Toulouse School of Economics

# Moving Beyond Efficiency: A Novel Framework to Measure Trade Flow Resilience

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by

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## Abstract

Measuring resilience is a key step in understanding why some systems suffer more from shocks than others. Resilience relevant for trade can be defined as a trade flow's ability to recover from a shock or reorient to a more desirable state. I show how both these dimensions can be parametrized and measured in a Multiple Regime Smooth Autoregressive Transition model. I test the limitations of this novel approach in a simulation framework and list caveats to consider in practical application. Lastly, I demonstrate the approach in two empirical applications, measuring the resilience of German car exports and US consumer electronics imports. Descriptive evidence suggests that well-established trade relationships correlate positively with trade flow resilience.

# Contents

# 1 Introduction

Recent crises, such as the Great Recession and the Covid-19 pandemic, direly highlighted the importance of resilient economic systems in mitigating welfare reducing effects of shocks. While some regions are able to withstand crises relatively unscathed, others suffer greatly. Unsurprisingly, researchers are increasingly interested in understanding the causes of locally differing responses to shocks and resilience starts to become an objective for policy making (Sánchez, De Serres, Gori, Hermansen, & Röhn, 2017). This has fueled a rich discussion on how to formalize and define the concept of economic resilience. Still, while many efforts were made to unify the theoretical concept of resilience, methods to measure resilience are scarce. I seek to contribute to this discussion by outlining how resilience can be parametrized and measured in a Smooth Transition Autoregressive (STAR) model framework.

Generally, this novel approach can be used for any economic variable that is observed as a univariate time series. I focus, however, on trade flows. Economic resilience naturally extends to trade, as trade comprises a multitude of economic transactions that are integral for the modern economy. On the macro level, resilient trade flows are important to guarantee provision of goods at the desired level. On the micro level, firms and logistics providers strive to build dynamic supply chains in order to work effectively and efficiently. The risk management literature highlights the value of building resilient supply chains in mitigating costs stemming from the inability to adapt to unforeseen shocks (Christopher & Peck, 2004). Indeed, Ponomarov and Holcomb (2009) describe the ability of supply chains to "incorporate event readiness, provide an efficient and effective response, and be capable of recovering to their original state or even better post the disruptive event" as the essence of supply chain resiliency. Disruptive events refer to any type of realized risk, such as the loss of a critical supplier, a major fire at a manufacturing plant, or an act of terrorism (Ponomarov & Holcomb, 2009).

An important trend when analyzing resilience is the growing interconnectedness of both trade relationships and economic regions in general. Naturally in a system of many interlinked entities a shock can propagate more easily, making many entities more susceptible to shocks than they have been historically (Ringwood, Watson, & Lewin, 2019). The Covid-19 crisis added fuel to this debate, with even the World Economic Forum recommending to "aggressively evaluate near-shore options to shorten supply chains and increase proximity to customers" (Betti & Hong, 2020). However, the evidence whether complex global value chains were more severely affected is not clear cut (Evenett, 2020). This underlines the importance of a well defined measure for resilience to properly identify determinants of resilience.

Despite the growing interest, there is currently no universally agreed upon definition of economic resilience (Sensier, Bristow, & Healy, 2016). Still, from the many efforts of defining economic resilience, a common denominator can be distilled. A precise definition of resilience is a key step in operationalizing the concept and prevents from using the term as a vacuous and ambiguous buzzword (Rose, 2004). In section 2 I provide an extensive review of the definitions of resilience in the academic literature. While the roots of the concept come from psychological and ecological research, I focus on economic and supply chain resilience. I argue that this does not reduce the generality of the resulting definition, as said roots are acknowledged in all papers considered. I continue in section 3 with an overview of existing measurements of resilience and a discussion of their shortcomings. Section 4 then presents the general STAR model framework. Section 5 discusses the reasoning and implications of applying a time series approach to trade data and section 6 outlines how resilience can be measured in a STAR framework, including examples of processes exhibiting different levels of resilience. The detailed steps of model selection are then presented in section 7 which naturally leads to a discussion of model estimation in section 8. To evaluate whether or not the outlined framework is successful in measuring resilience I evaluate the procedure in a simulation setting in section 9. Lastly, I present two empirical applications of the novel estimation framework in section 10.

In this thesis I show how the dimensions of resilience relevant for trade can successfully be parametrized in a STAR model framework. This approach has multiple advantages. First, for each dimension the underlying theoretical definition can clearly be matched to a parameter, avoiding overlap in measurement. Second, and contrary to existing measures, the resulting indicator does not depend on any subjective weighting of variables. It can therefore serve as the first step in thoroughly analyzing determinants of resilience. Third, the parametrization of resilience dimensions allows for a rigorous evaluation of estimator performance, highlighting limitations of the procedure. Knowledge of said limitations consequently guides cautious practical application of the outlined methods.

## 2 Defining Resilience

I employ the concise definition of Christopher and Peck (2004) and refer to resilience as "the ability of a system to return to its original state or move to a new, more desirable state after being disturbed". This definition was established in the context of supply chain resilience, but matches the dimensions commonly attributed to economic resilience. Generally, the concepts associated with resilience in the literature can be summarized as robustness, recovery and reorientation (Martin, 2012).

Robustness describes a system's ability to withstand a shock. An example of such behavior is the security of food supply during the first wave of Covid-19. In a system exhibiting strong robustness no food shortages should occur amid a global lockdown (Hobbs, 2020). There is currently disagreement as to whether robustness should be treated as a dimension of resilience or analyzed as a stand-alone concept (Han & Goetz, 2015). I side with authors distinguishing robustness from resilience[1]. Evenett (2020) argues that robustness has to be considered as a separate concept to derive sensible policy implications in building resilient global value chains. Indeed, measures that foster robustness (for example near shoring) might stand in contrast to resilience, as they limit the dynamic response capability of systems. On a similar note, I argue that robustness is prone to be confused with rigidity, especially in the context of trade. If

[1] See for example Christopher and Peck (2004) or Ponomarov and Holcomb (2009).

the shock manifests as a change in demand, a resilient process should be able to adapt accordingly. If the trade flow does not exhibit any change this might indicate a lack of flexibility and indeed result in a welfare loss, as the amount of traded goods does not match the demand. In this thesis I therefore do not consider robustness as an element of resilience and argue that resilience is a two dimensional concept, entailing recovery and reorientation.

Recovery refers to a system's capability of returning to its pre-shock state following a shock (Ringwood et al., 2019). This dimension has enjoyed popularity in economic analyses of resilience, as it is in line with the idea of stability of a system near its equilibrium and self-correcting forces driving the process towards said equilibrium (Fingleton, Garretsen, & Martin, 2012). Some authors, e.g. Foster (2007) and Hill, Wial and Wolman (2008), build their definition of resilience fully on the recovery dimension. Recovery is hence captured by the speed at which a series returns to its equilibrium path after a shock. A more resilient process is therefore one that recovers faster. As an illustrative example of a shock where recovery is the main focus one can imagine a container ship getting stuck in the Suez canal. A resilient trade flow is one which reacts to and recovers from the resulting supply bottleneck quickly.

Reorientation places emphasis on a system's ability to adapt and evolve in response to change (Martin, 2012). This dimension accounts for the dynamic behavior that is expected from a resilient system. Ponomarov and Holcomb (2009) argue that "a resilient supply chain must be adaptable, as the desired state in many cases is different from the original one". Similarly, Christopher and Peck (2004) note that resilient processes are flexible, agile and able to change quickly. The importance of reorientation is clearly highlighted in periods of paradigm shift, such as the Covid-19 crisis, Brexit or the China-US trade war. In all those instances existing global value chains had to adapt to new laws, changes in costs and a multitude of other challenges, as the rules of trade shifted profoundly. I therefore define reorientation as the speed with which a series moves to a new equilibrium.

In summary, I argue that a definition of resilience that is applicable to trade is two-dimensional and entails recovery and reorientation. This matches the definition of resilience proposed by Christopher and Peck (2004) as both the return to its original state as well as the possible transition to a new, better state are accounted for.

# 3 Measuring Resilience

The handful of existing measures of resilience can be categorized into two approaches. One uses regional properties or characteristics as determinants of resilience. For instance, Briguglio et al. (2009) develop an economic resilience index based on the adequacy of policy in areas such as macroeconomic stability and microeconomic market efficiency. Lu and Dudensing (2015) propose a resilience measure based on changes in sales by industrial sector following Hurricane Ike (September 2008). Similarly, Kahsai et al. (2015) create an index on West Virginia county level based on physical and human resources, employment and income diversity, entrepreneurial activity and scale and proximity. Ringwood et al. (2019) argue that "one advantage of using an index of regional characteristics is that it captures the unique and complex nature of each region". Still, a major drawback is that the choice of variables and their respective weighting is clearly subjective (Briguglio, Cordina, Farrugia, & Vella, 2009; Ringwood et al., 2019). Sensier et al. (2016) heavily criticize this approach by arguing that existing indices remain largely unproven and past indices failed to predict resilience of economic systems (Briguglio et al., 2009). They emphasize that before deciding on factors that determine resilience researchers first need to properly identify which systems have proven to be resilient to shocks and which have not.

The other approach is to analyze changes in representative measures in response to a shock. The framework proposed in this thesis falls into this category. Another example is Ringwood et al. (2019), which takes the deviations from an expected (forecasted) trend as an indication of resilience. I argue, however, that this measurement in fact captures robustness. A robust system does not react to a shock, hence the deviation from the expected trend will be small. For the reasons outlined in section 2 robustness should be separately analyzed. Other examples include Martin (2012) and Fingleton et al. (2012) which both analyze the structural composition of employment changes to investigate regional resilience. Their analyses, however, do not provide holistic measures of resilience, as they focus on sub-dimensions, i.e. reorientation (Martin, 2012).

My approach differs from the literature insofar as I propose to use a model framework in which recovery and reorientation can be parametrized. The advantage of this approach is that resilience can be measured holistically as both dimensions of resilience are jointly accounted for. Moreover, the resulting measure does not depend on any subjective weighting of determinants of resilience. On the contrary, given the objective nature of the resulting measure it can be used to further analyze determinants of resilience.

# 4 Smooth Transition Autoregressive (STAR) Models

Both dimensions of resilience can be parameterized in a Smooth Transition Autoregressive (STAR) model. STAR models belong to the family of regime-switching models, which are commonly used to model non-linearities in time series (Van Dijk & Franses, 1999). A regime is simply defined as a period in which the process takes on different parameter values (Teräsvirta, 1994). They typically consist of a set of linear models, where at each point in time, depending on the regime at that time, either only one model or a linear combination of multiple models dictates the series' evolution. A two-regime STAR model for a univariate time series $y_t$ can be written as

$$y_t = \boldsymbol{\phi}_\mathbf{1}'\mathbf{x_t} \times (1 - F(s_t, \gamma, c)) + \boldsymbol{\phi}_\mathbf{2}'\mathbf{x_t} \times F(s_t, \gamma, c) + \varepsilon_t \tag{1}$$

where $\mathbf{x_t} = (1, \tilde{\mathbf{x}}_t')'$ with $\tilde{\mathbf{x}}_t = (y_{t-1}, \ldots, y_{t-p})'$ and $\boldsymbol{\phi}_i = (\phi_{i,0}, \phi_{i,1}, \ldots, \phi_{i,p})$, $i = 1, 2$. $\varepsilon_t$ follows a white noise process with mean zero and variance $\sigma^2$. Here $F(.)$ denotes the so-called transition function which is a continuous function bounded between zero and one that governs the transition between regimes. Throughout this thesis I use the logistic function as the transition function, which is a common choice in the literature and yields the Logistic STAR (LSTAR) model (Dijk, Teräsvirta, & Franses, 2002).[2] The transition function is hence

$$F(s_t, \gamma, c) = (1 + exp(-\gamma(s_t - c)))^{-1}, \quad \gamma > 0 \tag{2}$$

where both $\gamma$ and $c$ are scalars and $s_t$ is the transition variable. The logistic function monotonically increases from 0 to 1 as $s_t$ increases and $F(c, \gamma, c) = 0.5$.

## 4.1 Regime Switches

I use this basic two-regime LSTAR model to describe the general functionality of STAR models. At any point in time the evolution of $y_t$ is determined by a weighted average of two different autoregressive (AR) models. The weights depend on the transition variable $s_t$, i.e. whether or not $s_t$ crosses the threshold $c$. Large values of $s_t$ result in a weight approximately equal to one, whereas small values of $s_t$ yield a weight approximately equal to zero. The choice of $s_t$ is an important step in model selection and is covered in greater detail in section 7. Generally, $s_t$ can be an endogenous or an exogenous scalar variable. Depending on the empirical setting, researchers might be able to identify variables that induce a regime shift. As an illustrative example, assume that trade of pharmaceutical products follows different regimes depending on whether or not a pandemic is taking place. In this case a sensible choice for $s_t$ could be the number of virus cases, as it indicates the state of the pandemic. In this thesis, however, I only consider an endogenous variable as the transition variable, namely lagged values of $y_t$. This is a common choice of transition variable and builds on the idea that the weights

[2] For certain cases where one expects a non linear relationship between transition variable and series behavior, the literature recommends using the exponential function as transition function, yielding the so-called Exponential STAR (ESTAR) model. For a discussion see Teräsvirta (1994) or Van Dijk et al. (2002).

depend on the recent history of $y_t$. I argue that using $y_{t-d}$ allows for a more general measurement of resilience which consequently yields better comparability across series. If the weights depend on $y_{t-d}$ this implies that all shocks that influence the series' behavior enter through $\varepsilon_t$. In other words, if $\varepsilon_t$ takes on an extreme value because of any kind of trade shock, $y_{t-d}$ will eventually cross $c$ and the model transitions to a different regime. Consequently, the model can capture all kinds of regime shifts, as long as $y_{t-d}$ is affected. Therefore the procedure can be used for any kind of empirical series and no prior selection on regime shift periods (and their respective $s_t$) is necessary. The speed at which these weights change as $s_t$ increases is governed by $\gamma$. The higher $\gamma$, the faster this change occurs. This is easily illustrated when considering the extreme cases of $\gamma \to 0$ and $\gamma \to \infty$. If $\gamma \to 0$ the weights become constant and equal to 0.5, resulting in a linear model. Contrarily if $\gamma \to \infty$ the logistic function approaches a unit step function, equalling 0 if $s_t < c$ and 1 if $s_t > c$.

## 4.2 Extending STAR to Multiple Regimes (MRSTAR)

Following Van Dijk, Teräsvirta and Franses (2002), McAleer and Medeiros (2008) and Hillebrand, Medeiros and Xu (2010) I extend the basic STAR model to allow for multiple regimes. This greatly increases the model's flexibility as it relaxes the assumption that the series' behavior can be described by only two regimes. I start by rewriting equation (1) as

$$y_t = \boldsymbol{\phi}_\mathbf{1}'\mathbf{x_t} + (\boldsymbol{\phi}_\mathbf{2} - \boldsymbol{\phi}_\mathbf{1})'\mathbf{x_t} \times F(s_t, \gamma, c) + \varepsilon_t. \tag{3}$$

I can now add another nonlinear component to obtain a 3-regime STAR model.

$$y_t = \boldsymbol{\phi}_\mathbf{1}'\mathbf{x_t} + (\boldsymbol{\phi}_\mathbf{2} - \boldsymbol{\phi}_\mathbf{1})'\mathbf{x_t} \times F_1(s_t, \gamma_1, c_1) + (\boldsymbol{\phi}_\mathbf{3} - \boldsymbol{\phi}_\mathbf{2})'\mathbf{x_t} \times F_2(s_t, \gamma_2, c_2) + \varepsilon_t \tag{4}$$

Note that the subscripts added to the transition functions indicate that they are evaluated for different values of $\gamma$ and $c$. A MRSTAR model with $M$ regimes can hence be written as

$$
\begin{aligned}
y_t = \boldsymbol{\phi}_{\mathbf{1}}'\mathbf{x_t} + (\boldsymbol{\phi}_{\mathbf{2}} - \boldsymbol{\phi}_{\mathbf{1}})'\mathbf{x_t} \times F_1(s_t, \gamma_1, c_1) + \dots \\
+ (\boldsymbol{\phi}_{\boldsymbol{M}} - \boldsymbol{\phi}_{\boldsymbol{M-1}})'\mathbf{x_t} \times F_{M-1}(s_t, \gamma_{M-1}, c_{M-1}) + \varepsilon_t
\end{aligned}
\tag{5}
$$

with $M-1$ smoothness parameters $\gamma_1, \dots, \gamma_{M-1}$ and $M-1$ location parameters $c_1, \dots, c_{M-1}$. It is hence implicitly assumed that the regimes can be characterized by a single transition variable $s_t$.[3] To illustrate how regimes change in this model consider a 4 regime model with $c_1 < c_2 < c_3$. In this case the autoregressive parameters change smoothly from $\boldsymbol{\phi}_{\mathbf{1}}$ to $\boldsymbol{\phi}_{\mathbf{2}}$ to $\boldsymbol{\phi}_{\mathbf{3}}$ and finally to $\boldsymbol{\phi}_{\mathbf{4}}$ for increasing values of $s_t$. This behavior is graphically shown in figure figure 17 in the appendix, where also $\gamma_1 = \gamma_2 = \gamma_3$ to highlight the smooth transition from one regime to the other.

# 5 A Time Series Model of Trade

By using the MRSTAR framework to model trade flows I implicitly assume that within each regime trade can be modelled as an autoregressive process of order $p$. This departs from the literature of modelling trade flows insofar as typically gravity models are used to model trade volumes where a set of explanatory variables (e.g. distance and GDP) determines trade between two entities. Compared to a time series approach this has the advantage that it can be theoretically motivated.[4] Still, efforts have been made to use autoregressive models to forecast import and export volumes and were generally found to be successful (Harvey & Todd, 1983; Keck, Raubold, & Truppia, 2010). It is important to keep in mind, however, that this type of modelling is only motivated by its goodness of fit and predictive power and hence results in a reduced form measure.

[3] Alternatively the basic STAR model can also be extended to a setting where regimes are determined by multiple transition variables $\mathbf{s_t} = (s_{1,t}, \dots, s_{j,t})$, where $j$ is the number of transition variables and $j = M-1$. This is achieved by nesting multiple two regime STAR models, as proposed by Van Dijk and Franses (1999).

[4] For an in-depth discussion see the seminal work of Tinbergen (1962).

As the MRSTAR framework allows for additional exogenous explanatory variables in $x_t$ an avenue for further research could be to write each regime as a gravity equation by including regressors such as GDP and distance. As such an extension of the MRSTAR framework would require an in-depth discussion of its theoretical properties and the additional autoregressive term in the gravity equation, this is out of scope for this thesis. Instead, I assume that within each regime trade follows an $AR(p)$ process. Usually selecting $p$ is a step in model selection where the standard Box-Jenkins procedure is applied as if the correct model were linear (Teräsvirta, 1994). In this thesis, however, I assume $p = 1$ for all series considered. The reasoning behind this choice is twofold. First, the literature has identified an $AR(1)$ model as a good fit, which is also confirmed by the empirical data considered in this thesis (Keck et al., 2010).[5] Second, with $p = 1$ recovery can directly be linked to the model's autoregressive parameters, as outlined below. In case of $p > 1$ one would need to add an additional step to the procedure, namely the computation of the impulse response function (IRF) of the MRSTAR model. A discussion of the IRF in the MRSTAR framework is given in Van Dijk et al. (2002).

# 6 Resilience in the STAR framework

I propose to measure resilience as follows. First, a series' capability of recovering quickly can be measured by evaluating the process' persistence. A persistent series is one in which an infinitesimally small shock influences future observations for a long time (Hamilton, 1994). For any shock $\varepsilon_t$ persistence hence indicates how long $\varepsilon_t$ influences $y_j$ where $t < j < T$. As recovery refers to a resilient system's ability to return to its pre-shock path quickly, I argue that this can be translated to a short influence of $\varepsilon_t$ on

[5] Following Box-Jenkins and selecting $p$ that yields minimal AIC for all trade flows considered in section 10 yields $\bar{p} \approx 0.84$.

$y_j$ and hence to persistence.[6] Given that the STAR model is a linear combination of AR models, persistence can be evaluated from the AR coefficients. Large values of the weighted average across regimes of $(\phi_{1,1}, \ldots, \phi_{M,1})$ indicate strong persistence (weak recovery) whereas small values of the weighted average of $(\phi_{1,1}, \ldots, \phi_{M,1})$ signal weak persistence (strong recovery). Second, $\gamma$ can be used as a measure for reorientation, as this parameter dictates the speed at which a series adjusts to a different regime. A large (small) value of $\gamma$ hence signals strong (weak) reorientation.

To further illustrate how resilience can be modelled and parametrized in a STAR framework I present examples of weaker recovery and weaker reorientation relative to a baseline model.

## 6.1 The Baseline Model

I simulate 100 observations from a basic 2-regime LSTAR model with parameters $\boldsymbol{\phi_1} = (1, 0.1), \boldsymbol{\phi_2} = (5, 0.3), c = 4.5, \gamma = 0.9$ and $s_t = y_{t-1}$. The resulting series is displayed in figure 1. In this figure the shape indicates the dominant regime at each point in time $t$, where regime 1 if $F(s_t, \gamma, c) < 0.5$ and regime 2 if $F(s_t, \gamma, c) \geq 0.5$. The series first follows regime 1 and oscillates around the intercept value of 1 with low autoregressive dependence. After being prompted by a sequence of large $\varepsilon_t$, resulting in $s_t$ crossing $c$, it moves to regime 2. The second regime is clearly identified by a larger intercept and stronger autocorrelation. In the end the series moves back to regime 1. A real world example of a series that might exhibit similar behavior is a temporary demand shock that fades after a while. Figure 2 shows the weight of each regime for increasing values of $s_t$. It is evident that the model transitions smoothly from one regime to the other. The steepness of this transition is driven by $\gamma$.

[6] Robustness, on the other hand, refers to the extent to which $\varepsilon_t$ directly influences $y_t$. A robust series is one in which $\varepsilon_t$ has a small effect on $y_t$. Measuring robustness would demand a richer model which places a coefficient on the error term. Then, however, the error terms would have to be process specific and each process could be formulated as an ARMA model. Solving such a model is non-trivial and out of scope of this thesis.

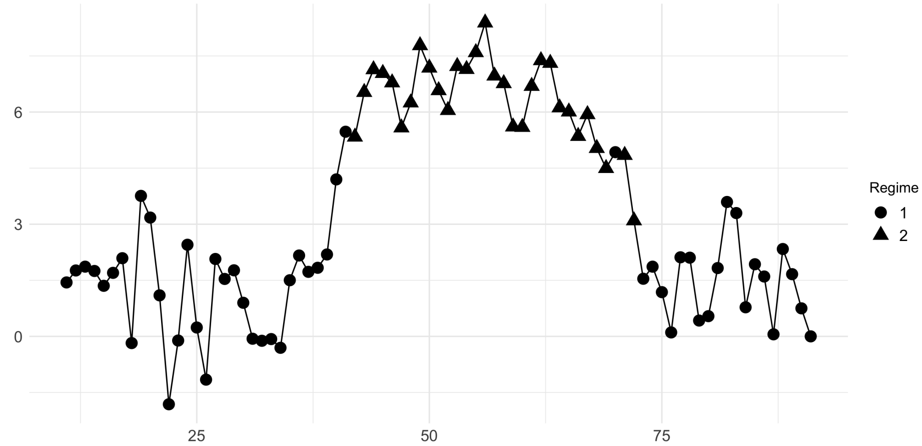


Figure 1: Simulated data from baseline 2 regime LSTAR model

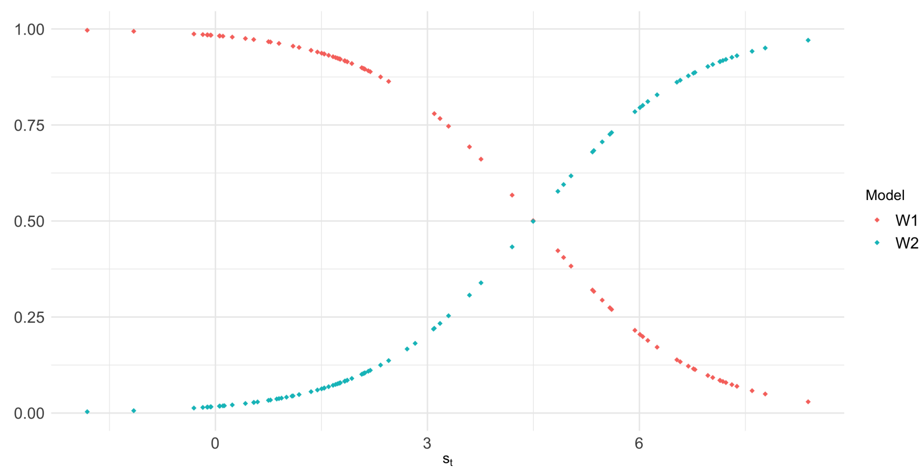


Figure 2: Regime weights in baseline 2 regime LSTAR model

### 6.2 Example I: Weaker Recovery

I now simulate a series that exhibits weaker recovery compared to the baseline model. This is achieved by increasing the values of the autoregressive parameters by 0.2. I hence simulate 100 observations from a 2 regime model with parameters $\boldsymbol{\phi_1} = (1, 0.3), \boldsymbol{\phi_2} = (5, 0.5), c = 4.5, \gamma = 0.9$ and $s_t = y_{t-1}$. The realizations of $\varepsilon_t$ are the same as in section 6.1. Figure 3 highlights two distinct differences to the baseline model. First, due to the stronger autocorrelation the realized values are further from the intercept. Second, while the initial shift to regime 2 is again taking place, the series does not move back to regime 1. Naturally, this is a consequence of the high autoregressive dependence of the second process as $s_t$ no longer crosses the threshold value $c$ a second time. From figure 3 it becomes indeed evident that the values of the transition function $F$ contain limited sample variation. It is therefore important to acknowledge the relationship between regime shifts and persistence in the subsequent analysis. The definition of resilience outlined in section 2 emphasizes flexibility. I associate higher autoregressive dependence with lower resilience, hence the lack of regime switches does not contradict the definition of resilience employed in this thesis. Moreover, the reorientation dimension only focuses on the speed of adaption, hence it is to some extent irrelevant if a regime shift occurs or not. In this specific case reorientation would be measured from only one regime shift, namely the initial shift from regime 1 to regime 2. If no regime shift occurs and a series can be described by a linear model, reorientation cannot be measured. In summary, I argue that the baseline process as shown in figure 1 exhibits the dynamic behavior that is expected from a resilient series and that a lack of such dynamic behavior is captured by the measure of recovery.

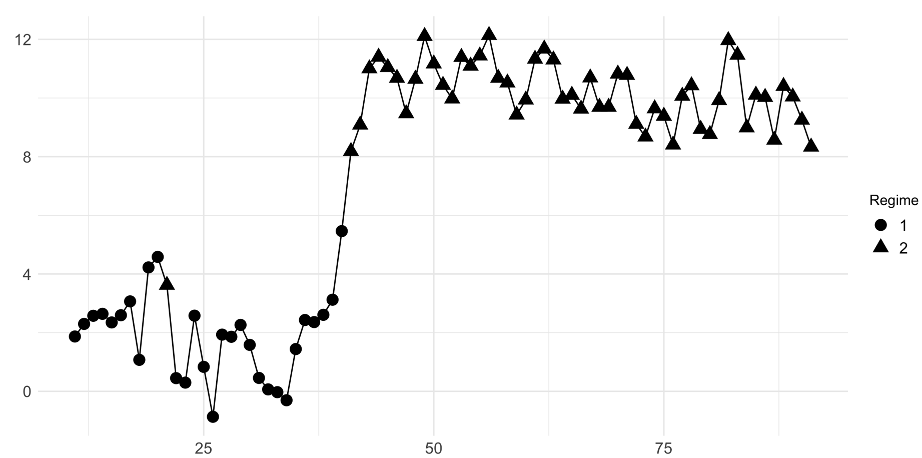


Figure 3: Simulated data from 2 regime LSTAR model with higher AR coefficients

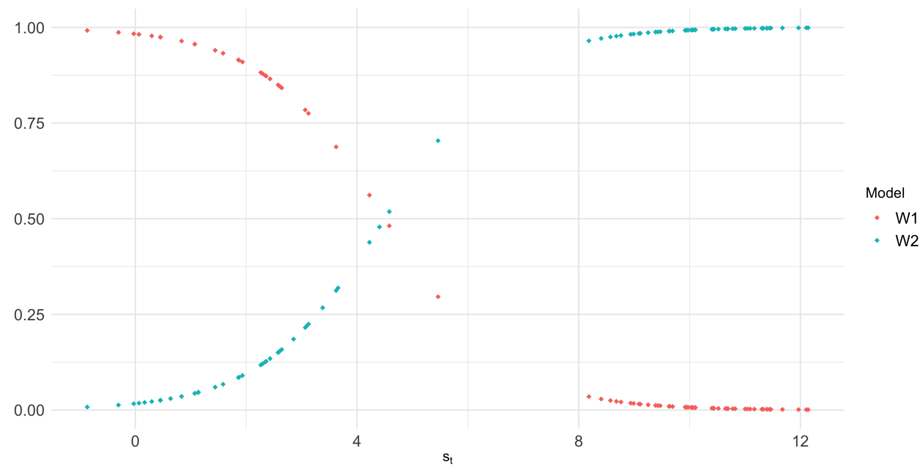


Figure 4: Regime weights in 2 regime LSTAR model with higher AR coefficients

### 6.3 Example II: Slower reorientation

Decreasing $\gamma$ relative to the baseline model changes the speed of adaption to a new regime. I again simulate 100 observations from a 2 regime model, now with parameters $\boldsymbol{\phi_1} = (1, 0.1), \boldsymbol{\phi_2} = (5, 0.3), c = 4.5, \gamma = 0.6$ and $s_t = y_{t-1}$. The realizations of $\varepsilon_t$ are again the same as in the preceding simulations. Figure 5 shows how the transitions between regimes are much slower than in the baseline model. The difference between the adjustment speed from regime 1 to regime 2 and the adjustment speed from regime 2 to regime 1 comes from the difference in AR coefficients. Figure 6 clearly shows how smaller $\gamma$ yields more smoothly changing weights across values of $s_t$.

## 7 Model Selection

I use a "specific-to-general" approach for building MRSTAR models. This approach is strongly recommended by Granger (1993) for non-linear time series models in general and has been applied by Van Dijk and Franses (1997) and Van Dijk et al (2002) for MRSTAR models. This strategy involves starting with a simple model and moving to more complicated models only when diagnostic tests indicate the inadequacy of the chosen model. (Dijk et al., 2002). Whether or not a selected model is adequate is hence

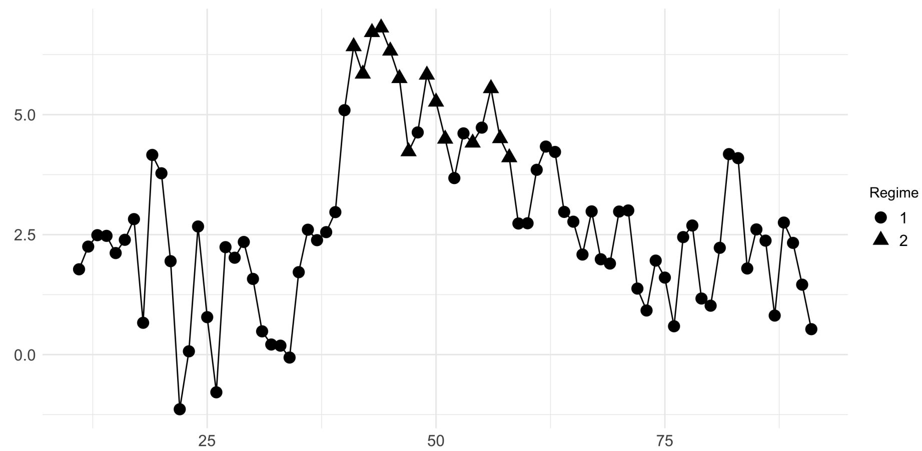


Figure 5: Simulated data from 2 regime LSTAR model with smaller $\gamma$

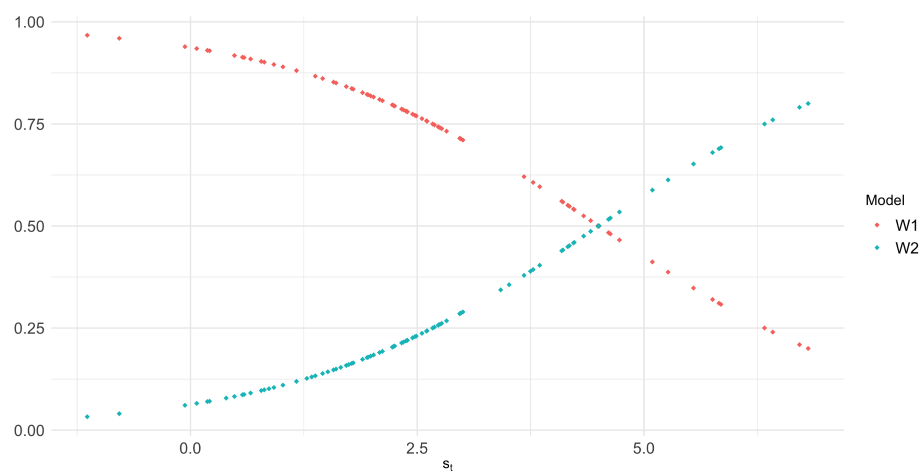


Figure 6: Regime weights in 2 regime LSTAR model with smaller $\gamma$

evaluated from its sample forecasting ability (Granger, 1993). Consequently, I employ the following model selection procedure.

1. Specify a linear AR model of order $p = 1$.

2. Test the null hypothesis of linearity against the alternative of STAR non-linearity for a set of transition variables $s_t$. If linearity is rejected, select $s_t$ for which linearity is rejected the strongest, based on the p-value of the test statistic. If linearity cannot be rejected, a linear model is estimated. Note that in this case

reorientation cannot be measured, as no regime shift occurs.

3. Estimate the model with selected $s_t$ and test the null hypothesis of no remaining non-linearity. If the null hypothesis is rejected, modify the model accordingly and repeat the test until the null hypothesis of no remaining non-linearity can no longer be rejected.

In a nutshell, this model selection procedure permits to test (1) whether or not the STAR model framework is applicable, (2) which selection variable $s_t$ should be used and (3) how many regimes the resulting model should comprise. Section 7.1 presents the linearity test used to evaluate if STAR non-linearity is present. Section 7.2 discusses how to select $s_t$. Finally, section 7.3 demonstrates how to select the number of regimes $M$. The significance level used for all tests is 10%.

## 7.1 Testing Linearity Against STAR

The natural first step of building a STAR model is testing whether or not this non-linear framework is appropriate. From equation (3) the null hypothesis of linearity can be expressed as either $H_0' : \boldsymbol{\phi_1} = \boldsymbol{\phi_2}$ or $H_0'' : \gamma = 0$. If $H_0''$ holds true, the weights become constant and equal to 0.5, resulting in a linear model. Testing these hypotheses is not straightforward, as nuisance parameters are not identified under the null. In other words, there are parameters that are not restricted by the null hypothesis, but which cannot be estimated from the data when the null hypothesis holds true. To be precise, $H_0'$ does not restrict $\gamma$ and $c$, but when $H_0'$ holds true, the likelihood is not affected by the values of $\gamma$ and $c$. Similarly, in the case of $H_0''$ $c$, $\boldsymbol{\phi_1}$ and $\boldsymbol{\phi_2}$ are not identified. Davies (1987) provides a general discussion of the problem of unidentified nuisance parameters under the null hypothesis. Luukkonen et al. (1988) propose a solution to this problem in the context of testing linearity against STAR alternatives. The transition function $F(s_t, \gamma, c)$ can be approximated by a suitable Taylor series. In the resulting auxiliary regression the identification problem is no longer present. Moreover, linearity can then be tested by means of a Lagrange Multiplier statistic with a standard asymptotic $\chi^2$ distribution under the null. From equation (2) I can approximate the logistic function with a first-order Taylor approximation around $\gamma = 0$. This results in the reparametrized equation

$$y_t = \boldsymbol{\beta_0'}\mathbf{x_t} + \boldsymbol{\beta_1'}\mathbf{x_t}s_t + e_t \tag{6}$$

where $\boldsymbol{\beta_i} = (\beta_{i,0}, \beta_{i,1}, \ldots, \beta_{i,p})$, $i = 0, 1$ and $e_t = \varepsilon_t + (\boldsymbol{\phi_2} - \boldsymbol{\phi_1})'\mathbf{x_t}R_1(s_t, \gamma, c)$. Here $R_1(s_t, \gamma, c)$ is the remainder term from the Taylor approximation. $\gamma = 0$ implies $\beta_{0,j} \neq 0$ and $\beta_{1,j} = 0$ for $j = 0, \ldots, p$. Hence testing $H_0'' : \gamma = 0$ (or $H_0' : \boldsymbol{\phi_1} = \boldsymbol{\phi_2}$) is equivalent to testing $H_0''' : \boldsymbol{\beta_1} = 0$. The test statistic has an asymptotic $\chi^2$ distribution with $p+1$ degrees of freedom under the null. Following the suggestion of Teräsvirta (1994) I use an $F$ approximation, which is more robust especially in small samples. The test can be carried out using a sequence of just linear regressions.

1. Regress $y_t$ on $\mathbf{x_t}$ and obtain the residual sum of squares.

$$SSR_0 = \frac{1}{T}\sum_{t=1}^{T} \widehat{\varepsilon}_t^2 \tag{7}$$

2. Regress $\hat{\varepsilon}_t$ on $\mathbf{x_t}$ and $\tilde{x}_t s_t$ and obtain the residual sum of squares.

$$SSR_1 = \frac{1}{T}\sum_{t=1}^{T} \widehat{v}_t^2 \tag{8}$$

3. Compute the test statistic

$$F = \frac{(SSR_0 - SSR_1)/p}{SSR_1/(T - 2p - 1)} \tag{9}$$

   which is approximately $F_{p,T-2p-1}$ distributed under the null of linearity.

For $s_t = y_{t-d}$ Luukkonen et al. (1988a) recommend using a third-order Taylor approximation as otherwise the test statistic does not have power in cases where only the intercept differs between regimes, i.e. when $\phi_{1,0} \neq \phi_{2,0}$ but $\phi_{1,j} = \phi_{2,j}$ for $j = 1, \ldots, p$. As such cases might well be present in empirical data I use a third-order

Taylor approximation in the subsequent analysis. The resulting procedure is similar to the one outlined above and described in greater detail in section 7.3 or Van Dijk et al. (2002).

## 7.2 Selecting the transition variable $s_t$

Tsay (1989), Teräsvirta (1994), Van Dijk and Franses (1997) and Van Dijk et al (2002) argue that the aforementioned linearity test can also be used to determine the appropriate transition variable. The test statistic is hence computed for a set of candidate transition variables $s_{1t}, \ldots s_{kt}$ and the one which yields the smallest p-value of the test is selected. The idea behind this approach is that the test should have maximum power in case the alternative model is correctly specified, i.e. the appropriate transition variable is specified. Simulation results in Teräsvirta (1994) indicate that this approach works well. Throughout this thesis the set of candidate transition variables considered is $y_{t-1}, \ldots, y_{t-5}$.

## 7.3 Testing the Hypothesis of No Remaining Non-Linearity

For given $s_t$ Eitrheim and Teräsvirta (1996) shows how to test a $M$ regime STAR model against the alternative of a $M+1$ regime STAR model as defined in equation (5). I illustrate the testing procedure in the case of testing a 2 regime model against a 3 regime model as it naturally extends to higher numbers of regimes. The test is similar to the linearity test presented in section 7.1 and evidently suffers from the same type of identification problem. From equation (4) the null hypothesis of no remaining nonlinearity (a two regime model) can be expressed as $H_0' : \boldsymbol{\phi_3} = \boldsymbol{\phi_2}$ or $H_0'' : \gamma_2 = 0$. The identification problem can again be circumvented by a third-order Taylor series approximation of $F_2(s_t, \gamma_2, c_2)$, this time around $\gamma_2 = 0$.

$$y_t = \boldsymbol{\beta_0}\mathbf{x_t} + (\boldsymbol{\phi_2} - \boldsymbol{\phi_1})'\mathbf{x_t} \times F_1(s_t, \gamma_1, c_1) + \boldsymbol{\beta_1'}\mathbf{x_t}s_t + \boldsymbol{\beta_2'}\mathbf{x_t}s_t^2 + \boldsymbol{\beta_3'}\mathbf{x_t}s_t^3 + e_t \qquad (10)$$

The null hypothesis of no remaining non-linearity translates into $H_0''' : \boldsymbol{\beta_1} = \boldsymbol{\beta_2} = \boldsymbol{\beta_3} = 0$. To obtain the test statistic I regress the residuals from estimating the model under the null on the partial derivatives of the regression function w.r.t. the parameters of the 2-regime model under the null and the auxiliary regressors $\mathbf{x_t}, s_t, s_t^2, s_t^3$. From this auxiliary regression the test statistic can be computed as $nR^2$. A more in-depth discussion of the procedure can be found in Eitrheim and Teräsvirta (1996). The resulting test statistic has an asymptotic $\chi^2$ distribution with $3(p+1)$ degrees of freedom.

# 8 Model Estimation

Once $s_t$ has been selected the model parameters can be estimated by nonlinear least squares (NLS). The following discussion focuses on estimating a basic 2 regime model as all steps and issues trivially extend to multiple regimes. The skeleton of a 2 regime model is

$$G\left(\mathbf{x_t};\boldsymbol{\theta}\right) = \boldsymbol{\phi_1'}\mathbf{x_t}\left(1 - F\left(s_t;\gamma,c\right)\right) + \boldsymbol{\phi_2'}\mathbf{x_t}F\left(s_t;\gamma,c\right) \tag{11}$$

and the parameters $\boldsymbol{\theta} = (\boldsymbol{\phi_1'}, \boldsymbol{\phi_2'}, \gamma, c)'$ can be estimated as

$$\widehat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta}}{\operatorname{argmin}} Q_T(\boldsymbol{\theta}) = \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \sum_{t=1}^{T} \left(y_t - G\left(\mathbf{x_t};\boldsymbol{\theta}\right)\right)^2 \tag{12}$$

Under the assumption that $\varepsilon_t \sim \mathcal{N}(\mu, \sigma^2)$, NLS is equivalent to maximum likelihood. The regularity conditions for consistency and asymptotic normality of NLS estimates are discussed in Wooldridge (1994).

## 8.1 Choice of starting values

One key step of NLS estimation that has great practical importance is the selection of starting values for each of the parameters $\boldsymbol{\theta}$. Poorly selected starting values result in the optimization algorithm not converging or converging to local minima that are far from the true parameter values. This issue can be circumvented to some extent by concentrating the sum of squares function, as suggested by Leybourne, Newbold and Vougas (1998). If the parameters $\gamma$ and $c$ are fixed, the model is linear in the remaining autoregressive parameters $\boldsymbol{\phi_1}$ and $\boldsymbol{\phi_2}$. Hence $\boldsymbol{\phi} = (\boldsymbol{\phi_1'}, \boldsymbol{\phi_2'})'$ can be estimated by ordinary least squares (OLS), conditional on $\gamma$ and $c$. The resulting estimator is then

$$\widehat{\boldsymbol{\phi}}(\gamma, c) = \left( \sum_{t=1}^{T} \mathbf{x_t}(\gamma, c) \mathbf{x_t}(\gamma, c)' \right)^{-1} \left( \sum_{t=1}^{T} \mathbf{x_t}(\gamma, c) y_t \right) \tag{13}$$

where $\mathbf{x_t}(\gamma, c) = (\mathbf{x_t}' (1 - F(s_t, \gamma, c)), \mathbf{x_t}' F(s_t, \gamma, c))'$. Thus, the sum of squares function $Q_T(\boldsymbol{\theta})$ can be concentrated with respect to $\boldsymbol{\phi_1}$ and $\boldsymbol{\phi_2}$ as

$$Q_T(\gamma, c) = \sum_{t=1}^{T} (y_t - \boldsymbol{\phi}(\gamma, c)' \mathbf{x_t}(\gamma, c))^2 \tag{14}$$

This simplifies the NLS estimation greatly, as now starting values need to be selected only for the two parameters $\gamma$ and $c$. Sensible starting values for $\gamma$ and $c$ can be found from a two-dimensional grid search. For each value in the grid the NLS estimation is performed and the starting values that result in the minimal sum of squares are selected. Similar to Hillebrand et al. (2010) I define the grids as $\gamma \in (1, 2, \ldots, 100)$ and $c \in (\eta_{.10}, \ldots, \eta_{.90})$ with step size $\frac{\eta_{.10} - \eta_{.90}}{200}$ where $\eta_{.i}$ denotes the $i^{th}$ percentile of $s_t$. Using percentiles of $s_t$ as minimum and maximum starting values for $c$ ensures that for each choice of starting values the values of $F(.)$ contain enough sample variation (Dijk et al., 2002).

# 9 Does it Work? A Monte Carlo Evaluation Approach

I simulate a set of series to evaluate whether or not MRSTAR models can be used as a framework to measure resilience. I specify two different data generating processes

(DGP), a two regime model and a three regime model, as most empirical data falls into these categories. For each DGP I then sequentially increase either its autoregressive parameters $\boldsymbol{\phi} = (\phi_{1,1}, \ldots, \phi_{M,1})$ (weaker recovery ) or $\boldsymbol{\gamma} = (\gamma_1, \ldots, \gamma_{M-1})$ (stronger reorientation) to evaluate if the estimation procedure accurately captures these changes in resilience. I simulate $T = 100$ observations from the respective models. For each value of $\boldsymbol{\phi}$ and $\boldsymbol{\gamma}$ the process is simulated $n = 200$ times.[7] For each simulated series the model selection procedure outlined in section 7 is applied. I am hence evaluating the full modelling procedure rather than just parameter estimation. For a general discussion of the estimator's asymptotic properties see for example Hillebrand et al. (2010). Naturally, the model selection procedure leaves additional room for error, as for example a wrong number of regimes $M$ might be selected. I evaluate recovery from the weighted average of $\boldsymbol{\phi}$ with the weights corresponding to the weight of each regime at time $t$,

$$\bar{\phi} = \frac{1}{T} \sum_{t}^{T} \sum_{m}^{M} w'_{tm} \phi_{tm} \tag{15}$$

where

$$w_m = \begin{cases} 1 - F_1, & \text{if } m = 1 \\ F_m - F_{m+1}, & \text{if } 1 < m < M \\ F_m, & \text{if } m = M \end{cases} \tag{16}$$

and $\sum_m^M w_{tm} = 1 \forall t$. Reorientation, on the other hand, is simply evaluated from the average of $\boldsymbol{\gamma}$ across all regimes,

$$\bar{\gamma} = \frac{1}{M} \sum_{m}^{M} \gamma_m. \tag{17}$$

[7]Due to computational limitations a greater number of simulations was not feasible. Generally the results appear to be stable for $n > 50$ (not reported).

The results are presented graphically. The underlying data for all figures can be found in the appendix.

## 9.1 Two regime model (DGP 1)

The starting model of DGP 1 is a 2 regime LSTAR model with parameters $\boldsymbol{\phi_1} = (0, 0.2), \boldsymbol{\phi_2} = (0.5, 0.4), c = 1.5, \gamma = 1$ and $s_t = y_{t-1}$. $\varepsilon_t$ is drawn from a standard normal distribution. First, the autoregressive parameters are sequentially increased by $(0.1, 0.2, 0.3, 0.4)$, resulting in increasingly weaker recovery. Each process is then simulated and estimated $n = 200$ times. Figure 7 displays the weighted average of $\hat{\boldsymbol{\phi}}$ across regimes and its 90% confidence interval. As the true $\bar{\phi}$ lies within the confidence interval of the estimator, the estimation is generally successful. Moreover, there is no evidence of changes in estimation success for weaker or stronger recovery. One caveat, however, exists for extreme cases where one regime dominates. I can simulate such behavior by increasing the threshold value $c$ so that the second regime has a very small weight. For $c = 5$ recovery is no longer estimated accurately, as shown in figure 8. Indeed the second regime is now only assigned a weight of approximately 0.002, as $s_t$ almost never crosses the threshold $c$.[8] Consequently the model is almost linear. In practical application I advise to evaluate $\hat{c}$ and compute the estimated weights of each regime to have an indication of whether or not an extreme case of an overly dominant regime is present. Fine-tuning the significance level used in the linearity tests does not mitigate this issue.

Estimating reorientation is not as successful. Similar to the evaluation of recovery I sequentially increase $\gamma$, resulting in increasingly stronger reorientation. To be precise, data is simulated from models with $\gamma \in (10, 30, 50, 70, 90)$, keeping all other parameters constant and equal to the starting model. As shown in figure 9 $\bar{\hat{\gamma}}$ heavily overestimates

[8] The notion of high values of $c$ naturally depends on the characteristics of the process and the scale of $s_t$. If $s_t$ (i.e. $y_{t-1}$) is scaled differently, $c = 5$ could constitute a small threshold which is crossed frequently.

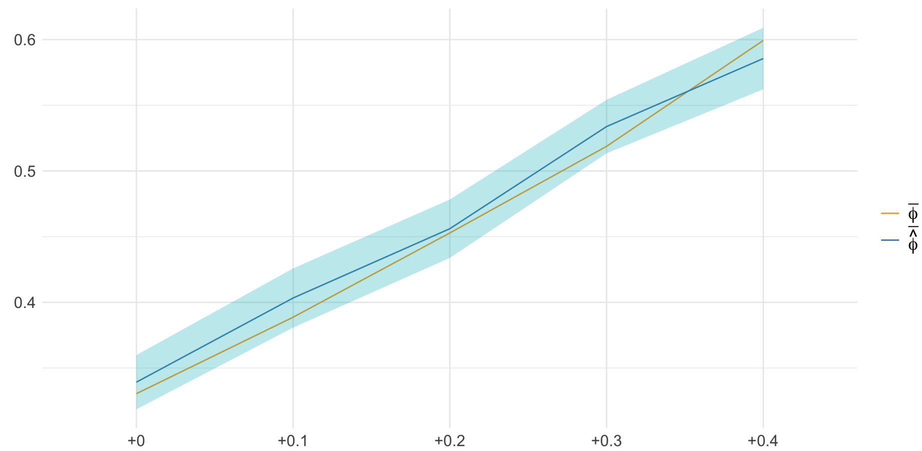


Figure 7: Estimator performance for $\bar{\phi}$ in two regime model

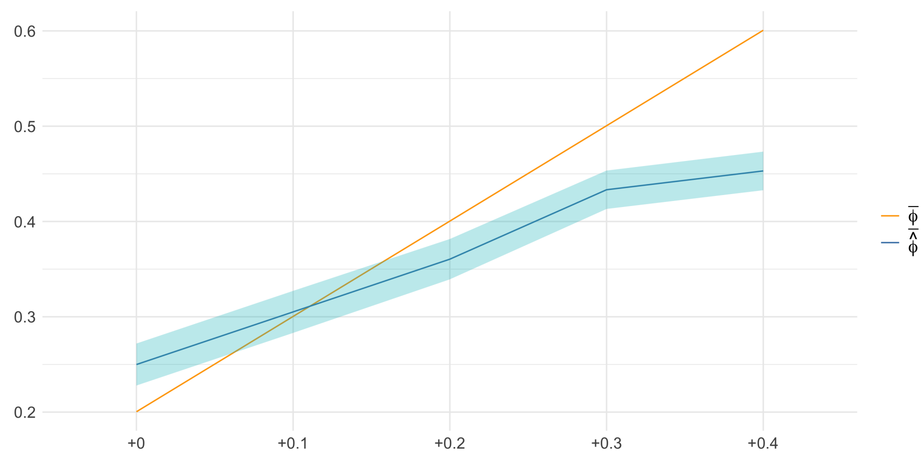


Figure 8: Estimator performance for $\bar{\phi}$ in two regime model with large $c$

$\bar{\gamma}$ for all values of true $\gamma$ except for very high $\gamma$. This issue of poor accuracy when estimating $\gamma$ is acknowledged in the literature.[9] This shortcoming results from the fact that many observations in the immediate neighborhood of $c$ are needed to deliver an accurate estimate of $\gamma$. Indeed increasing the number of observations simulated from each model to $T = 100000$ yields much more accurate estimates of $\bar{\gamma}$, as indicated by figure 10. However, in real world applications such as trade data, such vast amounts of observations are rarely available. Using $\hat{\bar{\gamma}}$ as a measure of reorientation should

[9]See e.g. Van Dijk et al (2002) for a discussion.

hence be applied with caution. With larger amounts of data one can expect more accurate estimates of $\gamma$. Table 1 in the appendix shows estimator precision for $T = (100, 1000, 10000, 100000)$, keeping $\gamma = 30$ constant. Evidently indeed a very large number of observations ($T \approx 10000$) is needed for $\hat{\bar{\gamma}}$ to accurately estimate reorientation.

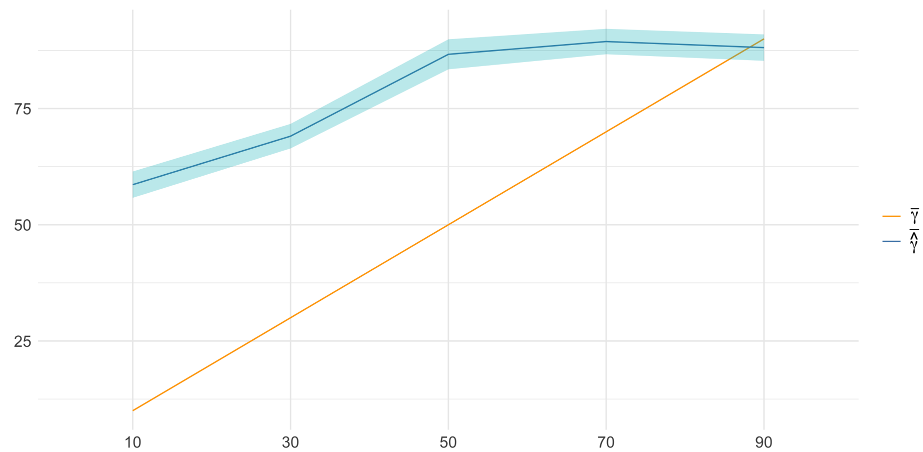


Figure 9: Estimator performance for $\bar{\gamma}$ in two regime model, $T = 100$

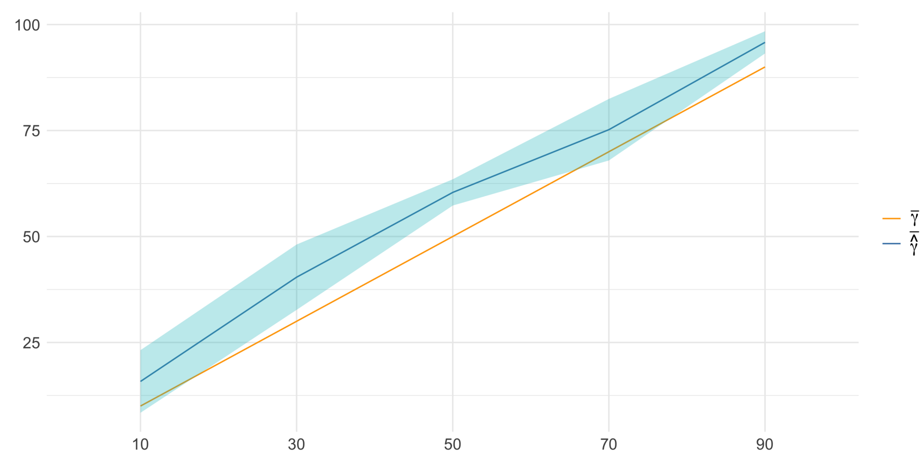


Figure 10: Estimator performance for $\bar{\gamma}$ in two regime model, $T = 100000$

Moreover, as seen from table 2 in the appendix, the number of regimes is slightly overestimated ($\hat{M} \approx 2.4$). The accuracy of this measurement (i.e. the linearity tests) is again greater for larger $T$. For both DGPs the number of regimes is correctly estimated when $T \approx 10000$, as seen from table 6 and table 7. Still, this does not seem to have great practical consequences as recovery is estimated with high accuracy even if $T$ is small.

## 9.2 Three regime model (DGP 2)

Estimator performance is similar when the true model is a three regime model and the same shortcomings are evident. For DGP 2 I simulate data from a 3 regime MRSTAR model with parameters $\boldsymbol{\phi_1} = (0, 0.1), \boldsymbol{\phi_2} = (0.5, 0.4), \boldsymbol{\phi_3} = (1, 0.15), \boldsymbol{c} = (0.4, 1.8), \boldsymbol{\gamma} = (1, 2)$ and $s_t = y_{t-1}$. Similar to the two regime case I first sequentially increase the autoregressive parameters by $(0.1, 0.2, 0.3, 0.4)$, corresponding to increasingly weaker recovery. The results from this exercise are again promising. The 90% confidence interval of $\hat{\bar{\phi}}$ generally captures the true $\bar{\phi}$. Only for very weak recovery the true $\bar{\phi}$ lies slightly outside the 90 % confidence interval, as seen from figure 11. The estimation is, however, still sensitive to $c$ (not reported). Moreover, accurate estimation of $\boldsymbol{\gamma}$ is again dependent on a large number of observations. This is clearly seen from figure 12 which displays estimates of $\gamma_1 = \gamma_2 \in (10, 30, 50, 70, 90)$ for $T = 100$.

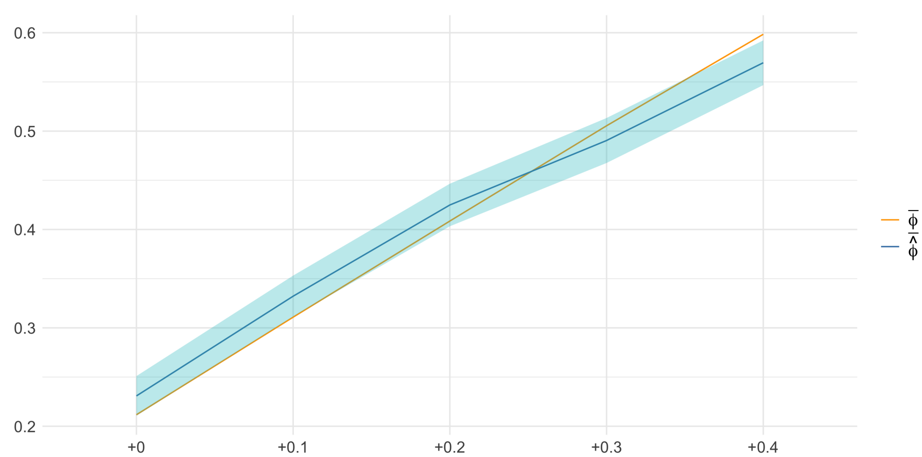


Figure 11: Estimator performance for $\bar{\phi}$ in three regime model

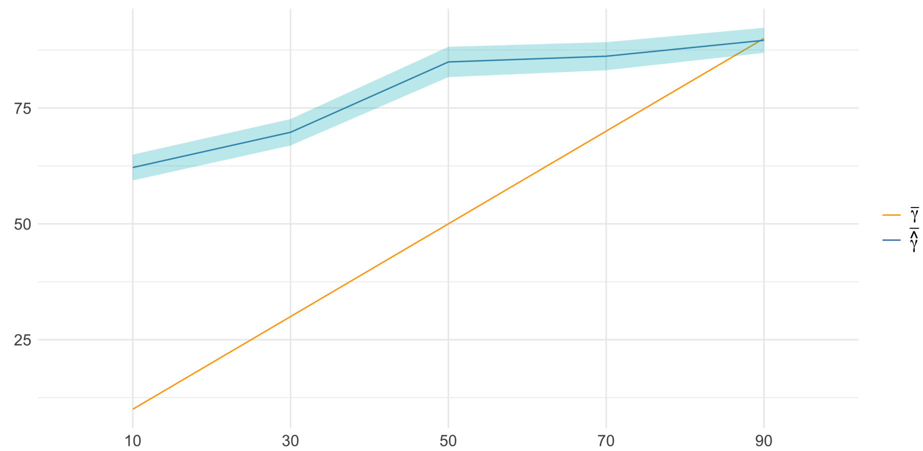


Figure 12: Estimator performance for $\bar{\gamma}$ in three regime model

# 10 Empirical Application

I estimate the resilience of German car exports and US imports of consumer electronics. Data comes from UN Comtrade and is seasonally adjusted. The data is monthly observations from 2010 to 2020 hence resulting in 132 observations for each pair of reporter and partner. I obtained data for the 50 largest trade partners of Germany and for the 35 largest trade partners of the US, according to national statistics.[10] I denote as "car exports" all trade in "Vehicles other than railway or tramway rolling stock, and parts and accessories thereof" according to level 2 of the Harmonized Commodity Description and Coding System (HS). Similarly, "consumer electronics" refers to all goods traded in "Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers, and parts and accessories of such articles". Summary statistics are presented in table 10 and table 11 in the appendix.[11] Given the relatively small sample size and the resulting limitations in es-

[10] Destatis for Germany and US Census Bureau for USA. Note that while Taiwan ranks among the 50 largest trading partners of Germany it is excluded from the sample as UN Comtrade does not provide data.

[11] Note that before estimation values are standardised as $z = \frac{X-\mu}{\sigma}$, where $X$ is the initial value, $\mu$ is the sample mean, $\sigma$ is the sample standard deviation and $z$ is the resulting standardised value.

timating $\gamma$ I evaluate recovery and reorientation separately. Figure 13 shows estimated recovery $\bar{\hat{\phi}}$ of German car exports.[12] Strong recovery is marked as dark green and weak recovery is indicated by light green. The borders of the reporting country, Germany, are marked red. Notably the final sample of partner countries is slightly reduced to 43 countries, for two reasons. First, for some partner countries (Luxembourg, South Africa) the optimization algorithm did not converge. This is likely due to a poor choice of starting values. Second, for certain partner countries (Denmark, Belgium, Norway, Netherlands) a single regime is estimated to dominate. As outlined in section 9.1 and section 9.2 this reduces the accuracy of the estimate and in fact the resulting estimates are not sensible. Generally, the pattern of recovery displayed in figure 13 makes intuitive sense. Countries in close proximity to Germany, such as Italy, Austria and the United Kingdom exhibit comparatively strong recovery ($\bar{\hat{\phi}} \approx 0.3$). This might be due to well-established trade relationships and the European economic area which facilitates trade. Recovery is slightly weaker, however, for Eastern European states. A similar argument of well-established economic relationships can be made for car exports from Germany to the US and Canada, both partner countries with long lasting trade agreements. This finding of cultural proximity increasing resilience (here at least through the recovery dimension) is in line with Carrére and Masood (2018), even though the definition of resilience employed in this work is just a decline in GDP. One surprising exception to this insight is France, which is one of Germany's most important and most established trade partners and only exhibits relatively weak recovery. This might be partly due to the inclusion of 2020 in the underlying trade data, as Germany and France experienced the Covid-19 crisis to a similar extent and took long to recover. Indeed when excluding 2020 from the data $\bar{\hat{\phi}}_{FRA} \approx 0.3$, which corresponds to much stronger recovery. Outside of Europe and North America recovery is generally estimated to be lower, with the exceptions of China and India, which exhibit strong recovery.

Reorientation of German car exports, on the other hand, is generally estimated to be high, as can be seen from figure 14. Notable exceptions to this general assessment

[12] See table 12 in the appendix for details.

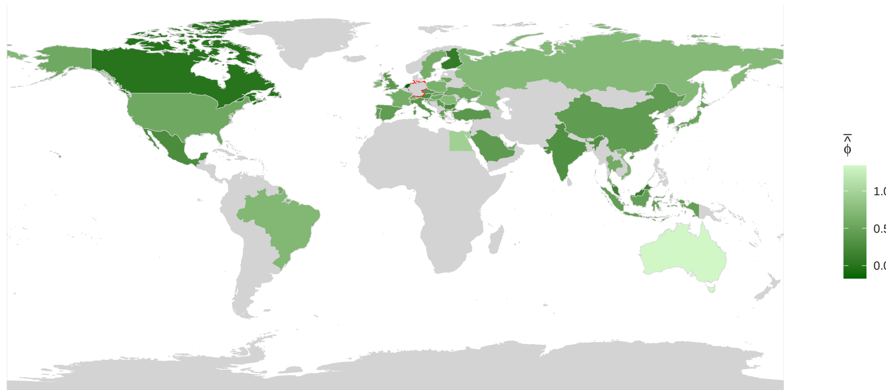


Figure 13: Estimated recovery of German car exports

are the US, the UK and Portugal. As I do not expect the estimates to be accurate with a sample size of 132 observations I refrain from interpreting these results further. Still, further research could shed light on these patterns.

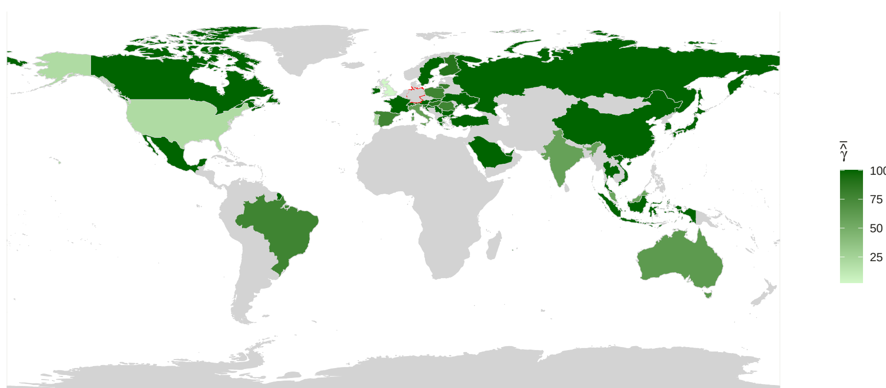


Figure 14: Estimated reorientation of German car exports

For US imports of consumer electronics again many results match intuitive expectations. As shown in figure 15 recovery is high for well-established trade partners, such as Canada, Germany and Japan.[13] Interestingly and in contrast to German car exports,

[13]See table 13 in the appendix for details.

recovery is weak for trade with Mexico and China. One possible explanation for this pattern are increased political tensions with those trading partners over the last decade. Trade with Russia, however, is estimated to recover quickly.
Reorientation, on the other hand, is estimated to be strong for almost all partner countries in this sample, except Mexico, Columbia and Malaysia. While for Mexico this behavior might stem from political tensions, the general pattern is not intuitively explainable and further research (as well as more data) is needed to properly assess the reorientation properties of the given sample.

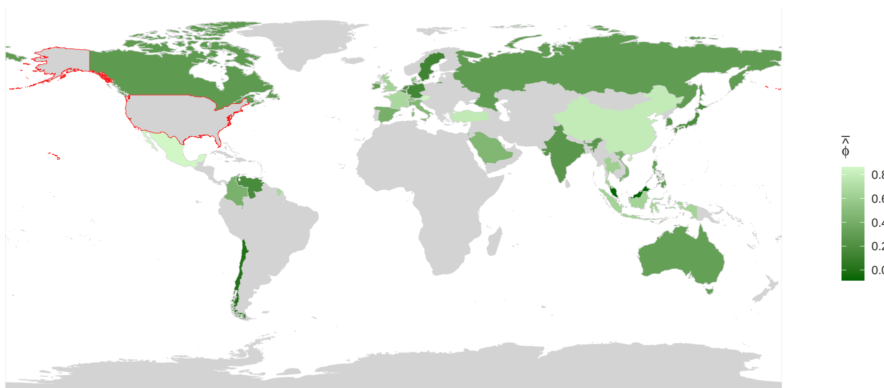


Figure 15: Estimated recovery of US consumer electronics imports

Generally these empirical exercises showcase how the STAR framework can be used to comparatively analyze resilience. The descriptive results overall underline the importance of well-established relationships in the context of resilient trade but do not necessarily support the call to "nearshoring", as voiced by e.g. the World Economic Forum (Betti & Hong, 2020). Naturally this is only the first step in understanding resilience, as further analysis of the underlying drivers is needed.

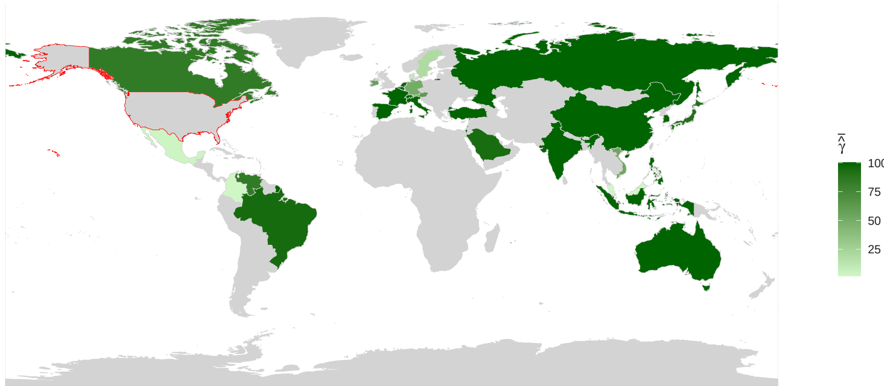


Figure 16: Estimated reorientation of US consumer electronics imports

# 11 Conclusion

In this thesis I presented how the concept of resilience can be operationalized in the context of trade and subsequently be parametrized and measured in a multiple regime STAR model framework. Following the literature I defined resilience as a two-dimensional concept entailing recovery and reorientation. Recovery refers to the speed at which a system is capable to return to its pre-crisis path following a shock, whereas reorientation denotes a system's ability to adjust to a new equilibrium. Recovery can be measured from the autoregressive coefficients in a STAR model while reorientation is captured by the smoothness parameter $\gamma$. Two main caveats have to be accounted for when estimating resilience through a STAR model approach. First, accurate estimation of reorientation is only possible in data rich environments. Second, when the model includes regimes with very low weight, estimation of recovery is likely to be inaccurate. In practice I therefore advise to consult the estimated weights in order to rule out such cases. Generally these insights allow for careful application of the outlined methods. I found the resulting estimates to be sensible and deem them as a good starting point to further analyze determinants of resilience.

Subsequent research can refine this approach in multiple ways. In the context of trade resilience, the theoretical foundation could be strengthened by modelling each regime as a gravity equation. Additionally, the generality of the approach could be widened by relaxing the assumption that each regime follows an AR(1) process. Recovery could then be measured from the impulse response function of the model. Moreover, as the model estimation is sensible to the choice of starting values I see potential in applying different selection procedures to make the estimation more robust.

The outlined procedure to measure resilience has multiple advantages over existing measures. First, the identified dimensions of resilience can be measured holistically within a single model, mitigating the risk of overlap of separate measures. Second, and in contrast to other measures, no subjective assessment of factors determining resilience had to be made to construct the measure. On the contrary, the resulting estimates allow for an objective analysis of determinants of resilience. Third, the parametrization of each dimension allows to test estimator performance which fosters greater understanding of the resulting estimates and mitigates the risk of wrong predictions of resilience.

Developing measures of resilience is a key step in understanding why some systems suffer less from crises than others. This thesis adds to the discussion by presenting a novel way of measuring resilience through parametrizing recovery and reorientation behavior of systems. I hope that subsequent research can build upon these insights to guide policy and system design that allows for mitigation of the welfare decreasing effect of crises. There is no doubt we will be in dire need of such.

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# Appendix

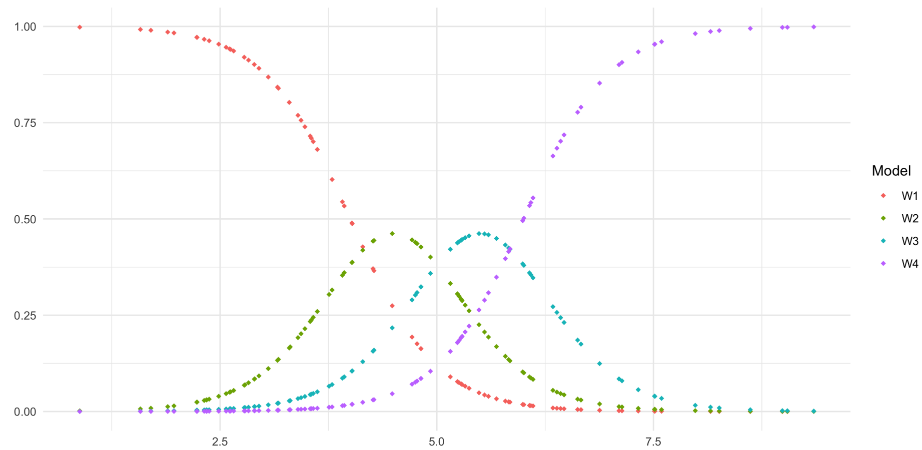


Figure 17: Regime weights in 4 regime MRSTAR model with parameters $\boldsymbol{\phi_1} = (3, 0.01)$, $\boldsymbol{\phi_2} = (8, 0.6)$, $\boldsymbol{\phi_3} = (7, 0.05)$, $\boldsymbol{\phi_4} = (0, 0.3)$, $\mathbf{c} = (4, 5, 6)$, $\gamma_1 = \gamma_2 = \gamma_3 = 2$ and $s_t = y_{t-1}$.

| T | $\bar{\gamma}$ | $\bar{\hat{\gamma}}$ | $\sigma_{\bar{\hat{\gamma}}}$ |
|---:|---:|---:|---:|
| 100 | 30 | 87.13 | 25.81 |
| 1000 | 30 | 82.22 | 35.63 |
| 10000 | 30 | 42.80 | 24.10 |
| 100000 | 30 | 38.30 | 10.56 |

Table 1: Accuracy of reorientation estimation

| $\bar{\phi}$ | $\sigma_\phi$ | $\bar{\hat{\phi}}$ | $\hat{\sigma}_\phi$ | $\bar{\gamma}$ | $\bar{\hat{\gamma}}$ | $\hat{\sigma}_\gamma$ | $\bar{\hat{M}}$ |
|---|---|---|---|---|---|---|---|
| 0.33 | 0.14 | 0.34 | 0.18 | 1.00 | 64.40 | 21.97 | 2.56 |
| 0.39 | 0.17 | 0.40 | 0.19 | 1.00 | 55.94 | 21.19 | 2.48 |
| 0.45 | 0.19 | 0.46 | 0.19 | 1.00 | 86.17 | 28.07 | 2.52 |
| 0.52 | 0.25 | 0.53 | 0.17 | 1.00 | 88.63 | 25.65 | 2.47 |
| 0.60 | 0.26 | 0.59 | 0.20 | 1.00 | 37.43 | 21.79 | 2.44 |

Table 2: Estimator performance for $\phi$ in two regime model, data for figure 7

| $\bar{\phi}$ | $\sigma_\phi$ | $\bar{\hat{\phi}}$ | $\hat{\sigma}_\phi$ | $\bar{\gamma}$ | $\bar{\hat{\gamma}}$ | $\hat{\sigma}_\gamma$ | $\bar{\hat{M}}$ |
|---|---|---|---|---|---|---|---|
| 0.20 | 0.04 | 0.25 | 0.19 | 1.00 | 88.33 | 25.35 | 2.65 |
| 0.30 | 0.08 | 0.31 | 0.19 | 1.00 | 77.91 | 23.32 | 2.54 |
| 0.40 | 0.13 | 0.36 | 0.18 | 1.00 | 83.19 | 27.44 | 2.56 |
| 0.50 | 0.18 | 0.43 | 0.17 | 1.00 | 19.73 | 26.44 | 2.58 |
| 0.60 | 0.20 | 0.45 | 0.17 | 1.00 | 39.54 | 22.69 | 2.58 |

Table 3: Estimator performance for $\phi$ in two regime model with large $c$, data for figure 8

| $\bar{\phi}$ | $\sigma_\phi$ | $\bar{\hat{\phi}}$ | $\hat{\sigma}_\phi$ | $\bar{\gamma}$ | $\bar{\hat{\gamma}}$ | $\hat{\sigma}_\gamma$ | $\bar{\hat{M}}$ |
|---|---|---|---|---|---|---|---|
| 0.25 | 0.11 | 0.31 | 0.20 | 10.00 | 58.62 | 24.33 | 2.42 |
| 0.25 | 0.13 | 0.27 | 0.20 | 30.00 | 69.06 | 22.69 | 2.45 |
| 0.25 | 0.11 | 0.26 | 0.20 | 50.00 | 86.67 | 27.76 | 2.42 |
| 0.25 | 0.10 | 0.26 | 0.22 | 70.00 | 89.42 | 23.52 | 2.46 |
| 0.25 | 0.11 | 0.23 | 0.19 | 90.00 | 88.11 | 24.43 | 2.42 |

Table 4: Estimator performance for $\gamma$ in two regime model, $T = 100$. Data for figure 10.

| $\bar{\phi}$ | $\sigma_\phi$ | $\bar{\hat{\phi}}$ | $\hat{\sigma}_\phi$ | $\bar{\gamma}$ | $\bar{\hat{\gamma}}$ | $\hat{\sigma}_\gamma$ | $\bar{\hat{M}}$ |
|---|---|---|---|---|---|---|---|
| 0.25 | 0.16 | 0.25 | 0.03 | 10.00 | 15.80 | 14.19 | 2.10 |
| 0.25 | 0.15 | 0.25 | 0.03 | 30.00 | 40.40 | 14.81 | 2.30 |
| 0.25 | 0.18 | 0.26 | 0.00 | 50.00 | 60.40 | 5.95 | 2.00 |
| 0.25 | 0.17 | 0.26 | 0.02 | 70.00 | 75.20 | 13.96 | 2.10 |
| 0.25 | 0.16 | 0.25 | 0.02 | 90.00 | 95.80 | 5.03 | 2.20 |

Table 5: Estimator performance for $\gamma$ in two regime model, $T = 1000000$. Data for figure 10.

| T | $\hat{M}$ | $\hat{\sigma}_M$ |
|---|---|---|
| 100.00 | 2.60 | 0.70 |
| 1000.00 | 2.30 | 0.48 |
| 10000.00 | 2.40 | 0.84 |
| 100000.00 | 2.10 | 0.32 |

Table 6: Accuracy of M estimation in two regime model

| T | $\hat{M}$ | $\hat{\sigma}_M$ |
|---|---|---|
| 100.00 | 2.30 | 0.67 |
| 1000.00 | 2.30 | 0.67 |
| 10000.00 | 2.70 | 0.48 |
| 100000.00 | 3.10 | 0.57 |

Table 7: Accuracy of M estimation in three regime model

| $\bar{\phi}$ | $\sigma_\phi$ | $\bar{\hat{\phi}}$ | $\hat{\sigma}_\phi$ | $\bar{\gamma}$ | $\bar{\hat{\gamma}}$ | $\hat{\sigma}_\gamma$ | $\bar{\hat{M}}$ |
|---|---|---|---|---|---|---|---|
| 0.21 | 0.11 | 0.23 | 0.17 | 1.00 | 14.23 | 25.81 | 2.48 |
| 0.31 | 0.13 | 0.33 | 0.18 | 1.00 | 85.78 | 26.19 | 2.58 |
| 0.41 | 0.17 | 0.42 | 0.19 | 1.00 | 33.49 | 26.46 | 2.53 |
| 0.51 | 0.21 | 0.49 | 0.20 | 1.00 | 45.67 | 25.78 | 2.49 |
| 0.60 | 0.24 | 0.57 | 0.20 | 1.00 | 90.84 | 27.87 | 2.62 |

Table 8: Estimator performance for $\phi$ in three regime model, data for figure 11

| $\bar{\phi}$ | $\sigma_\phi$ | $\bar{\hat{\phi}}$ | $\hat{\sigma}_\phi$ | $\bar{\gamma}$ | $\bar{\hat{\gamma}}$ | $\hat{\sigma}_\gamma$ | $\bar{\hat{M}}$ |
|---|---|---|---|---|---|---|---|
| 0.23 | 0.10 | 0.31 | 0.18 | 10.00 | 62.14 | 23.94 | 2.53 |
| 0.23 | 0.11 | 0.35 | 0.19 | 30.00 | 69.75 | 24.48 | 2.44 |
| 0.23 | 0.09 | 0.33 | 0.20 | 50.00 | 84.92 | 28.07 | 2.56 |
| 0.23 | 0.09 | 0.31 | 0.18 | 70.00 | 86.16 | 26.02 | 2.43 |
| 0.23 | 0.10 | 0.33 | 0.19 | 90.00 | 89.59 | 23.24 | 2.43 |

Table 9: Estimator performance for $\gamma$ in three regime model, data for figure 12

| Partner | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| BGR | 132 | 43,830,980.000 | 13,147,368.000 | 15,865,656 | 33,478,202 | 53,494,054.0 | 70,213,341 |
| CAN | 132 | 265,837,375.000 | 63,540,491.000 | 24,840,409 | 223,979,635 | 307,849,043.0 | 421,246,929 |
| CHN | 132 | 2,006,777,888.000 | 413,522,440.000 | 934,759,048 | 1,682,478,396.0 | 2,304,412,912.0 | 2,937,445,824 |
| HRV | 132 | 38,337,589.000 | 16,893,281.000 | 10,046,866 | 24,817,667 | 50,258,280.0 | 81,243,311 |
| CZE | 132 | 442,265,036.000 | 83,172,999.000 | 148,639,133 | 387,069,916.0 | 500,254,997.0 | 616,912,966 |
| DNK | 132 | 186,606,171.000 | 46,353,497.000 | 79,803,076 | 153,338,632.0 | 216,759,543.0 | 313,377,400 |
| FIN | 132 | 153,203,196.000 | 31,677,899.000 | 40,759,555 | 131,345,326.0 | 171,159,984.0 | 235,135,416 |
| FRA | 132 | 1,454,807,080.000 | 249,224,012.000 | 282,382,297 | 1,330,751,118 | 1,623,358,854 | 1,965,797,714 |
| GRC | 132 | 40,103,245.000 | 12,289,009.000 | 7,720,975 | 31,744,988.0 | 47,174,649.0 | 89,947,557 |
| HKG | 132 | 61,964,372.000 | 20,576,877.000 | 9,712,588 | 47,514,902.0 | 75,411,817.0 | 134,165,112 |
| HUN | 132 | 308,880,552.000 | 76,377,193.000 | 121,669,555 | 243,791,659.0 | 367,251,371.0 | 477,518,885 |
| AUS | 132 | 268,114,140.000 | 51,672,405.000 | 28,141,574 | 241,624,094.0 | 295,137,153.0 | 390,025,925 |
| IDN | 132 | 13,110,284.000 | 6,357,237.000 | 466,412 | 8,926,220.0 | 16,594,368.0 | 37,650,203 |
| IRL | 132 | 55,504,246.000 | 26,061,733.000 | 11,085,019 | 31,648,350.0 | 76,714,323.0 | 118,249,340 |
| ISR | 132 | 57,950,211.000 | 15,558,774.000 | 8,921,855 | 48,450,410.0 | 68,549,803 | 103,103,865 |
| ITA | 132 | 1,019,412,395.000 | 240,121,007.000 | 194,815,354 | 879,603,275 | 1,184,099,496.0 | 1,593,145,521 |
| JPN | 132 | 503,746,790.000 | 123,646,239.000 | 72,730,282 | 430,289,051 | 579,905,710.0 | 804,749,715 |
| AUT | 132 | 642,874,841.000 | 106,363,347.000 | 239,190,304 | 576,023,520.0 | 715,174,396.0 | 917,893,086 |
| KOR | 132 | 430,729,917.000 | 162,580,050.000 | 121,496,406 | 291,069,744.0 | 532,816,656.0 | 877,832,193 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| LTU | 132 | 47,718,575.000 | 18,035,222.000 | 8,471,497 | 34,043,540.0 | 61,518,132.0 | 90,750,343 |
| LUX | 132 | 75,906,641.000 | 14,781,144.000 | 22,994,085 | 66,404,030.0 | 85,621,411 | 112,856,705 |
| MYS | 132 | 43,957,198.000 | 11,377,834.000 | 10,131,095 | 38,151,126.0 | 51,332,279.0 | 66,406,237 |
| MEX | 132 | 197,476,390.000 | 55,626,411.000 | 60,000,972 | 153,355,505 | 239,101,988.0 | 353,107,721 |
| NLD | 132 | 609,756,714.000 | 123,069,514.000 | 234,260,787 | 531,389,806.0 | 690,128,414.0 | 1,021,871,773 |
| BEL | 132 | 692,665,767.000 | 127,888,020.000 | 167,234,197 | 619,851,798.0 | 776,211,128 | 995,358,252 |
| NOR | 132 | 231,638,206.000 | 40,665,998.000 | 62,827,788 | 206,148,816.0 | 256,637,947 | 335,676,195 |
| POL | 132 | 568,772,533.000 | 115,470,276.000 | 236,913,547 | 494,956,154.0 | 655,050,550.0 | 853,601,679 |
| PRT | 132 | 168,819,262.000 | 38,218,249.000 | 38,975,124 | 139,371,144.0 | 193,176,110.0 | 252,453,403 |
| ROU | 132 | 184,536,198.000 | 65,690,162.000 | 70,152,134 | 127,230,523.0 | 241,646,888.0 | 328,236,567 |
| RUS | 132 | 468,920,919.000 | 227,051,521.000 | 76,879,693 | 316,739,369.0 | 643,344,933.0 | 1,025,576,746 |
| SAU | 132 | 107,933,883.000 | 42,339,731.000 | 24,827,997 | 69,931,475.0 | 144,344,455.0 | 206,919,435 |
| SRB | 132 | 25,026,054.000 | 7,272,181.000 | 9,872,811 | 19,376,020 | 30,604,801 | 43,842,435 |
| IND | 132 | 50,968,174.000 | 13,720,038.000 | 14,908,796 | 42,595,887.0 | 60,262,792.0 | 80,296,782 |
| SGP | 132 | 66,124,642.000 | 15,508,088.000 | 21,299,453 | 57,367,387.0 | 75,977,840 | 113,379,664 |
| SVK | 132 | 233,400,631.000 | 63,307,114.000 | 76,033,173 | 185,514,064.0 | 274,614,228.0 | 404,045,329 |
| VNM | 132 | 12,918,442.000 | 6,173,098.000 | 2,834,017 | 7,811,984.0 | 17,633,376 | 28,888,586 |
| SVN | 132 | 63,547,824.000 | 20,836,179.000 | 25,820,407 | 46,501,164.0 | 77,927,982.0 | 160,869,562 |
| ZAF | 132 | 249,119,928.000 | 57,197,704.000 | 27,830,390 | 222,787,365.0 | 287,024,786.0 | 400,657,411 |
| ESP | 132 | 769,648,143.000 | 173,746,737.000 | 107,720,624 | 670,395,804.0 | 889,207,334.0 | 1,103,228,610 |
| SWE | 132 | 441,233,563.000 | 78,024,687.000 | 118,712,707 | 394,346,291 | 488,960,577.0 | 629,762,815 |
| CHE | 132 | 497,410,528.000 | 84,824,747.000 | 146,846,305 | 439,883,048.0 | 550,416,846.0 | 692,075,255 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| BRA | 132 | 119,214,223.000 | 43,138,578.000 | 28,313,347 | 89,198,126 | 148,984,752.0 | 255,709,191 |
| THA | 132 | 41,399,114.000 | 14,246,419.000 | 9,490,797 | 30,104,594.0 | 50,196,838.0 | 80,089,759 |
| ARE | 132 | 136,515,771.000 | 46,778,637.000 | 25,408,808 | 100,783,957.0 | 169,867,106 | 270,350,282 |
| TUR | 132 | 420,016,346.000 | 140,111,027.000 | 55,480,266 | 310,904,526.0 | 535,464,078 | 657,578,997 |
| UKR | 132 | 60,445,784.000 | 20,697,311.000 | 20,795,253 | 44,918,229.0 | 73,514,940 | 116,487,508 |
| EGY | 132 | 44,843,575.000 | 18,099,932.000 | 16,846,187 | 31,541,348.0 | 56,679,884 | 100,185,698 |
| GBR | 132 | 2,170,885,853.000 | 499,635,467.000 | 275,051,996 | 1,871,747,216.0 | 2,506,996,340.0 | 3,334,326,958 |
| USA | 132 | 2,461,006,639.000 | 570,297,487.000 | 276,859,471 | 2,135,217,389 | 2,839,994,602.0 | 3,706,873,086 |

Table 10: Summary statistics of German car exports

| Partner | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| CAN | 132 | 650,694,049.000 | 68,218,275.000 | 400,171,406 | 610,804,390.0 | 686,490,133.0 | 901,110,924 |
| CHL | 132 | 1,261,311.000 | 3,747,355.000 | 82,727 | 393,611.2 | 1,332,105.0 | 42,923,062 |
| CHN | 132 | 10,414,223,628.000 | 2,344,059,260.000 | 5,166,466,006 | 8,727,492,464.0 | 11,809,391,554.0 | 17,089,364,034 |
| COL | 132 | 5,146,568.000 | 3,213,432.000 | 860,259 | 2,753,783 | 6,807,478 | 15,576,890 |
| DNK | 132 | 56,078,456.000 | 38,728,403.000 | 23,684,973 | 32,363,308.0 | 59,168,316.0 | 203,570,563 |
| FRA | 132 | 172,554,032.000 | 28,342,804.000 | 116,900,707 | 152,815,390.0 | 197,012,482.0 | 255,654,002 |
| DEU | 132 | 669,945,941.000 | 78,372,445.000 | 362,476,446 | 630,084,152.0 | 718,586,206 | 811,718,286 |
| HKG | 132 | 67,025,203.000 | 21,947,996.000 | 19,050,767 | 55,554,726 | 79,861,356.0 | 128,233,549 |
| AUS | 132 | 20,057,899.000 | 4,008,067.000 | 11,455,402 | 17,104,291 | 22,783,670.0 | 31,291,542 |
| IDN | 132 | 140,129,193.000 | 26,561,756.000 | 82,556,415 | 123,214,916.0 | 154,457,185 | 220,378,759 |
| IRL | 132 | 74,952,936.000 | 87,256,536.000 | 9,625,534 | 15,023,918 | 108,376,716.0 | 494,671,873 |
| ISR | 132 | 140,893,142.000 | 30,921,277.000 | 98,927,465 | 119,461,416.0 | 153,156,298.0 | 243,512,609 |
| ITA | 132 | 157,123,214.000 | 31,055,999.000 | 105,697,571 | 137,139,832.0 | 170,548,249 | 276,851,482 |
| JPN | 132 | 1,485,394,709.000 | 175,865,632.000 | 890,618,389 | 1,363,031,942.0 | 1,599,376,711 | 1,997,142,591 |
| AUT | 132 | 92,414,044.000 | 25,536,378.000 | 41,618,549 | 71,562,619 | 109,766,932.0 | 151,028,100 |
| KOR | 132 | 1,249,110,867.000 | 176,940,219.000 | 921,714,215 | 1,131,583,281.0 | 1,358,990,477.0 | 1,678,334,891 |
| MYS | 132 | 1,667,791,209.000 | 512,917,741.000 | 738,026,798 | 1,169,501,422 | 2,106,188,467 | 2,829,038,830 |
| MEX | 132 | 4,969,776,313.000 | 637,556,982.000 | 2,516,159,022 | 4,598,798,446 | 5,351,519,615 | 7,035,172,113 |
| NLD | 132 | 51,111,450.000 | 11,435,741.000 | 29,990,263 | 43,476,439 | 58,442,020 | 90,514,305 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| BEL | 132 | 40,228,528.000 | 6,319,671.000 | 26,459,547 | 35,230,942 | 44,456,582.0 | 56,195,637 |
| BMU | 98 | 54,899.540 | 140,129.200 | 2,575.000 | 7,971.000 | 25,271.500 | 888,500.000 |
| PHL | 132 | 336,166,676.000 | 47,289,346.000 | 220,287,139 | 300,549,506.0 | 370,400,012.0 | 483,288,899 |
| RUS | 132 | 6,743,425.000 | 2,576,488.000 | 2,080,265 | 5,020,224 | 8,282,375.0 | 14,857,100 |
| SAU | 132 | 2,930,001.000 | 3,143,389.000 | 20,412 | 275,159.2 | 4,558,775.0 | 12,874,448 |
| IND | 132 | 137,400,467.000 | 44,741,013.000 | 91,229,658 | 110,605,034.0 | 143,464,578.0 | 320,468,797 |
| SGP | 132 | 222,609,774.000 | 32,287,458.000 | 146,360,620 | 200,087,027 | 240,878,466.0 | 334,048,174 |
| VNM | 132 | 754,057,516.000 | 753,996,357.000 | 50,716,626 | 127,655,358.0 | 1,049,244,258 | 3,479,301,738 |
| ESP | 132 | 63,973,014.000 | 33,004,878.000 | 21,908,227 | 37,482,344.0 | 81,611,044.0 | 158,188,820 |
| SWE | 132 | 73,079,279.000 | 30,007,527.000 | 42,473,154 | 54,335,074.0 | 81,189,666 | 214,174,583 |
| CHE | 132 | 102,559,493.000 | 13,085,045.000 | 70,343,063 | 93,878,120 | 109,726,491.0 | 136,956,459 |
| BRA | 132 | 49,637,683.000 | 10,456,494.000 | 28,394,534 | 43,691,517.0 | 56,024,091 | 84,812,276 |
| THA | 132 | 622,542,937.000 | 122,873,792.000 | 360,020,801 | 551,103,967.0 | 685,423,500.0 | 1,032,856,682 |
| TUR | 132 | 14,931,446.000 | 8,635,653.000 | 2,604,036 | 8,700,647 | 21,284,594.0 | 38,246,345 |
| GBR | 132 | 225,663,505.000 | 24,541,931.000 | 153,676,698 | 210,817,425 | 236,627,561.0 | 291,285,356 |
| VEN | 132 | 2,903,445.000 | 1,444,111.000 | 34,120 | 1,776,041.0 | 3,913,795 | 6,528,287 |

Table 11: Summary statistics of US consumer electronic imports

| Trade Partner | $\bar{\hat{\phi}}$ | $\bar{\hat{\gamma}}$ |
|---|---|---|
| ARE | 0.56 | 100.00 |
| AUS | 1.34 | 62.67 |
| AUT | 0.26 | 100.00 |
| BGR | 0.25 | 100.00 |
| BRA | 0.70 | 78.00 |
| CAN | 0.00 | 100.01 |
| CHE | 0.61 | 100.04 |
| CHN | 0.43 | 100.00 |
| CZE | 0.36 | |
| EGY | 0.96 | |
| ESP | 0.43 | 77.50 |
| FIN | 0.09 | 89.72 |
| FRA | 0.60 | 100.00 |
| GBR | 0.40 | 2.51 |
| GRC | 0.47 | 100.00 |
| HKG | 0.62 | 100.00 |
| HRV | 0.65 | 100.00 |
| HUN | 0.54 | 88.00 |
| IDN | 0.46 | 100.00 |
| IND | 0.30 | 58.00 |
| IRL | 0.68 | 100.00 |
| ISR | 0.32 | |
| ITA | 0.36 | 60.00 |
| JPN | 0.51 | 100.00 |
| KOR | 0.50 | 100.00 |
| LTU | 0.53 | 83.00 |
| MEX | 0.26 | 100.00 |

| | | |
|---|---|---|
| MYS | 0.15 | 55.01 |
| POL | 0.64 | 77.96 |
| PRT | 0.44 | 20.00 |
| ROU | 0.73 | 78.00 |
| RUS | 0.72 | 100.00 |
| SAU | 0.41 | 100.00 |
| SGP | 0.33 | 63.00 |
| SRB | 0.42 | 100.00 |
| SVK | 0.52 | 100.00 |
| SVN | 0.48 | 100.00 |
| SWE | 0.60 | 100.00 |
| THA | 0.58 | 100.00 |
| TUR | 0.39 | 100.00 |
| UKR | 0.55 | 100.00 |
| USA | 0.55 | 20.00 |
| VNM | 0.66 | 100.00 |

Table 12: Estimated recovery and reorientation of German car exports

| Trade Partner | $\bar{\hat{\phi}}$ | $\bar{\hat{\gamma}}$ |
|---|---|---|
| AUS | 0.31 | 100.00 |
| AUT | 0.85 | 62.00 |
| BEL | 0.24 | 100.00 |
| CAN | 0.28 | 84.00 |
| CHE | 0.51 | 100.00 |
| CHL | 0.00 | |
| CHN | 0.78 | 100.00 |
| COL | 0.42 | 2.48 |

| | | |
|---|---|---|
| DEU | 0.15 | 50.45 |
| DNK | 0.51 | 10.00 |
| ESP | 0.41 | 100.00 |
| FRA | 0.66 | 100.00 |
| GBR | 0.62 | |
| HKG | 0.72 | 62.00 |
| IDN | 0.64 | 100.00 |
| IND | 0.26 | 100.00 |
| IRL | 0.30 | 58.00 |
| ISR | 0.55 | 100.00 |
| ITA | 0.46 | 100.00 |
| JPN | 0.18 | 90.67 |
| KOR | 0.24 | 100.00 |
| MEX | 0.86 | 4.07 |
| MYS | 0.01 | 2.13 |
| NLD | 0.21 | 100.00 |
| PHL | 0.30 | 100.00 |
| RUS | 0.29 | 100.00 |
| SAU | 0.46 | 94.00 |
| SGP | 0.55 | 63.00 |
| SWE | 0.13 | 19.72 |
| THA | 0.61 | |
| TUR | 0.77 | 100.00 |
| VEN | 0.18 | 84.00 |
| VNM | 0.43 | 54.00 |

Table 13: Estimated recovery and reorientation of US consumer electronics imports