likelihood function for the quantile regression is given by:

$$
\begin{aligned}
p(\boldsymbol{\beta}_\tau \mid \mathbf{y}, \mathbf{X}) \propto \prod_{i,t} \left[\frac{\tau(1-\tau)}{\sigma_\tau} \exp\left(-\frac{|r_{it}|}{\sigma_\tau} \right) \right] \\
\times \prod_{j=1}^{p} \frac{1}{\sqrt{2\pi}\sigma_j} \exp\left(-\frac{(\beta_{\tau,j} - \mu_j)^2}{2\sigma_j^2} \right)
\end{aligned}
\tag{4.4}
$$

where r_{it} is a residual which captures the difference between the observed value of the variable $\Delta_4 FVC\_Loans_{it}$ and its predicted value based on a linear combination of: $\alpha_{i,\tau}$, which is the intercept specific to unit i and quantile τ; $\beta_{1,\tau}\Delta_4 FVC\_Loans_{it-1}$, the effect of the previous period's FVC_Loans on the current value, with a coefficient $\beta_{1,\tau}$; $\beta_{2,\tau}\text{MaPP}_{it-1}$, the impact of the previous period's macroeconomic policy variable MaPP_{it-1} on the current value, with a coefficient $\beta_{2,\tau}$; and $\gamma_\tau \mathbf{X}_{it-1}$, the contribution of additional covariates $\mathbf{X}_{it-1}$ from the previous period, weighted by γ_τ. $\mathbf{y}$ represents the observed changes in FVC loans, $\mathbf{X}$ is the matrix of covariates, and $\mathbb{I}$ is an indicator function enforcing the bounds of the prior distribution. The prior on $\beta_{\tau,2}$ (the coefficient for the macroprudential policy variable) enables regularisation of the posterior, reflecting the information obtained from the main specification.

I estimate the model using Markov Chain Monte Carlo (MCMC) methods, specifically the No-U-Turn Sampler (NUTS). Convergence is assessed using trace plots and the Gelman-Rubin statistic ($\hat{R}$).

The results are displayed in Figure 4.8. The estimated coefficient for a change in macroprudential policy on FVC loan growth increases across the quantiles. At the upper quantiles (eight and nine), posterior credible intervals do not overlap with zero, suggesting non-zero effects. In contrast, the lower quantiles display smaller estimated effects, with credible intervals encompassing zero.

These results suggest that the findings in section 4.3.3 are driven by countries/periods with high growth in FVC loans. A possible intuition for this result is that entities in these jurisdictions and/or periods having established channels to effectively utilise financial vehicles, enabling them to respond more rapidly and substantially when faced with tighter macroprudential regulations.

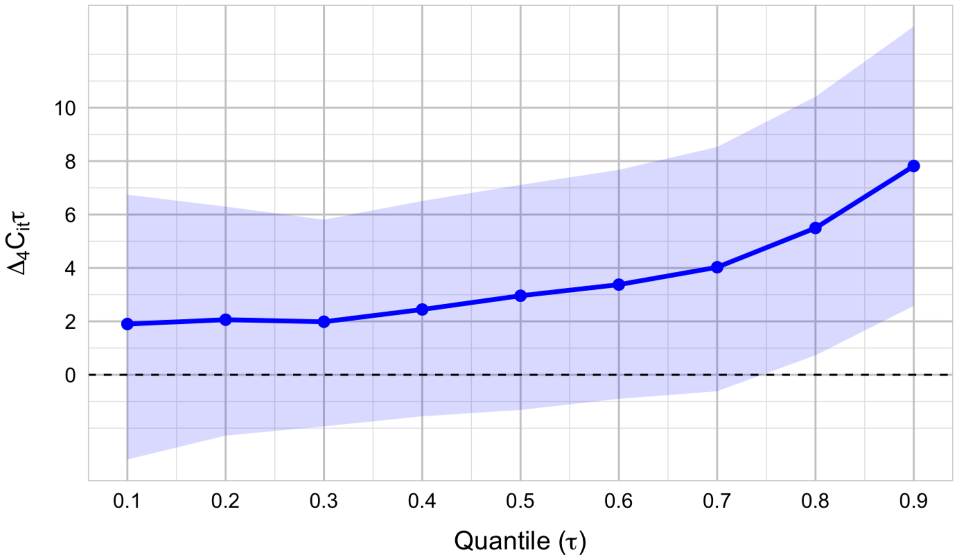


Figure 4.8: Coefficient of Lagged $MaPP$ on FVC Loans by Quantile

Note: Shaded area represents the 95% credible interval

4.4 Policy Implications: Impact of Monetary Policy on FVC Loans

Thus far, the analysis has shown that tightening macroprudential policies leads to an increase in FVC Loans, suggesting a shift in credit intermediation from traditional banks to these non-bank financial entities. This finding raises an important question: what implications does this have for the transmission mechanism of monetary policy? If macroprudential tightening redirects lending activity toward FVCs, it is essential to understand whether these entities respond to a monetary policy shock in the same way as traditional banks. As outlined in the introduction to this paper, this debate is still open in the US context (Elliott et al., 2022; Buchak et al., 2018).

Despite the growing importance of these nonbank intermediaries, the literature on their interaction with monetary policy remains limited, especially when compared to the extensive research on the bank lending channel (Bernanke and Blinder, 1988; Kashyap and Stein, 1995). The bank lending channel primarily examines how policy tightening impacts the supply of bank loans to the economy. Banks typically reduce their credit supply due to increased funding costs (Bernanke &

Blinder, 1992), higher agency costs (Jiminez et al., 2012), and balance sheet constraints (Kishan & Opiela, 2000; Jiminez et al., 2012). However, the extent to which these mechanisms influence non-banks remains contentious. In the United States, central bankers advocate that monetary policy should "get in all the cracks," implying that it should uniformly affect all financial intermediaries (Stein, 2013). Contrary to this view, Elliot et al. (2022) leverage granular data to demonstrate that non-banks mitigate the transmission of monetary policy to output, prices, and risk distribution through credit supply. Their findings reveal that higher policy rates prompt a shift in credit supply from banks to non-banks, thereby attenuating the intended effects of monetary policy. The European Central Bank (ECB) examined how non-bank financial intermediaries influence monetary policy transmission in Europe but reported conflicting evidence regarding the impact (ECB, 2021).

To assess the impact of monetary policy shocks on FVC Loans in a European context, I use the same dataset as in section 4.2.2, augmented with monetary policy shocks from Jarociński and Karadi (2020). They use high frequency changes in the price of Overnight indexed swap rates based on the EONIA during short intervals before and after governing council press conferences at the ECB to isolate monetary policy shocks. They use information about the co-movement of these high frequency interest rates and stock prices around policy announcements to decompose the shock into the "pure" monetary policy surprise and information conveyed by the Central Bank about its assessment of the economic outlook. The intuition is that a surprise tightening raises interest rates and reduces stock prices, while the complementary positive central bank information shock raises both. In this analysis, I use the "pure" monetary policy shocks, purged from the effects of the information shock.

For ease of interpretation, I normalise the shocks such that they have a mean of 0 and standard deviation of 1. As such, we can interpret the shock variable as a one standard deviation increase in the monetary policy rate. The shocks used in the regression are presented in figure 4.9.

The specification is very similar to equation 4.1, but the variable of interest on this occasion is the lagged standardised Monetary policy shock measure, mp_pm_sd.

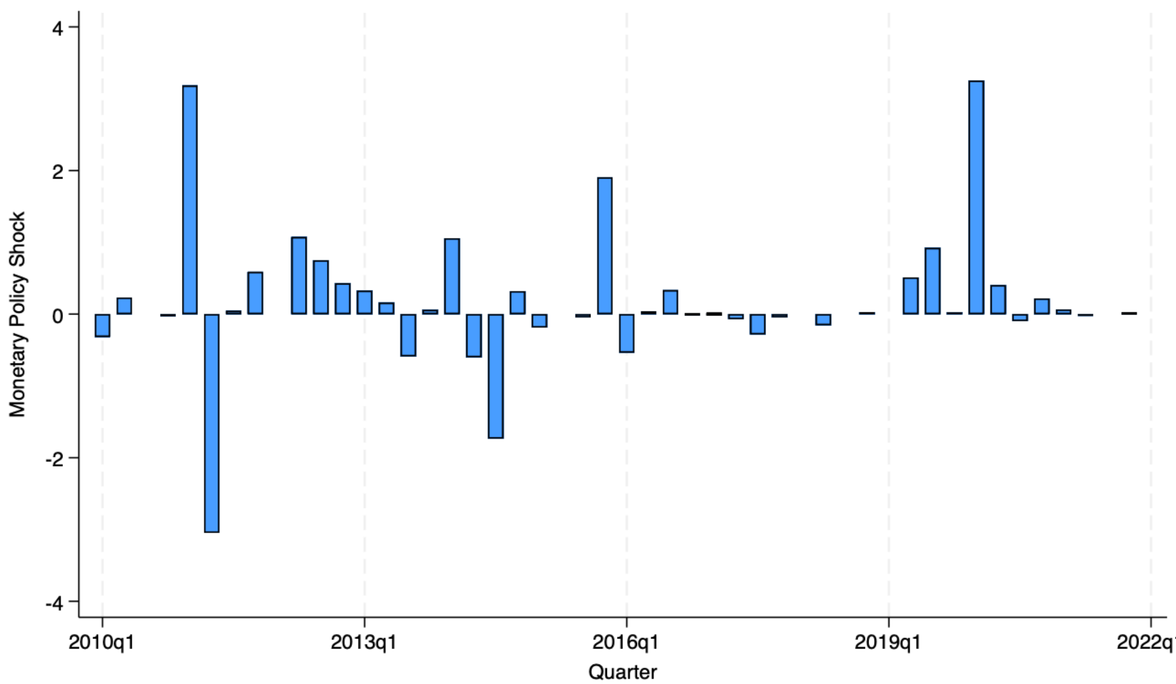


Figure 4.9: Standardised Monetary Policy Shocks.

Source: Jarocinski & Karadi (2020)
Notes: The shocks represent the effects of a surprise monetary policy tightening, where an unexpected central bank announcement raises interest rates and lowers stock prices. These monetary policy shocks are identified using sign restrictions and are purged of any central bank information effects to isolate the pure monetary policy component.

$$\Delta_4 FVC\_Loans_{it} = \alpha_i + \beta_1 \Delta_4 FVC\_Loans_{it-1} + \beta_2 Shock_{it-1} + \gamma \mathbf{X}_{it-1} + \gamma_t + \epsilon_{it}, \tag{4.5}$$

Table 4.6 presents the results of the panel regression. Across both specifications, the coefficient on the monetary policy shock is positive, suggesting that FVC loans grow in response to a contractionary monetary policy shock. However, the coefficient is only statistically significant in the specification excluding the control for total credit, The coefficient on total credit is negative, as per the textbook explanation. Taking these two findings together, the results provide suggestive evidence that the positive coefficient on the monetary policy shock is driven by a substitution effect, rather than the direct effect of the shock on FVC loans.

Table 4.6: Fixed Effects Regression Results for Monetary Policy Shocks

VARIABLES	(1) FVC_loans	(2) FVC_loans
FVC_loans_{t-1}	0.683***	0.684***
	(0.0501)	(0.0533)
$Shock_{t-1}$	2.632*	2.236
	(1.261)	(1.232)
IFI_{t-1}	-0.0118	-0.0108
	(0.0151)	(0.0142)
GDP_{t-1}	0.237	0.281
	(0.225)	(0.263)
$total\_credit_{t-1}$		-0.196
		(0.224)
Constant	-5.688**	-4.181
	(2.449)	(2.538)
Observations	428	428
R-squared	0.525	0.526
Number of ID	10	10
Country Fixed Effects	YES	YES
Time Fixed Effects	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The panel regression specification may however mask important temporal dynamics in the effect of the shock. To address this, I estimate the model from column 2 (controlling for total credit) of table 4.6 using the local projections method of Jordà (2005) in the same manner as outlined in section 4.2.2. The results are presented in Figure 4.10. While the effect is initially negative (and significant by the third quarter), I find that the effect turns positive and statistically significant after 18 months. This finding is consistent with the hypothesis that monetary policy tightening may affect non-banks differently than traditional banks Elliott et al. (2022).

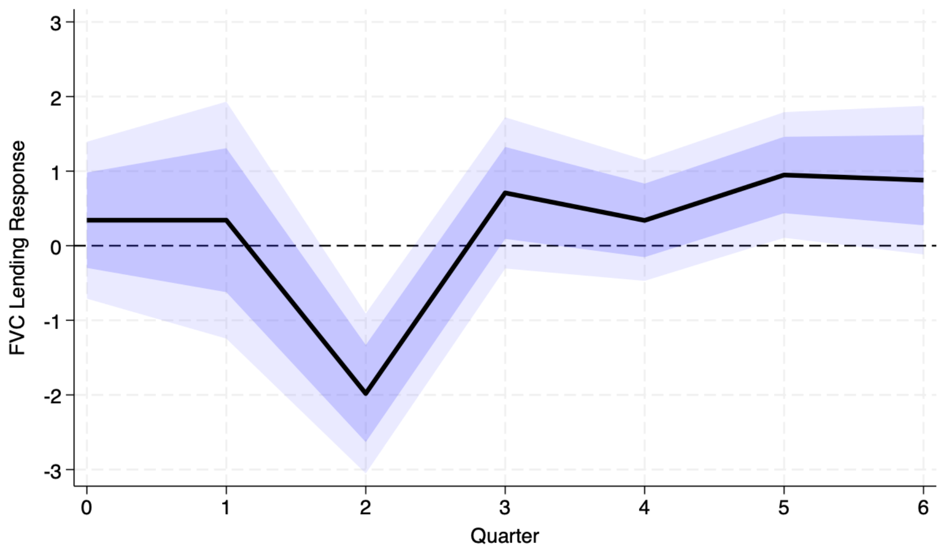


Figure 4.10: Dynamic Impulse Response from Local Projection

4.5 Conclusions

This paper investigates the link between macroprudential policies and credit intermediation through FVCs in a selection of European countries. A key contribution is the identification of a potential "cross-sectoral arbitrage" effect à la Farhi and Tirole (2017) or an increase in the interconnectedness of the Banking sector and the non-bank sector as per the "transformation view" of Acharya et al. (2024). Specifically, I find that a tightening of macroprudential policy is associated with a statistically and economically significant increase in the growth rate of FVC loans in a panel of ten European countries. Using local projections, I show the effect peaks after two quarters but remains statistically significant for three quarters. I make two additional findings in this regard. First, using a quantile regression approach, I show that this effect is driven by the top two quantiles of the distribution of FVC loan growth rates across countries and periods. The intuition for this result is that the arbitrage channel may be stronger in countries and periods where FVC loan growth is already established. Second, I find that “loan-targeted” macro prudential policies are not a statistically significant driver of this effect. The intuition for this finding is that macro prudential policies that target systemic risk (e.g. policies targeting bank capital and the use of bank profits), may be a more important driver of the result.

These findings also pose an important policy question. If regulatory measures divert lending from traditional banks to FVCs, how do these entities respond to monetary policy shocks? My findings suggest that FVCs increase the loan claims on their balance sheets following a contractionary monetary policy shock. This provides tentative evidence that, the increasing share of overall credit on the balance sheets of FVCs may have important consequences for the transmission of monetary policy.

These findings open several avenues for future work. In particular, using micro-data to more comprehensively document the interconnectedness between Banks and non-banks in Europe as per the findings of Acharya et al. (2024).

The implication of these findings is that macroprudential policies imposed in one segment of the financial system may inadvertently lead to a shift in credit activity into other, less regulated, areas of the financial system, with potential consequences for systemic risk.

Table 4.7: Robustness Check Results

Dependent Variable FVC_loans	(1) IFI	(2) Total Credit	(3) Driscoll-Kraay	(4) No winsor	(5) Contemporaneous	(6) Average others
FVC_loans_{t-1}	0.677***	0.681***	0.677***		0.682***	0.677***
	(0.0523)	(0.0553)	(0.0561)		(0.0462)	(0.0523)
$MaPP_{t-1}$	4.303*	5.570*	4.303*	4.907*		4.165*
	(2.253)	(2.662)	(2.407)	(2.672)		(2.235)
$total\_credit_{t-1}$	-0.221	-0.174	-0.221	-0.217		-0.221
	(0.220)	(0.239)	(0.220)	(0.267)		(0.220)
$MaPP_{t-1} * total\_credit_{t-1}$		-0.290				
		(0.216)				
IFI_{t-1}	-0.0204	-0.0165	-0.0204	-0.0287		-0.0204
	(0.0144)	(0.0151)	(0.0322)	(0.0166)		(0.0144)
GDP_{t-1}	0.230	0.157	0.230	0.234		0.230
	(0.271)	(0.290)	(0.274)	(0.320)		(0.271)
$FVC\_loans^{*}_{t-1}$				0.657***		
				(0.0576)		
$MaPP$					5.866**	
					(2.190)	
IFI					-0.0262*	
					(0.0138)	
$total\_credit$					-0.119	
					(0.274)	
GDP					0.392*	
					(0.189)	
Avg_Other_MaPP$_{t-1}$						-76.74
						(43.90)
Constant	3.003	2.888	4.182	4.548	2.445	11.54
	(4.025)	(4.008)	(5.224)	(4.941)	(4.106)	(8.499)
Observations	428	428	428	428	418	428
R-squared	0.529	0.529	20	0.511	0.534	0.529
Number of ID	10	10		10	10	10
Country Fixed Effects	YES	YES	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 5

General Conclusion

This thesis investigates key macroeconomic issues facing European policymakers in the post-crisis period, focusing on labour market dynamics, capital misallocation, and the role of non-bank financial intermediaries (NBFIs). The findings contribute to ongoing debates about wage stagnation, productivity divergence, and the unintended consequences of macroprudential regulation. This chapter summarises the main results, outlines their policy implications, and suggests directions for future research.

Chapter 2 makes two contributions to the literature. First, we construct the Non-Employment Index (NEI), a broader measure of labour market slack developed for the US by Hornstein et al. (2015), for a comprehensive panel of Euro member countries. Using a novel dataset collected from Central Banks in the monetary union that allows us to exploit the panel element of Labour force surveys in Europe, this chapter is the first to compute the NEI in a comparable way across European countries. The NEI incorporates wider cohorts of individuals who are not officially classified as unemployed, weighting them using their estimated probability of transitioning back into employment. This group includes discouraged workers and those marginally attached to the labour market. The second contribution is demonstrating that the NEI outperforms other measures of labour market slack, such as the unemployment rate, unemployment gap, and broader measures like U6, in predicting wage dynamics. In a conditional forecast comparison exercise, the NEI proves to be a more accurate indicator of labour market conditions - with the most significant improvement in countries most affected by the eurozone sovereign debt crisis

Chapter 3 examines capital misallocation across 19 European countries, decomposing misallocation into its sources at the sectoral and national levels. Firm-specific factors, including uncertainty and adjustment costs, account for a significant portion of misallocation, especially in Southern Europe. By linking misallocation to financial variables, the analysis highlights the importance of targeted policies to alleviate distortions that hinder productivity growth. These results imply that broad macroeconomic reforms may not suffice; country- and sector-specific interventions are needed.

Chapter 4 explores whether macroprudential policy tightening has shifted credit activity from traditional banks to NBFIs, particularly Financial Vehicle Corporations (FVCs). The evidence suggests that regulatory tightening in the banking sector has led to cross-sectoral arbitrage, with credit activity moving to less-regulated financial intermediaries. Moreover, FVCs expand their lending following monetary policy shocks, suggesting that their growth may weaken the traditional monetary policy transmission mechanism. This underscores the need for coordinated macroprudential and monetary policies.

The findings have several implications for policymakers. First, the analysis in Chapter 2 suggests that traditional measures of labour market slack are insufficient for accurately forecasting wage growth. Policymakers should consider adopting broader indicators, such as the NEI, to better gauge labour market conditions and improve wage inflation predictions.

The findings in Chapter 4 also have important implications for policymakers. The question of why productivity growth in Europe has lagged behind the US has been prevalent in policy debates in recent years. Our findings contribute to this discussion. We argue that productivity-enhancing policies should focus on sector-specific sources of inefficiency, particularly where comparable sectors across Europe exhibit greater capital misallocation. Countries with high levels of misallocation, particularly in Southern Europe, may benefit from reforms aimed at reducing firm-level uncertainty and adjustment costs.Financial reforms that enhance access to credit and reduce sectoral distortions could play a key role in improving aggregate productivity.

Third, the findings in Chapter 4 highlight the unintended consequences of macroprudential regulation. The shift and increased interconnectedness in credit activity between traditional banks and NBFIs complicates the transmission of monetary policy and may create new risks for financial stability. Policymakers could consider expanding the regulatory perimeter to include NBFIs and enhance coordination between macroprudential and monetary policy to address cross-sectoral spillovers.

Several avenues for future research emerge from this thesis. First, the Non-Employment Index could be produced on a regular basis in countries wishing to better understand the available slack in their labour market. This question has become important in Europe again in the post-pandemic environment where wage pressures have again remained subdued despite high consumer price inflation and record-low unemployment rates. Another question of interest is simply how the transition probabilities of the cohorts studied in chapter 2 have changed over the pandemic period.

Chapter three opens several avenues for future research on capital misallocation. In particular, our finding that there exists substantial heterogeneity in the level and drivers of capital misallocation within industries across countries is particularly interesting. For example, why would the “Manufacture of basic metals” industry in one country exhibit more substantial variation than in another similar country. My hypothesis is that some of this variation arises simply from the composition of firms in that NACE sector in different countries. In future research, we will exploit other information in the ORBIS database to derive a better measure of comparable firms to delve into this issue further.

The findings of chapter four also open several avenues for future research. In particular, using granular data (for example from information on securities holdings or credit registry data) to more comprehensively document how the interconnectedness between Banks and NBFIs change following a change in macroprudential policy. This future research is along the lines of that described in Acharya et al. (2024).

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