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Fernando
de la Torre Cuevas

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Expanding hybrid approaches to construct (inter)regional input-output models

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TESE DE DOUTORAMENTO

EXPANDING HYBRID APPROACHES TO CONSTRUCT (INTER)REGIONAL INPUT-OUTPUT MODELS

Fernando de la Torre Cuevas

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D. Fernando de la Torre Cuevas

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Expanding hybrid approaches to construct (inter)regional input-output models

D. Edelmiro López Iglesias e D. Xesús Pereira López

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Os resultados presentes nesta memoria foron obtidos coa axuda do financiamento da Consellería de Educación, Universidade e Formación Profesional da Xunta de Galicia a través das axudas de apoio á etapa predoutoral nas universidades do Sistema universitario de Galicia, nos organismos públicos de investigación de Galicia e noutras entidades do Sistema galego de I+D+i (códigos de procedemento ED481A e IN606A) cofinanciadas polo programa operativo Fondo Social Europeo Galicia 2014-2020.

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ABSTRACT

Regional input-output analysis is a widely used tool for regional scientists to study economic, social and environmental phenomena. Ever since its first steps, regional input-output analysis has suffered from the lack of adequate and detailed data at different subnational levels. The problem becomes particularly acute in less developed regions, where resources to gather information are seldom available. Scholars agree in that hybrid approaches to construct regional input-output models are the most cost-effective alternative. The aim of this thesis is to expand the toolbox that regional input-output modellers have in hand with new hybrid techniques. In this vein, I introduce three methodological alternatives that relax information requirements to solve certain modelling challenges. I provide a mathematical description of my methods and contrast my estimates against published data to assess how accurate our results are. I show it is still possible to expand the scope of regional input-output studies looking for techniques with flexible and efficient combinations of superior data and non-survey estimates.

RESUMO

Desde unha perspectiva económica, o desenvolvemento rexional ten cando menos tres dimensións: temporal, espacial e industrial. En primeiro lugar, o paso do tempo é necesario para que as economías evolucionen seguindo unha secuencia que normalmente vai desde os procesos de innovación cara o cambio estrutural. A perspectiva espacial é menos obvia, pero clave para a ciencia rexional. Por unha banda, a proximidade xeográfica, cultural e idiosincrática entre rexións favorece os intercambios económicos e de coñecemento entre territorios. Por outra, as rexións inflúen unhas noutras a través dos fluxos de investimento, o comercio, o consumo, a mobilidade da forza de traballo, etc. Por último, as conexións interindustriais inflúen no comportamento estratéxico dos axentes e son canles polas que tamén viaxan fluxos de coñecemento e innovacións. As ligazóns entre industrias poden expresarse a través das táboas e modelos input-output.

Desde os seus comezos, a análise input-output a nivel rexional sufriu pola ausencia de datos detallados necesarios para a construción de modelos. O problema faise particularmente agudo en aqueles países ou rexións menos desenvolvidos, dada a escaseza de recursos dispoñibles para conseguir a información necesaria. Ante esta dificultade, as persoas interesadas nos estudos rexionais poden (i) enfocar os seus intereses en liñas de investigación que demanden menos datos, (ii) realizar as súas investigacións en torno a rexións provedoras de bases de datos consolidadas ou (iii) obter os datos que precisan a través da observación directa ou e estimacións indirectas.

A presente tese busca expandir a caixa de ferramentas para aquelas persoas que opten pola terceira das opcións expostas. Na literatura especializada existe consenso á hora de sinalar os métodos de modelización híbridos como os máis custe-eficientes. Os métodos híbridos para a construción de modelos input-output caracterízanse por combinar datos derivados da observación directa (p. ex.: a través de enquisas) con estimacións derivadas doutras fontes de información. En liñas xerais, o propósito desta investigación é flexibilizar os requirimentos de información para a construción de modelos input-output rexionais combinando datos extraídos da observación directa e estimacións indirectas— isto é, a través de métodos híbridos. Este obxectivo xeral dá sentido aos catro capítulos que constitúen o núcleo fundamental da tese.

Capítulo 2. Unha revisión xeral da literatura que motiva a nosa investigación

O capítulo 2 está dedicado a motivar axeitadamente a nosa investigación. En primeiro lugar, discutimos como a análise input-output mantivo historicamente e mantén na actualidade unha intensa relación coa ciencia rexional. Durante a segunda metade do século XX, os modelos input-output rexionais tiveron gran protagonismo na literatura e serviron para a o estudo de cuestións relacionadas co crecemento económico, dos impactos sociais da política pública, as interaccións entre economía e medio ambiente, entre outros moitos temas. Na actualidade, a análise input-output rexional segue a ser un campo de estudo fértil. Entre as liñas de investigación que atopamos na literatura destacan:

- En primeiro lugar, os modelos input-output, tamén a nivel rexional, poden empregarse como base para a análise económica estrutural e os modelos de crecemento. Desde unha perspectiva estática, podemos mencionar neste apartado as análises de sectores clave ou os estudos de extracción hipotética. Desde unha perspectiva dinámica, as táboas input-output rexionais serven de base para estudar a contabilidade do crecemento, realizar análises de descomposición estrutural e análises de tipo *shift-share*.
- Así mesmo, as análises da economía ecolóxica (ou ecoloxía industrial) tamén empregan asiduamente este tipo de instrumentos para modelar as interaccións entre economía e medio ambiente. Modelar estas interaccións a nivel rexional resulta relevante en tanto que moitos impactos medioambientais, a pesar de teren causas globais, producen impactos altamente localizados territorialmente.
- En terceiro lugar, as táboas input-output constitúen unha das bases sobre as que se constrúen normalmente os modelos de equilibrio xeral computable. Os modelos de equilibrio xeral son, seguramente, un dos instrumentos máis empregados a nivel rexional para medir os impactos locais das políticas aplicadas por distintos niveis de goberno. Así mesmo, permiten aproximar a resposta dunha economía rexional ante posibles perturbacións.
- Relacionados cos anteriores, os modelos input-output econométricos tamén presentan certa relevancia para o estudo de temáticas rexionais. Nalgunhas ocasións, estes modelos toman como variables indicadores derivados máis ou menos directamente das táboas input-output. Noutras, os modelos econométrico e input-output retroaliméntanse.

Por último, algúns autores empregan os coeficientes derivados das táboas input-output para ponderar as regresións nos seus modelos.

- Outros desenvolvementos actuais da análise input-output a nivel rexional. Estes inclúen a endoxeneización dos fogares empregando matrices de contabilidade social, a síntese con modelos demográficos, a introdución de maior heteroxeneidade nos distintos axentes (industrias, fogares, etc.) ou a medición dos fenómenos relacionados coa economía dixital.

A dispoñibilidade ou ausencia de información é un tema recorrente dentro da ciencia rexional desde os seus inicios como disciplina. A gran variedade de liñas de investigación rexional que empregan —de maneira máis ou menos directa— a análise input-output vense limitadas en moitas ocasións pola ausencia de datos.

Nun primeiro momento, as contribucións relacionadas con modelos input-output a nivel (inter)rexional deixaban entrever un certo grao de optimismo respecto da cuestión dos datos. Este optimismo foi confirmado durante décadas pola elaboración de táboas input-output rexionais nun considerable número de países. Estas táboa eran construídas en base a información obtida por observación directa a través de enquisas a empresas, fogares, etc. Porén, a expansión do interese nos modelos input-output rexionais e a crecente capacidade de computación fixeron que a demanda de modelos superase con moito a capacidade dos institutos de estatística e dos investigadores para ofertalos.

Estimulados por este desequilibrio no mercado de modelos input-output rexionais, observamos na literatura unha gran variedade de contribucións que propoñen métodos de estimación indirectos. Estes métodos agrúpanse normalmente baixo a etiqueta de métodos *non-survey*, en contraposición a aqueles baseados en observacións directas. Moitos destes métodos enfócanse á estimación das distintas tecnoloxías rexionais a partir de observacións realizadas a nivel nacional. Outros céntranse na estimación dos fluxos comerciais entre rexións. Pese ao seu éxito, que continúa na actualidade, os modelos *non-survey* espertaron certo criticismo. Por unha banda, as estimacións derivadas destes modelos incorren en niveis de erro non aceptables cando son comparadas con datos derivados de enquisas. Por outra, algúns autores sinalan que moitos destes métodos carecen dun fundamento teórico sólido.

Os modelos híbridos xorden como unha sorte de compromiso entre métodos para a elaboración de táboas input-output baseados na observación directa (*survey*) e aqueles que empregan estimacións indirectas (*non-survey*). En esencia, os modelos híbridos combinan en distintas proporcións información obtida directa e indirectamente. Na actualidade semella existir un consenso en torno aos enfoques híbridos en tanto que alternativas máis custo-eficientes. Isto é especialmente certo a nivel rexional, dada a maior escaseza de recursos para a recollida directa de información. Podemos discernir tres principios que deben guiar a construción de modelos input-output híbridos a nivel rexional: (i) seleccionar axeitadamente o método *non-survey* a empregar para obter estimacións indirectas, (ii) concentrar os recursos dispoñibles para observar directamente aquela información que sexa máis relevante para o modelo e (iii) maximizar o emprego de datos certos —derivados de enquisas ou de estatísticas consolidadas— formalizando procedementos flexibles que permitan incorporalos á modelaxe. A presente tese ocúpase de estudar a implementación do terceiro principio en tres situacións específicas. Estas recóllense nos capítulos 3, 4 e 0.

Capítulo 3. Saltando sobre a información conflitiva

No capítulo 3 propoñemos unha alternativa metodolóxica para xestionar problemas derivados de conflitos de información á hora de axustar táboas input-output. Na literatura, e tamén na práctica, os métodos iterativos proporcionais son a alternativa máis empregada para o axuste de táboas input-output. O axuste iterativo proporcional, referido na literatura input-output como método RAS, permite estimar táboas combinando dúas pezas de información fundamentais: (i) un par de vectores que conteñen a suma das filas e das columnas da matriz a estimar e (ii) unha matriz que serve como base da estimación.

Pese á súa sinxeleza e efectividade, a aplicación do método RAS ou das súas distintas variantes pode verse comprometida ante a presencia de información conflitiva. Ao operar o método RAS de maneira multiplicativa, estes conflitos tenden a aparecer cando existe unha gran cantidade de celas nulas na matriz que serve como base para a estimación. Os conflitos de información poden facer que o método RAS non sexa capaz de chegar a unha solución no proceso de axuste. Así mesmo, pode suceder que exista unha solución matemática ao problema pero que esta careza de sentido económico.

Existe unha variedade de alternativas metodolóxicas descritas na literatura para circunvalar este tipo de problemas. Podemos agrupalas en tres grandes bloques.

- En primeiro lugar, os métodos baseados na programación lineal ou cuadrática ofrecen unha maior flexibilidade á hora de abordar estes problemas e, ata certo punto, equivalentes ao método RAS. Porén, cando xorden conflitos estes métodos tenden a incluír medidas de confianza nas distintas pezas de información que deben derivarse do xuízo de expertos (p. ex.: enxeñeiros ou estatísticos). En ausencia do mesmo, o investigador debe realizar unha escolla discrecional.
- En segundo lugar, algúns autores suxiren a substitución dalgunha cela nula por un valor o suficientemente pequeno. En favor desta alternativa arguméntase que moitos ceros nas matrices input-output aparecen debido aos procesos de redondeo. Porén, non é posible discernir estes casos daqueles onde unha cela nula representa un feito tecnolóxico verdadeiro. Substituír algúns ceros por valores pequenos pode introducir distorsións no modelo rexional ao contar relacións entre industrias onde en realidade non as hai.
- Por último, un terceiro bloque de propostas metodolóxicas céntrase en modificar o par de vectores que conteñen a suma das filas e das columnas da matriz a estimar para converter facer factible o axuste. Dentro destes métodos destaca o *konfliktfreies* RAS (KRAS), o cal é considerado o estado da arte na actualidade. Unha das principais virtudes do KRAS é que non precisa de información externa nin escollas discrecionais para resolver conflitos de información.

Pese á súa versatilidade e solidez, o método KRAS presenta tamén algunhas oportunidades de melloras que non foron aínda exploradas. Estas inclúen: a preservación dos principais agregados macroeconómicos das táboas input-output, a prevención fronte a posibles cambios non desexados nos signos dos fluxos recollidos na matriz, e evitar resolver o problema de axuste en base a un proceso de tenteo.

En consecuencia, presentamos unha modificación do método KRAS. A nosa proposta modifica os vectores que conteñen as sumas das filas e columnas desexadas para que o método RAS poida axustar a matriz. O noso algoritmo emprega información contida na matriz tomada como base, así como daquelas xeradas tras cada iteración no proceso, para realizar as modificacións nos vectores. O algoritmo asegura unha solución que preserva os principais agregados macroeconómicos, prevén cambios de signo non desexados e evitar o proceso de tenteo característico do método KRAS. Para ilustrar os nosos achados, realizamos un experimento empírico baseado nas táboas de orixe-destino de Galicia. Os nosos resultados suxiren que a nosa proposta metodolóxica é capaz de estimar táboas input-output cun nivel de precisión similar ao do método KRAS, evitando aquelas fallas que foron sinaladas como oportunidades de mellora.

Capítulo 4. Un camiño cara as táboas de orixe-destino en prezos constantes

No capítulo 4 presentamos unha alternativa metodolóxica para deflatar táboas de orixe-destino, pasando de prezos correntes a prezos constantes. As táboas de orixe-destino son unha peza fundamental dentro do sistema nacional de contas establecido polas Nacións Unidas. As táboas de orixe-destino aseguran (i) a contabilidade sistemática dos datos macroeconómicos, (ii) a consistencia entre as contas de produción de bens e servizos e as contas de ingresos e (iii) valores coherentes do produto interior bruto e doutros indicadores, tanto a nivel nacional como entre países. As táboas de orixe-destino son, ademais, a base sobre a cal se constrúen os modelos input-output tanto a nivel nacional como rexional.

De maneira xeral, os modelos presentes literatura económica distinguen as variacións operadas nos prezos das mercadorías e nas correspondentes cantidades producidas e comerciadas. Os modelos input-output non son unha excepción, tampouco a nivel rexional. Existen varios motivos polos cales é de interese obter un conxunto coherente de táboas de orixe-destino medidas a prezos correntes e a prezos constantes:

- En primeiro lugar, as táboas de orixe-destino son necesarias para medir o cambio estrutural. Este manifístase normalmente a través de cambios na tecnoloxía de produción dun ben ou servizo. Se consideramos datos unicamente medidos a prezos correntes, posibles variacións nos prezos relativos dos bens poden levarnos a crer que existe unha redistribución da actividade económica en favor das industrias onde os prezos medran a maior ritmo. Porén, pode suceder que a cantidade de bens producida ou comerciada por estes sectores se manteña constante, dando lugar a resultados enganosos. Algo semellante pode suceder se os niveis de prezos dunha mesma mercadoría varían con distinta intensidade entre rexións. Neste caso, posibles análises interrexionais poderían verse afectadas negativamente.

- En segundo lugar, o cálculo dos prezos necesario para a deflación das táboas de orixe-destino permite vincular os modelos input-output expresados en cantidades físicas con aqueles expresados en unidades monetarias. En principio, a relación entre ambos tipos de modelos é sinxela: o valor dun fluxo monetario é igual á cantidade comerciada multiplicada polo seu prezo unitario. Desde un punto de vista dinámico, os prezos dunha mesma mercadoría poden variar en distintas proporcións dependendo de que sector estea a mercala, de como sexa a estrutura do mercado onde se comercia, entre outros factores. En termos dunha matriz input-output: non basta con dispoñer de índices de prezos únicos para cada mercadoría, estes deben ser específicos para cada elemento da matriz.
- En terceiro lugar, existen unha serie de factores institucionais que requiren a elaboración de táboas de orixe-destino a prezos correntes e constantes. En primeiro lugar, o sistema nacional de contas das Nacións Unidas sinala que esta é a vía máis recomendable para obter unha contabilidade nacional (ou rexional) coherente en termos monetarios e de volumes físicos. En segundo lugar, certas políticas públicas comezan a introducir indicadores medidos a prezos constantes (p. ex.: o Pacto de Estabilidade e Crecemento da Unión Europea).

Dentro das alternativas dispoñibles para a deflación de táboas de orixe-destino o método de dobre deflación é o empregado habitualmente. Este método presenta algún inconvenientes sinalados na literatura. Como alternativa, algún autores propoñen o emprego do método RAS para a deflación. Este enfoque é preferido desde o punto de vista teórico e tense demostrado máis acertado en varios experimentos empíricos. O problema para a súa implementación sitúase normalmente nos seus elevados requirimentos de información, especialmente cando se trata de empregalo a nivel rexional ou en países menos desenvolvidos.

Co obxectivo de facilitar o uso do método RAS para a deflación de prezos neste capítulo presentamos unha alternativa metodolóxica con tres características fundamentais. En primeiro lugar, flexibilizamos os requirimentos de información. O noso algoritmo pode ser empregado incluso cando unicamente dispoñemos de información agregada sobre o volume da produción, a demanda final e as importacións. De dispoñer de información adicional, esta pode ser incorporada ao algoritmo. En segundo lugar, o noso método produce deflatores de prezos específicos para cada elemento das táboas de orixe-destino. En terceiro lugar, podemos xestionar posibles incoherencias na información dispoñible dunha maneira transparente, evitando solucións *ad hoc*. Por último, o noso método permite asignar distintos graos de confianza á información contida nas táboas de orixe e destino de maneira separada.

Para contrastar o desempeño da nosa proposta metodolóxica, realizamos un experimento empírico coas táboas de orixe-destino dos 27 países da Unión Europea. Nun escenario de mínima información, o noso algoritmo realiza peores estimacións que a súa competencia (máis demandante de datos). Porén, o noso método é capaz de estimar o valor engadido bruto a prezos constantes mellor que o de dobre deflación para unha maioría de países. Cando introducimos pezas adicionais de información, o desempeño mellora substancialmente. As nosas estimacións superan en xeral a aquelas realizadas empregando a dobre deflación e sitúanse case á altura de métodos que usan unha maior cantidade de datos.

Capítulo 5. Vencellando as rexións co mundo

Os modelos input-output multirrexionais foron concibidos inicialmente para dar conta das ligazóns entre industrias e rexións dentro dun mesmo país. Porén, o seu éxito inicial foi paulatinamente decrecendo dados os seus altos requirimentos de información e a necesidade dunha alta capacidade de computación para poder traballar con eles. Na actualidade, observamos unha revitalización no uso de modelos multirrexionais. Esta ben motivada, entre outras causas, polo xurdimento das cadeas globais de valor e polo carácter global dos desafíos medioambientais. Así mesmo, hai que destacar que as restricións na capacidade de computación son cada vez menores dados os avances da informática nas últimas décadas. Ironicamente, esta nova onda de modelos input-output multirrexionais ten deixado de lado a dimensión rexional: a meirande parte dos modelos multirrexionais son modelos globais que relacionan industrias e países.

Hoxe en día existen razóns para a (re) introdución da escala rexional nos modelos input-output multirrexionais. En primeiro lugar, a literatura apunta unha crecente heteroxeneidade das rexións e a un certo desacoplamento do seu desempeño económico respecto das economías nacionais nas que se insiren. Así mesmo, existen factores determinantes dos procesos de innovación que son específicos en cada rexión. Por último, pese a influencia cada vez maior das dinámicas económicas supranacionais, o impacto sobre determinadas variables sociais e medioambientais non se distribúe homoxeneamente entre territorios. Por tanto, a produción de modelos multirrexionais e multi-escala pode resultar de certo interese no campo da análise input-output.

Na actualidade, existen unha serie de modelos multirrexionais e multi-escala reportados na literatura. Porén, ningún destes está construído en base a datos publicados regularmente a nivel rexional. A ausencia de datos pode ser un dos principais motivos que impide a proliferación deste tipo de modelos. Dentro da literatura atopamos, cando menos, dous grandes bloques de propostas metodolóxicas para circunvalar esta situación:

- Por unha banda, existen unha serie de propostas baseadas no emprego de ponderacións para separar as importacións e exportacións que unha rexión realiza co estranxeiro daquelas rexistradas para o conxunto da nación. Estas ponderacións constrúense a partir de información detallada sobre a orixe/destino xeográfico e industrial das importacións/exportacións. Estes datos están dispoñibles soamente para un reducido número de países, o cal resulta problemático se o que buscamos é unha metodoloxía que poida ser aplicada de maneira máis ou menos xeral.
- Por outra banda, os modelos de gravidade estiman os fluxos comerciais seguindo un modelo análogo ao proposto pola física de Isaac Newton. Estes modelos funcionan con menores requirimentos de información e teñen en conta a distancia entre as rexións e os países para aproximar os efectos dos custos de transporte das mercadorías. En contrapartida, os modelos requiren da estimación de parámetros e non son aditivos (a suma dos fluxos rexionais estimados non coincide necesariamente cos totais nacionais).

Neste capítulo propoñemos unha combinación entre ambos enfoques. En esencia, a nosa proposta para por simplificar os modelos de gravidade que hipoteticamente definen os fluxos comerciais da rexión e da nación. Desta maneira obtemos ponderacións que (i) requiren de menos información para seren estimadas, (ii) teñen en conta a distancia ou os custos de transporte e (iii) son aditivas e reducen o número parámetros a empregar.

Seguindo o esquema dos capítulos anteriores, realizamos un experimento empírico para contrastar o rendemento da nosa proposta. Nun modelo multirrexional agregamos dous conxuntos de países —Bélxica, Países Baixos, Luxemburgo; Alemaña, Francia, Italia—

formando dúas nacións hipotéticas: Benelux e *The Big Three*. Estimamos o comercio internacional das rexións (países) agregados empregando ponderacións intensivas en requirimentos de información, un modelo de gravidade e a nosa proposta metodolóxica. Obtemos os parámetros necesarios para o modelo de gravidade e a nosa alternativa metodolóxica realizando unha análise de regresión sobre os fluxos comerciais do modelo multirrexional no que queremos inserir as nosas rexións hipotéticas. Nunha primeira proba, contrastamos os fluxos comerciais estimados empregando cada un dos métodos contra os datos publicados no modelo multirrexional orixinal. Nunha segunda, medimos a precisión das estimacións a través dos efectos de retroalimentación e desbordamento. Os nosos resultados suxiren que, empregando a mesma información que nun modelo de gravidade, é posible obter estimacións razoablemente achegadas aos datos que tomamos como reais.

ABBREVIATIONS

Acronym	Name
2D-LQ	Bidimensional location quotient
ACIM	Accelerated Cimmino algorithm
AIDS	Almost Ideal Demand System
BE	Belgium
BIG3	The big three (Germany, France and Italy)
BNL	Benelux
CGE	Computable general equilibrium model
CHARM	Cross-hauling adjusted regionalization method
CILQ	Cross-industry location quotient
DD	Double deflation
DE	Germany
EU	European Union
FIG	Rest of the World
FIGARO	Full International and Global Accounts for Research in input-Output analysis
FLQ	Flegg location quotient
FR	France

GA	Growth accounting
GBW	Gravity-based import export weights
GDP	Gross domestic product
GLS	Generalised least squares
GMRIO	Global multiregional input-output model
GRAS	Generalised RAS
GRIT	Generation of Regional Input-Output Tables
GVA	Gross value added
IGE	Instituto Galego de Estatística
IO	Input-output
IRIO	Interregional input-output model
IT	Italy
KRAS	Konfliktfreies RAS
LQ	Location Quotient
LU	Luxembourg
METI	Ministry of Economy, Trade and Industry
MIOT	Monetary input-output table
MKRAS	Modified KRAS

MRAS	Modified RAS
MRIO	Multiregional input-output models
MSCE	Minimum sum of cross entropies
MXW	Import/export weights
NASA	National Aeronautics and Space Administration
NL	Netherlands
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary least squares
OPE	Overall percentage error
PIOT	Physical input-output table
QP	Quadratic programming
R&D	Research and development
REIM	Regional econometric input-output model
RLQ	Round location quotient
RPC	Regional purchase coefficient
SAM	Social accounting matrix
SDA	Structural decomposition analysis
SDP	Supply-demand pool

SGM	Standard gravity model
SGP	Stability and Growth Pact
SHAIO	Hispanic-American Input-Output Society
SNA	System of national accounts
SSA	Shift-share analysis
SUT	Supply and use table
TL	Tolerance limits
TRAS	Three-steps RAS
UK	United Kingdom
US	United States
WAPE	Weighted average percentage error
WIOD	World Input-Output Dataset
WWII	World War II

GENERAL OUTLINE

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1 INTRODUCTION

1.1 SOME INITIAL WORDS

This is a thesis on regional development and economic integration. Within this vast field of research, I contribute by expanding the shared, prolific path that regional science and input-output (IO) analysis have travelled together for some decades now. This introductory chapter provides the impetus for my research while complying with some formal requirements established by university regulations.

From an economic perspective, subnational development has at least three dimensions: time, space, and industry. Time is required for economies to develop following a sequence that goes forward from entrepreneurial discovery—private, public, or both— towards structural change. Time reveals some path dependence: how an economy is doing today rests much on its earlier posture and how it performed yesterday and the days before.

Space is less obvious, but fundamental to regional science; spatial interactions can influence economic development in two different ways. One, geographical, cultural and idiosyncratic proximity favour interactions among agents, yielding more-intensive economic and knowledge exchanges. Two, capabilities that enable and sustain economic development are not necessarily deployed or contained within strict political boundaries. Regions influence each other economically by means of spatial spillovers and feedback effects induced by investments, trade, consumption, labour mobility, etc.

Analogously to space, interindustry connections signal exchanges among firms and territories. Such connections are expressed in IO tables as well as via logistical supply chains. Sales and purchases influence the supply and demand dynamics in firms, and therefore all components of their strategic behaviour—investments, research and development (R&D) expenditures, expansions, withdrawals, etc. Interindustry linkages are also channels through which knowledge—either formal or tacit—and innovation can travel. Other industry-based agglomeration economies might attach too, springing up as other establishments and/or people locate within the same spatial economic sphere.

1.2 RESEARCH GOALS AND STRUCTURE[1]

Of the three mentioned dimensions, it is the last—interindustry connection—upon which I focus most. By no means does such a choice imply neglecting the other two, nor does it mean ignoring any other relevant phenomena that might influence regional economic development. As I explain in following chapters and sections, the study of interindustry connections at the subnational level is often obstructed by a lack of adequate data. Literature on regional analysis is rife with examples. Confronted with this difficulty, regional scholars can (i) focus instead on research topics that are less data-demanding, (ii) study regions that already publish consolidated datasets or (iii) generate or obtain desired data via direct observation and/or indirect estimates.

My research expands the regional researcher´s toolbox for those who select the third option. In particular, I relax information requirements to construct regional IO models by combining survey and non-survey-based data. I break this main goal into four chapter-specific sub-objectives:

- In chapter 2, I motivate the main research goal while revisiting theoretical discussions and empirical experiences reported in prior literature.
- In chapter 3, I examine alternative ways to handle conflicting information when balancing IO tables.
- In chapter 4, I deflate supply-use tables when little information is available on prices.
- In chapter 0, I explore an alternative way of embedding regional IO models into more general (i.e.: national or international) IO datasets in a restricted context regarding trade data.

In addition, chapter 6 provides general conclusions for all chapters. I briefly elaborate on possible implications of my work as well. I conclude by outlining possible future research avenues.

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[1] Section 2.3 further develops this preliminary outline.

1.3 RESEARCH APPROACH: SHARED METHODOLOGICAL NOTES FOR CHAPTERS 3, 4 AND 0

Chapters 3, 4 and 0 are the core of this thesis. Each of the three chapters proposes a research approach that contributes to the main goal of the dissertation. In each chapter, there is a specific section describing the referent approach in detail. In section 3.2 of chapter 3, I describe a modification of Lenzen et al.'s (2009) Konfliktfreies RAS (KRAS). In section 4.4 of chapter 4, I present our extension of Pereira López et al.'s (2013) Path-RAS algorithm. Finally, in section 5.3 of chapter 0, I explain how to simplify gravity equations that parallel those employed by Sargento et al. (2012).

Nevertheless, some common methodological features apply to these three chapters. I summarise the research approach through the following workflow:

1. Spotting gaps in literature. I review literature relevant to the challenges posed in each chapter. The goal is double. First, it provides the context that motivates the inquiry, particularly an understanding of where and when the addressed problems are apt to arise. Second, it uncovers opportunities for improvements in the state of the art.
2. Suggesting alternative methods. In accordance with some of the improvement opportunities spotted in literature I ruminate upon methodological alternatives. I derive them in mathematical detail in corresponding sections. In addition, I discuss the economic rationale for the developments. Note, I keep my mathematical notation as homogeneous and consistent as possible although a few chapter-specific nuances inevitably arise.
3. Contrasting our estimates against published data. To assess the quality of the methodological proposals, I run several empirical experiments. In all cases, I try to reproduce, as accurately as possible, official published data. I measure the distance between our estimates and the "true" figures. Moreover, I compare the performance of the new methods with popular alternatives in the extant literature. The datasets I use are specific to a chapter. Each dataset is available online, so I include links and references to each for the convenience of other researchers. In addition, I describe in detail any transformations I perform on the data.

I now present a general note on my dataset choices. In chapter 3, I use regional data from Galicia (the most northwestern province of Spain) for the experiment. In contrast, for chapters 4 and 0, I use national data in the experiments. Namely, I use data from the "'Full International and Global Accounts for Research in input-Output analysis" (FIGARO) inter-country global input-output model. There is possible bias associated with these databases that is inherent in my results. But, as suggested by the extant contributions to the literature cited in the chapters, this is a standard practice in regional input-output literature since it circumvents the scarcity of regional data based on appropriate surveys.

2 A GENERAL LITERATURE REVIEW MOTIVATING OUR RESEARCH APPROACH

2.1 BROTHERS IN ARMS: INPUT-OUTPUT MODELS AND THE REGIONAL SCIENCE ATTACK

2.1.1 Introduction

Input-output (IO) analysis is the name of the economic modelling framework conceived and developed by Professor Wassily Leontief (1905-1999) during the 1930s. In recognition of his work, Leontief was awarded with the Nobel Prize in Economic Science in 1973. His lecture in Stockholm was published as Leontief (1974). The label interindustry analysis is also used as a synonym for IO analysis, since the main purpose of this modelling approach is to account for linkages between industries in one or various economies (Miller & Blair, 2022). One of IO´s main contribution relies on its *structural* component. This is, to portrait both of the individual agents in a given economy and of the meaningful way in which they are interconnected (Tarancón Morán, 2003).

Input-output tables were initially conceived as operational and empirical variants of François Quesnay´s *Tableau Économique* (Guilhoto, 2001; Phillips, 1955). In 1927, Wassily Leontief suggested representing the economy as a circular flow in his Ph.D. dissertation defended at the University of Berlin (see Leontief, 1991, 2007 for translated reprints). Leontief´s model moved from partial equilibrium towards a general equilibrium framework (Leontief, 1949). This has been typically interpreted as a practical simplification of León Walras’ (1898) work, see Kuenne (1954) for more details. Contributions by Richard Cantillon (Brems, 1986), Karl Marx (Leontief, 1938), Ladislau von Bortkiewicz (Baumol, 2000), Maurice Potron (Abraham-Frois & Lendjel, 2006), and Ragnar Frisch (Bjerkholt & Knell, 2006) have been discussed as additional IO precedents. Parallels between Leontief’s work and that of his contemporary Piero Sraffa (1898-1983) have also provoked some review and discussion (Marchionatti, 2019).

IO analysis is considered as one of the major advances in economic thought during the first half of the 20th century, alongside the contributions by Schumpeter and Keynes (Shackle, 1967). The first IO-related contributions (Leontief, 1936, 1937b) mark the foundational moment of this literature strand. Leontief’s first article on the matter presents a matrix that contains the outlays and revenues of several industries in the United States (US). He relied almost entirely upon data from the 1919 census. It also includes some partial remarks on the mathematical derivation of the framework. His second article on the matter yields a rich mathematical description of the new general equilibrium model. Note, these works were published almost in parallel with Keynes' *General Theory*. Leontief himself was engaged by that time in several discussions with the Cambridge school (1937a).

In the aftermath of World War II (WWII), IO took off as an empirical and policy-oriented tool for economic analysis. IO was successfully implemented for military and planning purposes during the conflict. On the one hand, it helped the Office of Strategic Services and other agencies in preventing production bottlenecks. On the other hand, it was also used to target specific German industries, enabling more effective bombardment. The closer the peace appeared on the horizon, the greater became the interest of governments on ways that army demobilisation could affect an economy in terms of production and employment (Leontief, 1960). At this point, a shift in interest towards open —demand driven — models arose (Kohli, 2001). The publication of the first comprehensive set of IO tables (Leontief, 1941) showed it was not only possible to feed the mathematical model with real data and but to also achieve meaningful results. In 1947, the US Bureau of Labour Statistics sponsored the publication of the first large scale IO table covering more than 400 sectors. Such a decision was the first step towards regularly published IO statistics by public agencies (Rose & Miernyk, 1989). Despite some theoretical criticism, IO analysis gained momentum as empirical tests started probing its usefulness (Christ, 1955). Government and academic enthusiasm was accompanied by generous funding and research opportunities (Dorfman, 1954). The establishment of the Harvard Economic Research Project in 1948 was a significant milestone in this regard (Leontief, 1953b).

2.1.2 Input-output and regional science: feedbacks and spillovers

Regional science and input-output analysis share a long history of collaboration. As a matter of fact, the first interactions between regional science and input-output took place *even before* regional science was established as a separate discipline. According to Isard (2003), during the school year 1949-1950 Leontief and the Harvard Economic Research Project expressed an interest in Isard's assistance in building a multiple region IO model of the US economy. The sole condition Isard imposed was that he be able to teach a course at Harvard University. Isard´s course on Location Theory was the first to include IO analysis in its syllabus. Leontief, following conventions of the time of not tooting one's own horn, taught little related to his field of research in his own courses (Carter, 1976). Isard´s involvement at the Harvard Economic Research Project was critical to the emergence of regional science as a field of inquiry. The project provided financial and secretarial support as well as some basic infrastructure (Boyce, 2003).

The publication of three volumes — *Location and Space-Economy: a General Theory Relating to Industrial Location, Market Areas, Land Use, Trade and Urban Structure* (Isard, 1956); *Industrial complex analysis and regional development* (Isard et al., 1959); and *Methods of regional analysis: an introduction to regional science* (Isard, 1960) — consolidated regional science as a new paradigm in the sense described by Kuhn (1970). All three books described different techniques suited to address regional problems. In addition, they stressed the importance of finding "channels of synthesis" across different approaches. Note, the definition of regional science encompassed as much as thirteen different angles (Isard, 1975). Integration responded to the belief that some of the important regional challenges lay at the interface between techniques (Hewings et al., 2004). This "interdisciplinary attack" approach justified, at least partially, the existence of a "regional science". As a consequence, some institutional advances started to parallel academic consolidation. By 1954, the Regional Science Association was founded; it published its first proceedings in 1955 in a journal that is now called *Papers in Regional Science*. In 1956, the University of Pennsylvania started a Ph.D. program on regional science with William Alonso as the first student. Finally, in 1958, the first issue of the *Journal of Regional Science* was published by the Regional Science Research Institute.

Unlike other subfields of regional science, the development of regional IO analysis occurred almost contemporaneously with the growing interest in national IO modelling (Hewings & Jensen, 1986). Isard presented the first (inter)regional IO models (1951, 1953b) shortly after he enrolled in the Harvard Economic Research Project. Isard´s interregional IO models (hereafter IRIO) accounted for linkages between different industries within a region and addressed interrelationships between industries situated in different regions within a nation too. The IRIO was built upon some controversial assumptions. Not only interindustry relationships were set to be fixed within, shipments between industries situated in different regions were also to follow constant proportions. Isard made his case by arguing that many commodities were likely to show such constant behaviour in their trade patterns within a nation. Only for those products with negligible transport costs, slight differentiation and no cultural/institutional barriers, constant trade patterns was not considered realistic. Isard´s model could also be used for regions in different countries sharing a single currency or showing stable exchange rates. Nevertheless, many-regions IO models were largely confined within national boundaries in early applications.

Early on, regional economic research mainly focused on sector-specific studies. Regional IO models permit a real look at interindustry interconnections (or linkages) within any given subnational area. Those linkages can, in addition, be related to a variety of location-specific characteristics. Hence, the scope of regional economic research was expanded. See Isard and Kuenne (1953), and Isard and Schooler (1959) for early examples of such an expansion. These contributions presented for the first time a joint analysis of industrial location and interindustry linkages. They identify profitable situations and activity combinations considering resource endowments and market distribution. In addition, they account for spatial integration economies, leading to superior insights compared to studies conducted upon economic activities and regions independently.

As for their empirical implementation, IO models spread quickly in regional science. According to Tiebout (1957), post WWII regional research was dominated by regional applications of IO models. In a similar vein, Meyer (1963) discusses regional IO models as a technique of “great importance” for regional economists. Giarratani, Maddy and Socher’s (1976) annotated bibliography gives an idea of how regional IO analysis expanded. Some contributions focused on methods: table construction; statistical and computational methods; non-survey techniques; among other topics. But the listing includes a great variety of applied studies too. These include research on regional growth and development; forecasting and simulation; impact and multiplier analysis; urban studies; interregional trade; and environmental and water resource analysis. Note, from the latter mentioned topic, that regional IO practitioners paralleled the call made by Leontief (1970) on the use of extended IO models to address ecological challenges. Isard et al. (1968, 1972) pioneered this research line. Appraisals by Hewings and Jensen (1986) and Richardson (1985) provide comprehensive reviews about advances during the 1980s.

The success of regional IO might be explained, at least partially, by some differential properties with respect to national IO models. Both in national and regional contexts, IO models are conventionally said to apply for short-run impact periods in an imperfect competitive setting with capital and labour excess supply (Richardson, 1985). However, Georgescu-Roegan (1951), Koopmans (1951) and Samuelson (1951), among others, proposed that under certain conditions IO models could correspond in the long run with closed-economy neoclassical models. Their alternative mathematical proofs were given the name of non-substitution theorem. Essentially, under this conditions, input and commodity prices do not vary with changes in final demand. Therefore, coefficients cannot change—no substitutions in the input mix caused by final demand disturbances is permitted, not even in the long run (Akhabbar, 2015). The conditions for the theorem to hold are (i) linear homogeneous production functions, (ii) only one non-produced input: labour, (iii) a fixed interest rate, (iv) elastic labour, capital and land supply. Stiglitz (1970), Johansen (1972) and ten Raa (1995) provide further analytical insights on the theorem and its assumptions.

Providing a subnational perspective in the discussion, McGregor et al. (1996) argue that regional economies are more likely to meet conditions (iii) and (iv) than are their national counterparts. Regions are price takers in (inter)national financial markets and can increase their labour supply through inflows of new workers through interregional migration. In addition, Evans (1993) argues that regional land supply is more elastic in the long run. This point should be considered with some caution, however, since it is largely based on the US case. As for condition (ii), it is more credible for the regional case to assume fixed wage rates. If interest and wage rates are fixed, imports can be used as a numerarie, i.e., commodity prices can be identified relative to import prices (McGregor et al., 1996, p. 482). The authors also provide an empirical proof for their argument. They show how an IO investment-endogenous system replicates long-run results of a neoclassical general equilibrium model.

2.1.3 Present challenges and emerging trends

Hewings and Jensen (1988) draw attention towards three related "emerging trends" in applied regional IO analysis. Many of these emerging trends have now become present challenges for regional IO practitioners. In a more recent appraisal, Lahr (2018) rearranges terms and expands Hewings and Jensen´s research program recommendations. His article portrays regional IO analysis as a fertile field during the last decades, still presenting some riveting challenges to be explored by scholars. In this section, we elaborate on the observations contained in the aforementioned reviews focusing on consolidated applications and emerging challenges. Our aim is to illustrate the usefulness that regional IO models still have nowadays. If this last statement holds, it might be worthwhile taking the trouble to produce regional IO data. Note, many emerging challenges in the field of the regional IO relate closely to general IO topics (Dietzenbacher, Los, Lenzen, et al., 2013).

2.1.3.1 Economic structures and interindustry growth models

Interindustry growth models were popularised among IO practitioners by Hirschman (1958), among others. From a static perspective, key sector analysis (Rasmussen, 1956) provides intuition about which are the most important links in an interindustry framework. Seung (2020), among others, shows how this approach can be applied to a multiregional social accounting matrix (SAM). Alternatively, the hypothetical extraction methods can be applied to both sectors and entire regions (Dietzenbacher et al., 1993). Hypothetical extraction measures sectoral output variations for an IO model should a sector/region disappears (i.e., all its entries are set to zero). Miller and Lahr (2001) provide additional detail. Other alternative methods to assess regional economic structures include fields of influence (Hewings et al., 1988; Sonis et al., 1996) and network analysis (García Muñiz et al., 2008).

From a dynamic perspective, Oosterhaven (2021) suggests that growth accounting (GA), structural decomposition analysis (SDA) and shift-share analysis (SSA) are alternative growth decomposition techniques. From a GA perspective, Acemoglu et al. (2012, 2016) provide insights on how sectoral fluctuations in interindustry networks affect aggregated economic growth. The bigger asymmetry in the roles some sectors play as suppliers in a given network, the greater aggregated impacts when they suffer a shock. Barauskaite and Nguyen (2022) present an empirical assessment for the US (1958-2011) by showing robust correlations between aggregated total factor productivity (TPF) and interindustry linkages.

SSA focuses on differences in a region´s industry mix. Therefore, growth is decomposed into region-specific and national effects. See Lahr and Ferreira (2021) for a comprehensive review on these techniques. Furthermore, SDA splits growth fluctuations between final demand and technological change effects. Contributions by Rose and Casler (1996), Tarancón Morán (2003, pp. 121–138) and de Boer and Rodrigues (2020) provide overviews regarding SDA and its many variants. According to Lahr and Dietzenbacher (2017), SDA and SSA parallel within regional IO analysis and may as well converge. Oosterhaven (2021) also makes a case for closer collaboration between the three approaches.

2.1.3.2 Economic-ecological analysis

According to Miller and Blair (2022, pp. 601–665), environmental IO analysis includes a wide variety of techniques and approaches. As mentioned in section 2.1.2, economic-ecological analysis was introduced into regional IO modelling even before Leontief ́s (1970) call for environmentally extended models. Ever since then, this kind of model has received much interest in the literature. Xie et al.'s (2018) bibliometric analysis suggests strong relationships between IO modelling and environmental research. The relationships are supported by the growing expansion of MRIO models (Sánchez Chóez, 2021). Specific inquiries into embodied flows (Tian et al., 2018) and urban metabolism (Tang et al., 2021) point in the same direction. Survey articles on the matter (e.g., Malik et al., 2019) suggest that most MRIO models are multi-national. Onat and Kucukvar’s (2020) review of carbon footprint analyses of the construction industry reports that 75% of the studies between 2009 and 2020 were national level.

Subnational studies on economic-ecological problems using IO models broadly take two different approaches. On the one hand, many papers are based on models built from scratch using more or less comprehensive (multi)regional datasets. Examples include Daniels et al. (2011) for Australia; Cazcarro et al. (2013) for Spain; Többen (2017b) for Germany; and Lu et al. (2019) and Mi et al. (2018) for China. City-level analysis to assess urban environmental sustainability has also benefited from the use of environmentally extended IO models. Baynes and Wiedmann (2012) mention a number of studies linking urban consumption levels and patterns with environmental impacts such as water usage, energy use or carbon footprints. These authors note, however, that completeness of IO tables is counterbalanced by their limited geographical resolution. In addition, Long et al. (2020) built an interregional model to describe city-level carbon footprints and show that single region models cannot capture such footprints properly. needed (Zheng et al., 2019), therefore, suggest a link between lower and higher geographical scales is. Song et al. (2019) suggest the addition of a dynamic approach for local level empirical simulations using IO as well.

But other works have benefited from so-called virtual laboratories that include data from global IO databases (Lenzen et al., 2017). Research based on this type of arrangement tends to be international, but some is county-focussed including Lenzen et al. (2014) for Australia; Wang (2017) for China; and Wakiyama et al. (2020) for Japan; among many others. Wieland et al.'s (2022) use of a global physical IO dataset indicates ways that virtual labs can expand.

2.1.3.3 Regional computable general equilibrium models

Arguably, regional computable general equilibrium (CGE) models are an extension of regional IO analysis. Regional CGE are mainly used to assess regional effects for supra-regional shocks (Giesecke & Madden, 2007), analyse fiscal federalism and calculate the impact of regional policies and events (Giesecke & Madden, 2013). These subnational models face challenges that their national counterparts do not (Ghaith et al., 2021). First, they often must endogenize the mobility in factors of production since at the subnational level workers are more apt to commute and capital typically can even more freely across subnational political boundaries and get redistributed. As a result, distances among geographical areas become a more important consideration. That is, transportation costs, carrying costs, trade margins, and transactions costs among economic agents become more critical. Third, in many cases, different government levels are to be disaggregated. National and subnational governments may present different fiscal policies depending on the constitutional setup of a country or the political believes of the public.

Broadly, one can classify regional CGE models into three types: top-down, single region and bottom-up approaches. Dixon et al. (1978) who pioneered top-down models spatially disaggregating some results from ORANI: a general equilibrium model for Australia. They extended the work by Leontief et al.'s (1965) in which they measure the industrial and regional impacts of possible cuts in military spending. Single region models appeared soon after (Hertel & Mount, 1985). According to Partridge and Rickman (1998) single region models had some momentum at least during the first impulse of regional CGE. However, single region CGE models cannot capture feedback effects derived from interregional linkages (Lofgren & Robinson, 2002). Bottom-up models, also known as multiregional CGE, lie somewhere between top-down and single region models and are used overcome top-down oversimplifications. More importantly, they account for the effects of interregional exchanges

(Partridge & Rickman, 2010). Despite their promising features, multiregional CGE modelling requires a full specification of intra- and inter-regional flows (Isard et al., 1998).

2.1.3.4 Econometric input-output models

Econometric and regional IO integration was pioneered, among others, by L´Esperance et al. (1977), Conway (1979) and Stevens et al. (1981). Rey (2000) suggests that, from a theoretical standpoint, econometric IO modelling relaxes some restrictive assumptions in IO’s components: linear production functions, constant returns to scale, homogeneous consumption functions, and price inflexibility. But the data needs for econometric models are extensive and model calibration can be quite time-consuming. Moreover, such models often lack a priori theoretical guidance and data requirements inevitably force heavy industry aggregation. Still, from a practical point of view, integrated models tends to be better for forecasting purposes. Moreover, impact analyses are improved since technical coefficients can become price-responsive and confidence intervals are inherent to this form of model.

Econometric IO models have been implemented in both single and multiple region scenarios (Rey & Dev, 1997). In the latter case, they face additional challenges such as accounting for interregional transportation costs and the openness of the economy, among other possible region-specific features.

Rey (1997) identifies three different integration strategies: linking, coupling and embedding. Through the linking strategy some contributions use inputs of one model to feed another one. For instance, Conway (1990) uses econometric estimates for interregional exports, consumption, residential investment, government expenditures in a simulation model for the State of Washington. His model uses regressions to update the IO coefficients adjusting them by rows. Kratena and Zakarias (2004) and Mínguez et al. (2009) use econometric time-series analysis to update/regionalise IO matrices with biproportional (i.e., row/column) adjustments. In a more applied vein, Frenken et al. (2007) and Kitsos et al. (2023) use explanatory variables derived from IO models to feed their regression analyses. The former paper uses a variant of the Los’s (2000) index as one possible measure for industrial relatedness, an IO-derived self-sufficiency measure meant to explain regional economic resilience.

The coupling strategy presents circular interactions between the IO and the econometric modules. For example, we can have econometric estimates for final demand feeding an IO model. IO models can provide estimates of output, income or other macroeconomic variables which, in turn, can be introduced into an econometric model for subsequent calculations (Kim et al., 2015). The authors expand Deaton and Muellbauer’s (1980) Almost Ideal Demand System (AIDS) and couple it with Israilevich et al.’s (1997) regional econometric input-output model (REIM) . This enables accounting for household heterogeneity and how migration can affect different sectors differently depending on characteristics of the population cohorts moving into and out of a region. Note that this strategy resembles regional CGE modelling to some extent (Treyz, 1993). Still, differences can arise between empirical outcomes of these two approaches (West, 1995).

The embedding strategy consists of using IO coefficients to weight some econometric model specification. Models can be fed with a full technological specification or a partially restricted one as in White and Hewings (1982). LeSage and Rey (2002) compare both embedding approaches and suggest combining them to improve forecasts. Tian (2014) and Tian et al. (2020) illustrate how the embedding approach can be further extended to account for industrial and spatial interactions. They introduce a variant of the space-time filter proposed by Parent and LeSage (2012). The temporal dimension is substituted by an interindustry dimension using a technical coefficient matrix. Consequently, their econometric models measure spatial and interindustry spillovers of the regressand, as well as cross-effects.

2.1.3.5 Other developments: household endogenization, demo-economic models, and beyond

So far, I have identified challenges closely related to regional IO analysis. Some share a fuzzy frontier with the topics described in prior subsections of this dissertation. For instance, models based on multiregional social accounting matrices are increasingly used to endogenize household consumption. Thus, insights on income multipliers and distribution a la Miyazawa (1976) have been considered from both regional and, more importantly, an interregional perspective see, e.g., Carrascal Incera and Hewings (2022) on income interdependence across a multiregional model for the United Kingdom. and Batey and Madden‘s (1983) extended framework, which adds a population constraint. Such innovations have been called “demo-economic models" (Batey, 1985). See Batey and Hewings (2021) for a comprehensive review of such models and some suggestions for future inquiries.

Oosterhaven and Hewings (2014) point out several additional challenges. First, they suggest more work should be done regarding household disaggregation due to the size of the labor/household sector in most western economies. Oosterhaven and Polenske, (2019) go so far as to suggest international/interregional migration modelling within interregional frameworks such as that by Ferreira et al. (2020). Agent heterogeneity can also be applied to firms. In this vein, there is some work in progress to compile extended supply-use tables[2] (ESUT) yielding promising and interesting results (Bernard et al., 2012; Chong et al., 2019; Fetzer et al., 2018; Fortanier et al., 2020). Note that, in broader terms, agent heterogeneity has been identified as one of the main challenges faced by macroeconomic theory (Donaghy, 2021). Moreover, the expansion of the digital economy (Barefoot et al., 2018) poses additional challenges to regional impact analysis (Horoshko et al., 2021) in terms of production, income distribution and environmental footprints, among many other issues. The 9th Conference of the Hispanic-American Input-Output Society (SHAIO) recently[3] held a lively debate on this particular subject.

2.2 WISH YOU WERE HERE: THE PROBLEM OF DATA AVAILABILITY

2.2.1 Early discussions

Early on IO practitioners were concerned about data availability. Indeed, Leontief (1937b) stated that his research program was subdivided into three closely interrelated tasks: formulating appropriate theoretical schemes, gathering and arranging necessary statistical material, and applying data to previously developed theoretical devices. According to Solow (1998), Leontief was, first and foremost, and economic theorist. A characteristic feature of Leontief was his insistence on the empirical relevance of economic research (Bjerkholt, 2016).

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[2] The Organization for Economic Cooperation and Development (OECD) has set an expert group on this matter with the purpose of compiling best practices and elaborating a handbook. Further information can be found in: https://www.oecd.org/sdd/na/OECD-Expert-Group-on-Extended-Supply-Use-Tables.htm

[3] The conference took place during September 22-23, 2023, in Aveiro, Portugal.

In his view, theory should guide empirical inquiries through necessarily observable concepts (Akhabbar, 2019; Rosier & Leontief, 1986). He even issued several warnings against the cleavage induced by purely hypothetical-deductive economics and radical empiricism (Leontief, 1952), some of them were harsh public rebukes (Leontief, 1971). IO analysis was meant to be operational: apt to empirical implementation and falsifiable in the sense described by Karl Popper (Blaug, 1992).

Perhaps through Leontief's colleague Walter Isard, regional science adopted a similar view. That is, the linkages between the IO field and regional scientists summarised in section 2.1.2 likely influenced such a parallel behaviour. Isard (2003) notes that minutes of informal meetings of regional scientists held prior to the establishment of the Regional Science Association, inevitably mentioned data availability issues. Indeed, even at the very first (unsponsored) meeting in 1950, attendees expressed three basic focal points of future activity: (i) the need for an interdisciplinary attack, (ii) the need for new concepts and techniques and (iii) *the need for an increase in the supply of available data*. Later meetings included some preliminary comments on how to obtain additional information. Some attendees suggested use of census data as benchmarks with a sample of intercensal studies to secure census-consistent regional data at a relatively low cost. In a similar vein, sampling data techniques in rural counties started to be used in combination with more complete datasets from urban counties to economize data collection efforts. While, soon afterward, some researchers introduced solutions to circumvent the lack of data , data unavailability at the subnational level remains an issue, particularly in less developed nations.

Due to its data demands, IO analysis undoubtedly suffers most from data scarcity at the subnational level. The first (inter)regional IO model (Isard, 1951) is a straightforward extension of a national IO model. It asks for the geographical/sectoral origin and destination of each transaction— interregional coefficients. Isard noted that such an ideal dataset was unlikely ever to be assembled. Note, interregional coefficient estimation can be broken down into two separate, yet interrelated, problems: regional domestic technology and regional/sectoral trading patterns (Batten & Martellato, 1985).

As for regional domestic technology, initial studies used national coefficient matrices, essentially by assuming that production processes are geographically invariant. Freutel (1952) adopted this approach in his study on the balance of trade between eight Federal Reserve districts. Isard (1953a) used national input coefficients to calculate regional input requirements in his New England model. Using something akin to location quotients, he cautioned that the approach undoubtedly yielded crude estimates only. Assuming national technology, Moore and Petersen (1955), introduced available information on individual industries (i.e., technical data, partial information, etc.) to account for regional heterogeneity in their Utah model but called for researchers to introduce superior[4] data into models. Gosfield (1955) applied a similar approach but with the advantage of having some real data on transportation interregional flows into and out of Puerto Rico. Hirsch (1959) noted that spatially invariant technology is, at least, a strong assumption. In this vein, some early regional researchers (e.g., Su, 1970) highlighted how substantial distortions could be introduced when using national coefficients at the regional level.

As for regional trading patterns, Chenery (1953) and Moses (1955) proposed alternative model specifications, noting how lowering information requirements demanded certain assumptions. Chenery-Moses' models modify the national coefficients' matrix according to a set of trade shares. So, once more, technology is assumed to be space-invariant. To estimate their trade shares they relied on an avant-la-lettre Armington (1969) type approach that considers production capacity by region of origin, industry competitiveness and distance to destination (i.e.: transportation costs). Riefler and Tiebout (1970) further refined the Chenery-Moses' model by applying Isard´s approach for intraregional trade and Chenery-Moses' for interregional shipments. Moreover, Leontief (1953a) and Leontief and Strout (1963) introduced the use of gravity models to estimate trade coefficients. In their model trade coefficients are directly proportional to a given set of supply and demand pools, and inversely proportional to the national output, for each commodity. Subsequent developments introduced transportation costs and distance measures as we will discuss in chapter 0. These models came to be known in the literature as multiregional input-output (MRIO) models.

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[4] Superior data refers to data collected through specific surveys, official statistics or similar. In general terms, data that is to be regarded as certain.

2.2.2 Those were days! The purebred regional IO models era

One cannot help but get an optimistic feeling when reading this pioneering regional IO literature. While the first models and inquiries were built upon extremely scattered data, researchers clearly believed that the requisite census or survey-based data would soon be made available to scholars and practitioners. Regionalists' prayers were answered during regional IO´s "classical era" (Jensen, 1990). The integrity of the tables was a prime priority. Regional IO models were complements to regional accounting systems (Leven, 1964).

The US was probably the main factory of survey-based regional IO models. During the 1960s and 1970s a number of survey-based regional models were produced. Bourque and Cox (1970) inventory 82 single-region models covering 71 geographical areas. The apex of these efforts was the NASA-funded 510-sector model of Philadelphia, Pennsylvania, (Isard et al., 1966; Isard & Langford Jr, 1971; Isard & Langford, 1967). Nowadays, only the state of Washington provides a regularly updated survey-based model in the US. The Harvard Economic Research Project directed the construction of an US MRIO covering 44 regions and 78 sectors. Even though the US MRIO project was not based entirely on survey results, Polenske et al. (1972) assembled a great amount of raw data on intraregional transactions as well as on interregional commodity trade (Rodgers, 1973). The process involved considerable human and financial resources in other to take advantage of the many datasets available. Polenske (1980) provides a summary description accompanied by an extensive survey on regional and multiregional models in the US up to that date.

The US was arguably the epicentre of regional science during its initial stages (Boomsma & Oosterhaven, 1992). It is not my purpose to comprehensively review models constructed outside the US. Instead, I simply mention other countries beyond the cradle of regional science that started developing survey-based regional models.

In Europe, the Netherlands probably conducted the first regional IO studies. A single region model was built for the municipality of Amsterdam as early as in 1948. After this pioneering experience, a comprehensive regional breakdown was compiled by the Dutch Central Bureau of Statistics (Oosterhaven, 1980). Hewings (1971) reports the existence of several models based in the United Kingdom (UK), at least partially, on survey data for the regions of Wales, Northern Ireland, Scotland and Bristol. Kronenberg and Wolter (2017) report that the compilation of survey-based models lasted until the 1990s in some regions of Germany, which were henceforth discontinued. In Italy at least four survey-based regional models existed by the 1990s covering the regions of Lombardia, Veneto, Toscana and Friuli Venezia Giulia (Benvenuti et al., 1995). Statistics Finland compiled a consistent set of regional IO tables for 1995 (Koutaniemi & Louhela, 2006) and an IRIO model for 1996 (Kauppila, 1999). To conclude this European overview, Spain is probably one of the countries with the largest number of survey-based regional IO models. In his inventory, del Castillo Cuervo-Arango (1988) reports 42 subnational models ranging from aggregated 14-sector models (Canary Islands, Galicia and Murcia) to the most detailed 80-sector model of Madrid.

Outside the US and Europe, we can report some experiences too. In Canada, for instance, provinces developed their own government-sponsored regional tables for at least 1974, 1979, 1984 and 1990 (Lal, 2001). Apparently, some survey-based work was also done to derive interregional flows between Canada's provinces (Généreux & Langen, 2002). In Asia, Japan anticipated the US and built a multiregional model for the year 1960 according to Polenske (1970). Japan is arguably nowadays the country with the most systematic survey-based (inter)regional IO data (see METI, 2010). Bazzazan et al. (2005) report three rounds of regional IO tables in Iran during the 1970s, the 1990s, and 2000s. The first and third round were built upon expert judgement and survey data respectively. After the "Cultural Revolution" was crushed, China launched a considerable effort for the compilation of IO data (Polenske & Chen, 1991). At the regional level Chen et al. (2005) report a number of models based on surveys, among many other using non-survey techniques. The Republic of Korea has more recently joined the same dynamic with survey-based IRIO models[5] every five years (see Bank of Korea, 2022 for a short letter on their latest release). Furthermore, Australian regional governments were also committed to the construction of survey-based models. This was true until the Generation of Regional Input-Output Tables (GRIT) procedure was proposed (West, 1980). From this point forward, survey-based approaches were abandoned. Finally, van der Westhuizen (1992) reports in his Ph.D. dissertation 9 regional models in South Africa.

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[5] As in the Japanese case, Korean models are probably not strictly survey-based. However, both are laureated as the most data intensive, and therefore closer to reality.

2.2.3 Non-survey methods take over

The expanding interest in regional research, alongside with increasing computational capacity available, stimulate the demand for regional IO models. Supply cannot possibly keep up with demand´s pace without incurring in prohibiting costs. Fuelled by such imbalances in the regional IO data market, literature presents a myriad of contributions devoted to non-survey methods for building subnational IO models. Most contributions focus on methods to derive intraregional flows. I do not provide a detailed mathematical description of all alternatives. Rather, I outline the wide (and still increasing) variety of instruments that have been incorporated into the regional IO toolbox in the recent decades. Table 1 overviews some suggested methods. See Miller and Blair (2022, pp. 441–492) and other contributions quoted below for further explanations.

Most methods derive regional input coefficients from their national counterparts. We can draw a distinction between unidimensional and bidimensional methods. In both cases, it is assumed that technology within a country is space invariant. Unidimensional adjustments of national technology, initially elaborated on the concept of location quotient[6] (LQ), were introduced by Haig (1928) and popularised among scholars interested in economic base analysis (Andrews, 1953). The underlying assumption in this approach is that regional input coefficients vary according to each region´s capacity to satisfy their own demand (Miller & Blair, 2022). The supply-demand pool approaches (SDP) operate in a similar way (Isard, 1953a). An estimated output vector is multiplied by the national coefficient matrix. The result is row-summed together with final demand. If the sum exceeds the output estimate, coefficients are downscaled. If not, they remain as their national counterparts.

Elaborating on the LQ literature, Stevens et al. (1983, 1989), among others, studied alternative ways to estimate the supply proportions covered by domestic establishments within a region. Such proportions were termed regional purchase coefficients (RPCs). RPC estimation has been evolving ever since. See Lindall et al. (2006) and Lahr et al. (2020) for two examples of recent developments. Conversely to RPCs, the cross-hauling adjusted regionalization method

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[6] Also known as simple location quotients (SLQ).

(CHARM) estimates the regional supply proportion involved in interregional trade (Kronenberg, 2009; Többen & Kronenberg, 2015; Fujimoto, 2019).

Method	Adjustment	Main assumptions	Parameters
LQ	Unidimensional	• No cross-hauling: demand is satisfied with regional commodities by default. Imports only happen if there is excess demand. • Regional input coefficients vary only according to each region´s capacity to satisfy its own demand.	—
SDP	Unidimensional	• No cross-hauling: demand is satisfied with regional commodities by default. Imports only happen if there is excess demand.	—
RPC	Unidimensional	• Regional input coefficients vary only according to each region´s capacity to satisfy its own demand.	—
CHARM	Unidimensional	• Cross-hauling is the result of product heterogeneity: the shares of actual cross-hauling in national trade with the rest of the world applies to the regional level.	—
CILQ	Bidimensional	• Specialised industries in a region (LQ > 1) satisfy their demand for intermediates through local suppliers by default. Imports only happen if there is excess demand.	—
RLQ	Bidimensional	• Specialised industries in a region (LQ > 1) satisfy their demand for intermediates through local suppliers by default. Imports only happen if there is excess demand. • Import propensity is an inverse nonlinear function of regional size.	—
FLQ	Bidimensional	• Specialised industries in a region (LQ > 1) satisfy their demand for intermediates through local suppliers by default. Imports only happen if there is excess demand. • Import propensity is an inverse nonlinear function of regional size.	1
2D-LQ	Bidimensional	• Specialised industries in a region (LQ > 1) satisfy their demand for intermediates through local suppliers by default. Imports only happen if there is excess demand. • Import propensity is an inverse nonlinear function of regional size. • Cross-hauling has upper bounds.	2

Table 1. Methods to estimate regional IO models assuming a national invariant technology — summary table.
Source: own elaboration.

Garhart and Giarratani (1987) and Ralston et al. (1986) were among the first to note that the RPCs were each row's average regional supply share, although the concept was implicit to Su's (1970) work; that is, the regional supply share for any given element in a row is likely to vary from the row average RPC. Thus, a full matrix of domestic transactions only estimated with an understanding of cell-specific import shares to meet technological demands would be ideal; that is, while a diagonal matrix of RPCs is imprecise, albeit approximately correct.

The cross-industry location quotient (CILQ) is arguably the simplest method that can enable such cell-specific rectifications. Schaffer and Chu (1969) note that Charles Leven first proposed this method. Elaborating on the CILQ method, Round (1978) argues that any adjustment formula should incorporate three elements: (i) the relative size of the supplying sector *i*, (ii) the relative size of the purchasing sector *j* and (iii) the relative size of the region. The CILQ satisfies (i) and (ii) but not (iii), whereas the LQ satisfies (i) and (iii) but not (ii). Round therefore suggested a new formula (RLQ) where he accounts for the mentioned three elements through a semilogarithmic smoothing in the supplying industry`s LQ.

Like many others before them Flegg et al. (1995) criticize the LQ, CILQ, and RLQ approaches on the grounds that they tend to underestimate the inflows of commodities to relatively small regions. To overcome this drawback, the Flegg`s location quotient (FLQ) was introduced. The crucial hypothesis underpinning the FLQ is that a region’s propensity to import from other domestic regions is inversely and nonlinearly related to its relative size. The FLQ has received some criticism related to this assumption and also for relying in an unknown parameter (McCann & Dewhurst, 1998), among other aspects. See Flegg et al. (2021) for a recent review of variants and answers to latest sceptical comments.

Pereira López et al. (2020) opened yet another strand within LQ literature with their bidimensional reformulation (2D-LQ). Its main novelty is a modified hyperbolic tangent curve to describe the indirect relationships between input coefficients and location economies. Such a function imposes upper bounds to interregional cross-hauling. Papers presenting the 2D-LQ and subsequent variants (Martínez-Alpañez et al., 2023; Sánchez Chóez et al., 2022) report better results than previous strictly LQ regionalization methods. Such promising results come at the cost of an additional trouble: providing estimates for ***two*** parameters instead of ***one***. Nevertheless, using a dataset of European Union (EU) countries, Pereira López et al. (2021) suggest that the 2D-LQ’s accuracy appears to be less sensitive to variation in these two parameters than is true for the FLQ and its lone parameter.

In parallel, other approaches have relaxed or even rescinded the assumption of a national homogeneous technology. Czamanski and Malizia (1969) were among the first to use the RAS biproportional balancing method (Stone & Brown, 1962) to derive regional technologies from national tables. Work by Malizia and Bond (1974), as well as McMenamin and Haring (1974), soon confirmed the superiority of this approach in terms of accuracy. In the latter case, RAS was applied to regionalise intermediates, final demand and value-added matrices combined (Giarratani, 1975). However, it was soon noted that using RAS to estimate regional models is much more data demanding. For instance, regional intermediate inputs and outputs (alternatively, output, value added and final demand) need to be known. Some other studies (see, e.g., Tiebout, 1969) opt to "borrow" coefficients from another region by assuming they represent well those of the region to be analysed. Hewings (1977) evaluated this possibility upon two survey-based regional models for the states of Washington and Kansas. He reports that the aggregate accuracy of his estimates coexists with large errors in some entries of the interindustry table.

2.2.4 Towards the hybrid compromise

Non-survey methods allow regional IO modellers to keep up with the model demands from academia, governments and private sector. Despite their momentum, some harsh criticism arose from the ranks of regional science and IO analysis. Miernyk (1976) points out the existence of high and theoretically unsystematic errors yielded by non-survey short-cuts. He concludes by arguing in favour of expanded and more uniform data collection efforts. Brucker et al. (1987) suggest that regional IO models' market lacks adequate information to promote efficiency. They try to address this problem comparing five modelling packages available in the US at the time. Jensen (1990) also shares Miernyk´s view. He lamented that non-survey methods were, in general, not based on logical terms. Accordingly, the debates between different alternatives have been given only by empirical examples rather than by examination and testing their theoretical foundations. While their results offer some valuable guidance when it comes to choose which method should be applied, Lamonica & Chelli (2018, p. 1178) report that "there is no method that is able to replicate the [regional] true technical coefficients". Not at least able to get close enough estimates to be considered as generally satisfactory. But Beemiller (1990) laments that model inaccuracy is all too often overshadowed by the rough estimates of direct effects employed in the course of economic impact analysis, just one of the many uses of regional IO models. Therefore, it should now be clear that hybrid models are a compromise between costly, but accurate, survey-based models; and their inexpensive, less inaccurate, competitors.

From a theoretical point of view, scholars interested in hybrid regional modelling try to answer the following question: Where should we focus our limited resources in order to generate a more accurate model? In what parts of a model do non-survey methods suffice? Inquiries about which sectors in a model are more important were not new in IO analysis by the time hybrid models appeared. In a non-exhaustive way, literature in this regard can be traced back to the key-sector approach summarized by Hirschman (1958), who mentioned concepts developed by Rasmussen (1956) and Chenery and Watanabe (1958) (see Miller & Lahr, 2001). Alternatively, Jensen et al. (1988) proposed the fundamental economic structure approach, which attempt to identify cell-specific regularities in direct requirements matrices across regions with the hope of assuming they are represent shipments demanded of all economies. This implies that such flows are more readily predicted by non-survey methods. Therefore, resources in hybrid modelling should be devoted to the region-specific sectors and transactions. In a similar vein, Sonis and Hewings (1992) presented the field of influence notion. Their idea is to study the elasticity of the Leontief´s inverse to potential error in technical coefficients as in Sherman and Morrison (1949, 1950), Woodbury (1950), Dwyer and Waugh (1953) and Evans (1954). They note that most attention should be paid to the more influential (Jensen & West, 1980). Finally, an alternative way to assess which sectors are more relevant to an economic system is the hypothetical extraction approach (Miller & Lahr, 2001). The idea is to nullify all flows related to a sector (set them to zero) and then estimate the hypothetical model for the remaining sectors to observe the extent to which the output levels the rest of the economy are affected by the nullification of the one sector. Again, the greater the impact of a sector on the system, the more attention the modeller should pay to that sector.

2.3 THE AIM OF THIS THESIS: EXPANDING HYBRID APPROACHES TO CONSTRUCT (INTER)REGIONAL INPUT-OUTPUT MODELS

In previous sections, I hope to have provided a sufficient argument that regional science is grounded in interindustry analysis. The two are at least linked by shared historical developments (see section 2.1.2). Plenty of challenges and topics in regional research remain, in which IO analysis is important to regional scientists. Growth models, economic-ecological analysis, computable general equilibrium models, econometric IO models and other developments explained in section 2.1.3 are examples. In some cases (e.g., growth models), key indicators for analysis can be directly derived from the IO tables. In others (econometric models), regional IO data play a secondary role.

Anyhow, to become meaningful, the empty boxes of our regional models need to be filled with reliable data. Growth models, and growth decomposition analysis demand comparable IO data across time and space. When the goal is to measure technological change, we also need to separate changes in quantities from changes in prices. This is particularly important when we focus in time periods with significant price volatility (Sánchez Chóliz & Duarte, 2006). A related problem is posed by ecological-economic analysis. In the absence of IO tables strictly compiled in physical units, prices need to be known to translate monetary values into useful units of measurement (Hoekstra & Van Den Bergh, 2006)[7]. Regional CGE modelling can also be hindered by data scarcity as commented by de Boer et al. (2023). Data problems have also been reported regarding econometric IO models, even at the national level (Cazcarro et al., 2022). Moreover, all mentioned research topics need information on trade if they want to move from a single regional towards an interregional perspective.

Even in our days, data scarcity prevents scholars moving forward in particular interesting research topics. What’s more, it also induces an involuntary or natural bias in scholars and practitioners.

> “Faced with the dauting task of finding an enormous quantity of data to implement a regional model accurately, most regional economists have chosen to concentrate on less demanding problems” (Batten, 1982, p. 54).

This natural bias towards research topics or approaches where consolidated datasets already exist does not operate homogeneously across territories. As Hewings and Romanos (1981), among others, point out: the less developed the country, the smaller the region; the more limited financial resources to conduct data gathering studies. This is a source of concern for us, since less developed regions and countries are more apt to face development issues.

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[7] As we will comment in chapter 4, it is far from being the only issue when working with monetary and physical IO models.

The common aim of the three chapters compiled in this thesis[8] is to relax information requirements in hybrid regional IO modelling. West (1990) lists three principles that should guide hybrid regional IO data compilation. Rearranging his terms, the list can be expressed as follows: (i) carefully selecting non-survey methods, (ii) concentrating survey resources on the more significant region-specific items, and (iii) maximising the use of the more reliable (i.e., superior) data by formalising procedures to properly incorporate it into the model. As for the first principle, section 2.2.3 accounted for an extensive and yet increasing body in literature covering non-survey methods for regional IO modelling. As for the second principle, a significant part of the hybrid model literature has focused on studying how can the researcher allocate limited resources more efficiently (see section 2.2.4).

The leitmotiv of the following chapters relates with the third principle. I am interested in providing greater flexibility between non-survey estimates and superior data for three specific situations. In chapter 3, I provide an alternative way to jump over conflicting information when balancing IO tables that can handle different proportions of superior data (alternatively, expert judgement) and solve for the remainder unknows mechanically. Chapter 4 deals with price deflation in supply-use tables, which is normally calculated by official statistics organisations based on detailed information. I present an alternative procedure that lowers minimum information requirements and enables cell-specific deflators. Provided they are non-conflicting, my algorithm can handle as much additional pieces of superior information as available. Finally, Chapter 0 explores a more recent strand of literature: multiscale multiregional IO models. Herein, I seek to embed regional IO models into global MRIO datasets. My methodological proposal can be implemented with accessible aggregate data on trade (imports/exports) and transportation costs (distance). As in previous chapters, I can impose more constraints whenever additional data is available. Admittedly, all methodological proposals that I suggest are mere incremental innovations.

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[8] Besides the legitimate interest of the candidate in getting closer to a stable and decently paid job.

3 JUMPING OVER CONFLICTING INFORMATION[9]

Abstract. Balancing input-output (IO) tables using iterative proportional fitting techniques can be stymied by conflicting information. What is to be done in such cases? Literature suggests a wide variety of alternative methods. Within iterative proportional fitting techniques, modifying the constraint set to circumvent conflicting information problems has been suggested as a promising avenue. Following this approach, I identify some opportunities for improvement not yet addressed. As a result of this research, I present an iterative proportional fitting variant. The algorithm uses information contained in the matrix to be balanced for dynamically modify a given constraint set. The algorithm also ensures economically meaningful solutions, avoiding unsought sign flips. It also respects all macroeconomic aggregates. To illustrate my findings, I provide an empirical example based on the supply-use tables (SUTs) for the region of Galicia (Northwest Spain). Results suggest that my methodological proposal can yield estimates almost as accurate as other alternatives while avoiding undesired outcomes.

3.1 INTRODUCTION

3.1.1 Biproportional matrix balancing: not always a feasible alternative

Among non-survey methods, RAS is a widely used technique for updating and balancing IO tables or SUTs on the basis of given benchmarks (Lahr & de Mesnard, 2004). The origins of RAS can be traced back to Stone (1962) and subsequent theorizations by Bacharach (Bacharach, 1965, 1970). Outside economics and input-output analysis, algorithms for matrix balancing have followed parallel paths in multiple research areas (Schneider & Zenios, 1990). Kruithof (1937) seems to have been the first one to use biproportional matrix balancing techniques to study telephone traffic. Bregman (1967) relates RAS with early contributions made by soviet architect Sheleikhovskii in the 1930´s. Holý & Šafr (2023) mention the work by Deming & Stephan (1940) when dealing with census data as a precedent too.

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[9] This chapter partially reproduces the article: de la Torre Cuevas, F., Pereira López, X. and López Iglesias, E. (2023). A new alternative for matrix balancing under conflicting information. *Economic Systems Research*, 1-27. https://doi.org/10.1080/09535314.2023.2170217.

RAS iteratively scales an initial matrix $\mathbf{Z}^{(0)}$ considering an exogenously given set of row and column targets $(\boldsymbol{\mu}^*, \boldsymbol{\upsilon}^*)$. These targets correspond to the row and column sums of an unknown matrix $\mathbf{Z}^*$. As a result, we estimate a third matrix $\mathbf{Z}^{(T)}$ which has the same margins as $\mathbf{Z}^*$ after $t = 1, \cdots, T$ iterations. RAS was initally conceived only for balancing semipositive matrices. Günlük-Şenesen (1988) first, and then Junius and Oosterhaven (2003), formulated a generalised RAS variant (GRAS) which could manage negative entries too. Subsequent extensions include consideration for subset and block constraints (Gilchrist & St. Louis, 1999; Valderas Jaramillo & Rueda Cantuche, 2021) and for conflicting data with different reliabilities (Dalgaard & Gysting, 2004; Lahr, 2001; Lenzen et al., 2009). In this chapter we focus on this later feature of GRAS variants.

Applying RAS or GRAS may not always be possible due to conflicting data. Feasibility and convergence issues have been described in several contributions. These problems are typically caused by insufficient degrees of freedom due to a high proportion of zeros or the presence of (semi)fixed entries in the matrix. When this happens, the entire burden of change is forced onto the non-zero/non-fixed elements of certain rows or columns (Miller & Blair, 2022, pp. 434–435).

3.1.2 What is the problem with conflicting information?

3.1.2.1 Convergence conditions

Problems may arise due to the constraint structure we impose to our benchmark. Bacharach (1965, p. 304, 1970, p. 51) and Macgill (1977, p. 695) explore necessary conditions for RAS convergence. It may happen that target values are incoherent, making it impossible to reach a solution. Consider two matrices, $\mathbf{Z}^{(0)}$ and $\mathbf{Z}^*$ with $i = 1, \cdots, k$ rows and $j = 1, \cdots, l$ columns. Formally, convergence is possible when:

$$\sum \boldsymbol{\mu}^* = \sum \boldsymbol{\upsilon}^* \tag{1}$$

and, for every row and column with null entries:

$$\begin{aligned} \mu_i^* &\leq \sum_{j \in j'} \upsilon_j^*; \quad \forall i = 1, \cdots, k \\ \upsilon_j^* &\leq \sum_{i \in i'} \mu_i^*; \quad \forall j = 1, \cdots, l \end{aligned} \tag{2}$$

Where i' and j' are the complements of each i and j respectively. We define the complement of a specific row i and a column j as the set of rows with non-zero entries in column j. Conversely, we define the complement of a specific column j and a row i as the set of columns with non-zero entries in row i.

In addition, Pukelsheim (2014) notes that sparse matrices can split matrix balancing into independent sub problems. In these cases, conditions (1) and (2) must hold for all independent blocks. Sparse matrices can also affect the speed of convergence. This is not a problem when algorithms balance small matrices, but it could be a difficulty with large and sparse enough IO tables.

3.1.2.2 Additional information: better estimates, more conflicts

Paelinck and Waelbroeck (1963), Allen (1974), Lecomber (1975) and, more recently, De Mesnard and Miller (2006) have suggested that introducing accurate exogenous information generally leads to superior RAS outcomes. For example, we may know some elements of matrix $\mathbf{Z}^*$ in advance because an industrial survey has been conducted (Lenzen et al., 2006). This has been labelled in literature as *modified* RAS (MRAS).

However, if a high proportion of elements are fixed externally, convergence may be difficult, or even impossible (Cole, 1992). Moreover, even when convergence is possible, over-determined elements in the matrix might lead to a solution that does not reconcile all the conditions required in these contexts. Namely, solutions might appear associated to negative scaling coefficients and unwanted sign flips.

Let $\mathbf{P}^*$ and $\mathbf{N}^*$ be matrices containing exogenous information for positive and negative entries, respectively.

The GRAS solution with fixed superior data would have the form:

$$\mathbf{Z}^{(T)} = \mathbf{P}^{*} + \hat{\mathbf{r}}(\mathbf{P} - \mathbf{P}^{*})\hat{\mathbf{s}} + \mathbf{N}^{*} + (\hat{\mathbf{r}})^{-\mathbf{1}}(\mathbf{N} - \mathbf{N}^{*})(\hat{\mathbf{s}})^{-\mathbf{1}} \tag{3}$$

In addition, we sometimes have only row or column information available. Some contributions suggest ways for endogenously generate this missing information (Pereira López et al., 2013; Temursho & Timmer, 2011; Valderas Jaramillo et al., 2019). Alternatively, we can apply a one-side RAS to some entries as for Timmer (2005). A similar situation arises with double deflation methods (United Nations, 1973) to estimate SUTs or IO tables measured in constant prices. Note, double deflation is still widely used (Li & Kuroko, 2016) and has been described as particular case of biproportional balancing (Hoen, 2002).

Formally, in these cases we balance benchmark matrices considering only row or column targets. Let $\vec{\mathbf{P}}$ and $\vec{\mathbf{N}}$ be the matrices containing positive and negative entries to be only row balanced, respectively. Let $\downarrow \mathbf{P}$ and $\downarrow \mathbf{N}$ be the matrices containing positive and negative entries to be only column balanced, respectively. The solution of a matrix GRAS problem would have the form:

$$\begin{gathered}\mathbf{Z}^{(T)} = \hat{\mathbf{r}}\vec{\mathbf{P}} + \downarrow \mathbf{P}\hat{\mathbf{s}} + \hat{\mathbf{r}}\big(\mathbf{P} - \vec{\mathbf{P}} - \downarrow \mathbf{P}\big)\hat{\mathbf{s}} \\ + (\hat{\mathbf{r}})^{-\mathbf{1}}\vec{\mathbf{N}} + \downarrow \mathbf{N}(\hat{\mathbf{s}})^{-\mathbf{1}} + (\hat{\mathbf{r}})^{-\mathbf{1}}\big(\mathbf{N} - \vec{\mathbf{N}} - \downarrow \mathbf{N}\big)(\hat{\mathbf{s}})^{-\mathbf{1}}\end{gathered} \tag{4}$$

Note that equation (4) generalises equation (3).

3.1.2.3 Strict and economic infeasibilities

Let $\bar{\boldsymbol{\mu}}^{(t)} = \downarrow \mathbf{P}^{(t)}\mathbf{i} + \downarrow \mathbf{N}^{(t)}\mathbf{i} + \mathbf{P}^{*}\mathbf{i} + \mathbf{N}^{*}\mathbf{i}$ and $\bar{\boldsymbol{\upsilon}}^{(t)} = \big[\vec{\mathbf{P}}^{(t)}\big]'\mathbf{i} + \big[\vec{\mathbf{N}}^{(t)}\big]'\mathbf{i} + [\mathbf{P}^{*}]'\mathbf{i} + [\mathbf{N}^{*}]'\mathbf{i}$ be the vectors containing the sum of fixed cells for every row or column in iteration t. Conflicting data make the adjustment problem *strictly infeasible* if there are no elements different from 0 in a row or column that can be modified to achieve its target.

For a GRAS context, we define a strict infeasibility situation in a row i or a column j as follows:

$$\begin{aligned} \bar{\mu}_i^{(t)} \neq \mu_i^* \quad \text{and} \quad \nexists\, z_{ij}^{(t)} \neq 0 \; / \sum_j r_i^{(t)} p_{ij}^{(t)} - \sum_j \left[r_i^{(t)}\right]^{-1} n_{ij}^{(t)} = \mu_i^* \\ \bar{\upsilon}_j^{(t)} \neq \upsilon_j^* \quad \text{and} \quad \nexists\, z_{ij}^{(t)} \neq 0 \; / \sum_i p_{ij}^{(t)} s_j^{(t)} - \sum_i n_{ij}^{(t)} \left[s_j^{(t)}\right]^{-1} = \upsilon_j^* \end{aligned} \tag{5}$$

The combination between the technological structure of the matrix and the constraints imposed for balancing makes it mathematically impossible to achieve a solution.

It might also happen that an existing mathematical solution of a row or column balancing induces undesired sign flips in a rows or columns. This way, the economic meaning of an IO matrix can be compromised since some parts of it (e.g., intermediate transactions) do not admit negative values. Formally, we describe *economic infeasibility* in a GRAS context as follows.

If:

$$\begin{aligned} \exists\, z_{ij}^{(t)} \neq 0 \; / \sum_j r_i^{(t)} p_{ij}^{(t)} - \sum_j \left[r_i^{(t)}\right]^{-1} n_{ij}^{(t)} = \mu_i^* \\ \exists\, z_{ij}^{(t)} \neq 0 \; / \sum_i p_{ij}^{(t)} s_j^{(t)} - \sum_i n_{ij}^{(t)} \left[s_j^{(t)}\right]^{-1} = \upsilon_j^* \end{aligned} \tag{6}$$

but:

$$\begin{aligned} \bar{\mu}_i^{(t)} > \mu_i^* \quad \text{and} \quad \sum_j p_{ij}^{(t)} = 0 \quad \text{or} \quad \sum_j n_{ij}^{(t)} = 0 \\ \bar{\upsilon}_j^{(t)} > \upsilon_j^* \quad \text{and} \quad \sum_i p_{ij}^{(t)} = 0 \quad \text{or} \quad \sum_i n_{ij}^{(t)} = 0 \end{aligned} \tag{7}$$

then:

$$\begin{aligned} r_i^{(t)} < 0 \\ s_j^{(t)} < 0 \end{aligned} \tag{8}$$

Following Paelinck & Waelbroeck (1963) and Lecomber (1975), if an entry is fixed then its value must be discounted from the correspondent row/column target. Considering GRAS' r_i

and s_j definition (Temursho et al., 2013), it is straightforward to probe that if (10) holds μ_i^* and v_j^* will be negative (positive) for the case of a strictly positive (negative) row or column. Hence, $r_i < 0$ and $s_j < 0$.

This disturbs the economic meaning of the updated matrix because it changes the signs of the cells multiplied by the negative r_i and s_j coefficients. The problem can be mathematically solved. However, conflicting information makes the problem economically infeasible. Technological features of the economic structure to be studied would be distorted since trade-flows and technical coefficients would adopt (negative) values that are beyond the boundaries set by economic theory.

3.1.3 Alternatives for matrix balancing under conflicting information

3.1.3.1 Moving out from biproportional balancing?

Literature suggests the use of other equivalent balancing procedures, sometimes arguing RAS infeasibility problems. Within IO analysis, several other approaches exist for matrix balancing (Jackson & Murray, 2004). One of the most extended is minimum sum of cross entropies (MSCE). MSCE has been proved to be equivalent to RAS balancing (McDougall, 1999). Introduced in an IO context by Golan, et al. (1994), MSCE approaches have the advantage of increasing flexibility for constraint management (Termursho et al., 2020). Extensions to MSCE include consideration of sign flips and data reliability (Fernández Vázquez, 2016), various initial matrices (Fernández Vázquez et al., 2015) and subset constraints (Zheng et al., 2022) among other features.

Quadratic programming (QP) methods also appear in literature as alternatives for matrix balancing. Basic mathematical properties of these approaches can be found in van der Ploeg (1982). More recently, Canning and Wang (2005) developed a methodology based on the data´s variance. Rassier, et al. (2007) followed the same approach by using variance-covariance matrices of the coefficients. Nonetheless, these same authors point that these matrices are seldom available in practice. An application of this approach to SUT balancing can be found in Nicolardi (2013). In addition, Geschke et al. (2019) proposed the Accelerated Cimmino (ACIM) algorithm in the same fashion. ACIM divides the matrix into several blocks that receive different treatment and ensures a solution with no negatives. In order to reconcile the information of the different blocks, a convex combination step is introduced.

Despite their advantages, MSCE and QP approaches also present their own drawbacks. First, subjective judgement is not eliminated in MSCE contexts when dealing with conflicting information. In some cases, subjective measures for data quality are introduced, such as the reliability coefficient introduced by Rodrigues (2014) or the penalty function formulated by Tsionas (2020). Other proposals use standard deviation as an uncertainty measure (Rodrigues & Lahr, 2018). Data reliability is a priori fixed and kept constant throughout the reconciliation process. Second, despite some simplification efforts, algorithms such as ACIM have been reported as demanding in terms of computing performance and skills. Third, in their empirical test for different matrix balancing alternatives, Termursho, Webb and Yamano (2011) suggest that biproportional techniques presents the best balance between accuracy and speed/simplicity. Hence, we look for a biproportional technique alternative to balance matrices under conflicting information.

3.1.3.2 Turning zeros into small values

To deal with conflicting information in a RAS context, a first alternative appeared with the substitution of some zero entries by small values. Geoffrey J.D. Hewings' Ph.D. dissertation in 1969 has been credited as one of the first contributions in this direction (de Mesnard, 2003). Möhr, Crown, & Polenske (1987) went one step further and systematised these changes in the benchmark matrices. Their contribution presented a systematic method for choosing which zero entries are to be modified into non-zero elements. After that, they introduce small new trade flows in the tables.

This procedure is justified by the fact that some zeros in IO tables or SUTs appear due to rounding. But no matter how systematic this procedure might be, some other zeros constitute true technological facts. As a consequence, these solutions can alter the technological structure of the matrix introducing unreal linkages between industries for mathematical purposes. Moreover, since fixed values must be discounted when balancing, we convert them to zeros. Therefore, changing these entries by introducing small values would neglect this additional information. Consequently, in this research we look for alternatives that can handle conflicting information problems through target modifications in a biproportional balancing framework.

3.1.3.3 Target modification: spotting improvement opportunities

A third alternative is based on target modification according to information reliability. Lahr (2001, p. 220) introduced the concept of “tolerance limits” (TL). If data is collected from sources with different reliabilities, then it would be reasonable to let RAS solution diverge from the desired targets in different ways too. The more information is trusted the less targets should be allowed to be modified. TL were defined based on scholar, practitioner, or expert judgement.

Dalgaard and Gysting (2004) re-interpreted Lahr´s tolerance limits as convex combinations between two different sets of information available. The use of convex combinations for conflicting data reconciliation can be traced back to Jensen and McGaurr (1976) and Gerking (1976). Finally, Lenzen et al. (2009) presented a GRAS variant that, among other novelties, could handle conflicting external data: the *konfliktfreies* RAS (KRAS). This methodology is, to date, the most advanced alternative for solving inconsistency problems in a non-manual way (Mahajan et al., 2018, p. 562). We describe it in detail to discuss possible improvement opportunities and introduce notation.

KRAS formulation rewrites biproportional GRAS as follows:

$$\mathbf{G}\mathbf{z} = \mathbf{c} \tag{9}$$

with

- $\mathbf{G}$ = appropriate size matrix formed by ones and zeros.
- $\mathbf{z}$ = column vectorisation of the benchmark matrix $\mathbf{Z}^{(0)}$.
- $\mathbf{c}$ = vector which includes row, column, and subset constraints.

GRAS balancing then becomes:

$$\text{Minimise } \mathrm{f}(\mathbf{z}, \mathbf{z}^*) = \sum_{ij} \left| z_{ij}^* \right| \ln \frac{z_{ij}^*}{e z_{ij}} \quad \text{subjected to} \quad \mathbf{G}\mathbf{z} = \mathbf{c} \tag{10}$$

where e is the basis of the natural logarithm.

For the sake of simplicity, let us consider the case in which no subset constraints are stated. For $k + l$ constraints and every iteration t, scaling coefficients are calculated as:

$$r_i^{(k)} = \frac{c_i^{(k)} + \sqrt{c_i^{(k)2} + 4\sum_{j,z_j^{(k-1)}g_{ij}>0} g_{ij} z_j^{(k-1)} \sum_{j,z_j^{(k-1)}g_{ij}<0} g_{ij} z_j^{(k-1)}}}{2\sum_{j,z_j^{(k-1)}g_{ij}>0} g_{ij} z_j^{(k-1)}}$$

$$z_j^{(k)} = z_j^{(k-1)} \left[r^{(k)}\right]^{\mathrm{Sgn}\left(z_j^{(k-1)} g_{ij}\right)} \tag{11}$$

$$\text{with} \quad i = 0, 1, \cdots, k + l \quad \text{and} \quad j = 1$$

The algorithm converges if:

$$|\mathbf{Gz} - \mathbf{c}| < \varepsilon|\mathbf{c}| \tag{12}$$

for a sufficiently small tolerance error ε.

We can translate (10)-(11) to a biproportional balancing set up. Extending Temurshoev, Miller, & Bouwmeester (2013, p. 365) we derive row coefficients as:

$$r_i^{(t)} = \begin{cases} \dfrac{\mu_i^* + \sqrt{(\mu_i^*)^2 + 4\sum_j p_{ij}^{(t)} \sum_j n_{ij}^{(t)}}}{2\sum_j p_{ij}^{(t)}} & \text{for} \quad \sum_j p_{ij}^{(t)} > 0 \quad \text{and} \quad \sum_j n_{ij}^{(t)} > 0 \\ \dfrac{\mu_i^*}{\sum_j p_{ij}^{(t)}} \quad \text{for} \quad \sum_j p_{ij}^{(t)} > 0 \quad \text{and} \quad \sum_j n_{ij}^{(t)} = 0 \\ -\dfrac{\sum_j n_{ij}^{(t)}}{\mu_i^*} \quad \text{for} \quad \sum_j p_{ij}^{(t)} = 0 \quad \text{and} \quad \sum_j n_{ij}^{(t)} > 0 \end{cases} \tag{13}$$

$$p_{ij}^{(t)} = p_{ij}^{(t-1)} s_j^{(t-1)}$$

$$n_{ij}^{(t)} = n_{ij}^{(t-1)} \left[s_j^{(t-1)}\right]^{-1}$$

And for column coefficients:

$$s_j^{(t-1)} =$$

$$\begin{cases} \dfrac{\upsilon_j + \sqrt{\left(\upsilon_j^*\right)^2 + 4\sum_i p_{ij}^{(t-1)} \sum_i n_{ij}^{(t-1)}}}{2\sum_i p_{ij}^{(k-1)}} & \text{for} \quad \displaystyle\sum_i p_{ij}^{(t-1)} > 0 \quad \text{and} \quad \displaystyle\sum_i n_{ij}^{(t-1)} > 0 \\ \dfrac{\upsilon_j^*}{\sum_i p_{ij}^{(t-1)}} & \text{for} \quad \displaystyle\sum_i p_{ij}^{(t-1)} > 0 \quad \text{and} \quad \displaystyle\sum_i n_{ij}^{(t-1)} = 0 \\ -\dfrac{n^{(t-1)}}{\upsilon_j^*} & \text{for} \quad \displaystyle\sum_i p_{ij}^{(t-1)} = 0 \quad \text{and} \quad \displaystyle\sum_i n_{ij}^{(t-1)} > 0 \end{cases} \tag{14}$$

Analogously, equation (12) is equivalent to:

$$\begin{aligned} &\left|\left[\hat{\mathbf{r}}\mathbf{P}^{(0)}\hat{\mathbf{s}} - (\hat{\mathbf{r}})^{-1}\mathbf{N}^{(0)}(\hat{\mathbf{s}})^{-1}\right]\mathbf{i} - \boldsymbol{\mu}^*\right| < \varepsilon \\ &\left|\left[\hat{\mathbf{r}}\mathbf{P}^{(0)}\hat{\mathbf{s}} - (\hat{\mathbf{r}})^{-1}\mathbf{N}^{(0)}(\hat{\mathbf{s}})^{-1}\right]'\mathbf{i} - \boldsymbol{\upsilon}^*\right| < \varepsilon \end{aligned} \tag{15}$$

KRAS allows for the consideration of subset constraints, non-unity coefficients and conflicting information. We focus on the later feature. When GRAS fails to reach convergence, the original targets are allowed to change. An amount $\alpha\sigma_i$ is added or subtracted from the constraint c_i. Formally:

$$\text{if} \quad |\mathbf{Gz} - \mathbf{c}|^{(t)} - |\mathbf{Gz} - \mathbf{c}\,|^{(t-1)} < \varepsilon$$

$$c_i^{(t)} = c_i^{(t-1)} - \mathrm{Sgn}[c_i^{(t-1)} - \sum_j g_{ij} z_j^{(t-1)}] \times \mathrm{Min}\left[\left|c_i^{(t-1)} - \sum_j g_{ij} z_j^{(t-1)}\right| \quad , \quad \alpha\sigma_i\right] \tag{16}$$

The maximum adjustment allowed is the actual distance between the target entry and the realization achieved in the previous iteration in order to avoid “overshooting” problems.

Equation (16) can be rewritten in a biproportional set up for each row i, column j and iteration t as:

$$\mathbf{c}^{(t)} = \begin{bmatrix} \boldsymbol{\mu}^{(t)} \left\{ \mu_i^{(t)} = \mu_i^{(t-1)} - \mathrm{Sgn}\left[\mu_i^{(t-1)} - \kappa_i^{(t-1)}\right] \times \mathrm{Min}\left[\left|\mu^{(t-1)} - \kappa_i^{(t-1)}\right| \quad , \quad \alpha\sigma_i\right]\right\} \\ \boldsymbol{\upsilon}^{(t)} \left\{ \upsilon_j^{(t)} = \upsilon_j^{(t-1)} - \mathrm{Sgn}\left[\upsilon_j^{(t-1)} - \lambda_i^{(t-1)}\right] \times \mathrm{Min}\left[\left|\upsilon_j^{(t-1)} - \lambda_i^{(t-1)}\right| \quad , \quad \alpha\sigma_j\right]\right\} \end{bmatrix} \tag{17}$$

As I have briefly shown, KRAS presents several useful extensions to GRAS. However, it also presents some limitations. The following improvement opportunities are addressed in the present research:

1. First, in the absence of subset constraints, row and column target sums in the modified constraints are not necessarily preserved. Feasibility problems are solved at the cost of modifying some aggregated figures. Consider for example a macroeconomic aggregate such as gross domestic product (GDP). This could be a problem if official published figures are to be respected. When conflicting information hinders convergence, KRAS adds (subtracts) an amount $\alpha\sigma$ to (of) every target until it finds a feasible solution. In doing so, KRAS alters the overall sum of $\mathbf{c}^{(t)}$ because no scaling factors are applied. Section 4.2 in Lenzen et al. (2009, p. 38) provides an example of this issue.

2. Second, KRAS does not exclude undesired sign flips when:

$$\begin{gathered} \left|\mu^{(t-1)} - \kappa_i^{(t-1)}\right| > \alpha\sigma_i \\ \left|\upsilon_j^{(t-1)} - \lambda_i^{(t-1)}\right| > \alpha\sigma_j \end{gathered} \tag{18}$$

Adding (subtracting) $\alpha\sigma_i$ or $\alpha\sigma_j$ to negative targets $\mu_i^{(t-1)}$ or $\upsilon_j^{(t-1)}$ does not ensure positive $\mu_i^{(t)}$ or $\upsilon_j^{(t)}$. Therefore, solving equations (13)-(15) for strictly positive/strictly negative rows or columns yields negative $r_i^{(t)}$ and $s_j^{(t)}$ if an economic infeasibility situation appears. This happens because KRAS considers data reliability but not how large incoherencies are. Thus, results' economic interpretation could become unclear.

3. Third, the choice of values for α and σ is made a priori and cannot be modified during the process. KRAS only considers information given in matrices $\mathbf{Z}^{(t)}$ when (18) does not hold. When this is not the case, an a priori fixed value $\alpha\sigma$ is added or subtracted to each target. In doing so, we get a trial-error dynamic that speeds up convergence. However, this feature could be further improved by directly exploring the frontier between feasibility and infeasibility.

3.1.4 Handling conflicting information without additional information?

The purpose of this chapter is to present a RAS variant that manages conflicting information through target modification. In section 3.1.3 I have identified several alternatives in the literature. Since KRAS can be considered as the current state of the art to this regard, I will take it as a departure point. In the remainder of this chapter I address the improvement opportunities listed in section 0. Nevertheless, I consider ideas contained in previous proposals too. My main point is to solve conflicting information problems in a more efficient way without using additional information (e.g.: expert judgement).

3.2 METHODOLOGICAL PROPOSAL

3.2.1 Information requirements

The following information is required to apply the algorithm:

- $\mathbf{Z}^{(0)}$ = initial matrix.
- $\boldsymbol{\mu}^{*}$ = initial row target vector.
- $\boldsymbol{\upsilon}^{*}$ = initial column target vector.

Note that these are the same information requirements of standard GRAS.

3.2.2 Preserving macroeconomic aggregates

We can define for every iteration an alternative set of targets as follows:

- Let $\boldsymbol{\kappa}^{(t)}$ and $\boldsymbol{\lambda}^{(t)}$ be the vectors containing row and column sums in each iteration t[10].

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[10] For the sake of simplicity, each iteration stands for a row or column balancing step.

- Let $\boldsymbol{\pi}^{(t)}_{(\boldsymbol{\mu})} = \left\{\pi^{(t)}_i = \sum\boldsymbol{\mu}^* / \sum\boldsymbol{\kappa}^{(t)} \quad \forall i\right\}$ and $\boldsymbol{\pi}^{(t)}_{(\boldsymbol{\upsilon})} = \left\{\pi^{(t)}_j = \sum\boldsymbol{\upsilon}^* / \sum\boldsymbol{\lambda}^{(t)} \quad \forall j\right\}$ be the scaling vectors that ensure convergence condition (1): preserving overall target sums.
- Let $\widetilde{\boldsymbol{\mu}}^{(t)} = \widehat{\boldsymbol{\pi}}^{(t)}_{(\boldsymbol{\mu})}\boldsymbol{\kappa}^{(t)}$ and $\widetilde{\boldsymbol{\upsilon}}^{(t)} = \widehat{\boldsymbol{\pi}}^{(t)}_{(\boldsymbol{\upsilon})}\boldsymbol{\lambda}^{(t)}$ be the alternative target vectors to be considered for every iteration.

Note, the scaling process resembles the third step in the Three-steps RAS (TRAS) algorithm (Gilchrist & St. Louis, 1999, 2004). After every iteration, the algorithm scales the row and column sums in order to preserve fundamental equilibria and respect the original constraint sums or other a priori known figures. Thus, constraint management includes three dimensions: row targets, column targets and matrix or matrix (sub)total row/column sums. I calculate vectors $\boldsymbol{\mu}^{(t)}$ and $\boldsymbol{\upsilon}^{(t)}$ as combinations between two pairs of targets: $\boldsymbol{\mu}^*$; $\boldsymbol{\upsilon}^*$ and $\widetilde{\boldsymbol{\mu}}^{(t)}$; $\widetilde{\boldsymbol{\upsilon}}^{(t)}$ in every iteration. Vectors $\boldsymbol{\mu}^{(t)}$ and $\boldsymbol{\upsilon}^{(t)}$ are defined as follows:

$$\begin{aligned} \boldsymbol{\mu}^{(t)} &= \widehat{\boldsymbol{\alpha}}^{(t)}\boldsymbol{\mu}^* + \left[\mathbf{I} - \widehat{\boldsymbol{\alpha}}^{(t)}\right]\widetilde{\boldsymbol{\mu}}^{(t)} \\ \boldsymbol{\upsilon}^{(t)} &= \widehat{\boldsymbol{\beta}}^{(t)}\boldsymbol{\upsilon}^* + \left[\mathbf{I} - \widehat{\boldsymbol{\beta}}^{(t)}\right]\widetilde{\boldsymbol{\upsilon}}^{(t)} \end{aligned} \tag{19}$$

Where **I** stands for an identity matrix of appropriate dimensions.

The alternative set of targets $\widetilde{\boldsymbol{\mu}}^{(t)}$; $\widetilde{\boldsymbol{\upsilon}}^{(t)}$ preserve macroeconomic aggregates, do not distort overall sums of $\boldsymbol{\mu}^*$ and $\boldsymbol{\upsilon}^*$ and may include subset constraints if additional information is available. This point can be probed this since $\sum\boldsymbol{\mu}^* = \sum\widetilde{\boldsymbol{\mu}}^{(t)} = \sum\boldsymbol{\upsilon}^* = \sum\widetilde{\boldsymbol{\upsilon}}^{(t)}$. Hence, any combination — $\boldsymbol{\mu}^{(t)}$, $\boldsymbol{\upsilon}^{(t)}$ — between the alternative pairs and using $\boldsymbol{\alpha}^{(\mathrm{t})}$ and $\boldsymbol{\beta}^{(\mathrm{t})}$ vectors as here defined will have the same overall sum.

3.2.3 Preventing undesired sign flips

Three possibilities may arise for $\alpha^{(t)}_i$ and $\beta^{(t)}_j$ in every row, column, and iteration. I now consider them separately. After doing so, I set a mechanism to determine which values are to be assigned in vectors $\boldsymbol{\alpha}^{(t)}$ and $\boldsymbol{\beta}^{(t)}$. This subsection describes the core innovation of my work in this chapter.

First, for every row/column with no feasibility problems, the algorithm chooses $\alpha^{(t)}_i = 1$ and $\beta^{(t)}_j = 1$. Note that if $\boldsymbol{\alpha}^{(t)} = \mathbf{I}$, then $\boldsymbol{\mu}^{(t)} = \boldsymbol{\mu}^*$. Analogously, if $\boldsymbol{\beta}^{(t)} = \mathbf{I}$ then $\boldsymbol{\upsilon}^{(t)} = \boldsymbol{\upsilon}^*$. Second, if balancing a row/column is strictly infeasible, then $\alpha_i^{(t)} = 0$ and $\beta_j^{(t)} = 0$. Once again, note that if $\boldsymbol{\alpha}^{(t)} = 0$ and $\boldsymbol{\beta}^{(t)} = 0$, then $\boldsymbol{\mu}^{(t)} = \tilde{\boldsymbol{\mu}}^{(t)}$ and $\boldsymbol{\upsilon}^{(t)} = \tilde{\boldsymbol{\upsilon}}^{(t)}$.

Third, if the problem is economically infeasible, values different from 0 or 1 can be assigned to the $\alpha_i^{(t)}$ and $\beta_j^{(t)}$. The target to be considered must be situated between the initial targets and the scaled sum of a specific row or column in every iteration, our alternative targets. In the absence of superior data or expert judgement, we use information contained in matrix $\mathbf{Z}^{(t)}$ to calculate these values. I define the frontier between economic feasibility and infeasibility as:

$$\begin{aligned} {\bar{\mu}_i}^{(t)} &= {\alpha_i}^{(t)}\mu_i^* + \left[1 - {\alpha_i}^{(t)}\right]\kappa_i^{(t)} \\ {\bar{\upsilon}_j}^{(t)} &= \beta_j^{(t)}\upsilon_j^* + \left[1 - \beta_j^{(t)}\right]\lambda_j^{(t)} \end{aligned} \tag{20}$$

Values contained in vectors $\bar{\boldsymbol{\mu}}^{(t)}$ and $\bar{\boldsymbol{\upsilon}}^{(t)}$ mark the turning point from which the fixed elements of a row or column start introducing undesired sign flips in the matrix balancing. Solving for ${\alpha_i}^{(t)}$ and $\beta_j^{(t)}$:

$$\begin{aligned} {\alpha_i}^{(t)} &= \frac{{\bar{\mu}_i}^{(t)} - \kappa_i^{(t)}}{\mu_i^* - \kappa_i^{(t)}} \\ \beta_j^{(t)} &= \frac{{\bar{\upsilon}_j}^{(t)} - \lambda_j^{(t)}}{\upsilon_j^* - \lambda_j^{(t)}} \end{aligned} \tag{21}$$

Scalars are dynamically modified considering the frontier between economic feasibility and infeasibility arising in each iteration. This way I can consider cases of underconstrained entries as well as priori fixed information described in section 3.1.2.3.

3.2.4 Avoiding trial-error dynamics

To avoid trial-error dynamics I set a straightforward mechanism to decide to what extent targets are modified in each iteration. We choose unique $\alpha^{(\mathrm{t})}$ and $\beta^{(\mathrm{t})}$ values to solve infeasibility problems and achieve a coherent solution at the same time. The algorithm selects these values so as to ensure feasibility for the largest conflicting information problem.

Formally:

$$\begin{aligned}\widehat{\boldsymbol{\alpha}}^{(t)} &= \operatorname{diag}\left[\operatorname{Min}_i\left[{\alpha_i}^{(t)}\right] \otimes \mathbf{i}\right]\\ \widehat{\boldsymbol{\beta}}^{(t)} &= \operatorname{diag}\left[\operatorname{Min}_j\ \left[\beta_j^{(t)}\right] \otimes \mathbf{i}\right]\end{aligned} \tag{22}$$

Where $\mathbf{i}$ stands for a vector of ones with appropriate dimensions and $\otimes$ for the Kronecker product.

If additional information about the total sum of different parts of the matrix is available, different α and β values can be chosen during the same iteration t. For example, consider the overall sum of rows $i = 1, \cdots, \rho$ to be known on the one hand. On the other hand, the overall sum of the remaining rows $i = \rho + 1, \cdots, k$ is known too. In the case of columns, let me consider only the overall sum of all columns $j = 1, \cdots, l$. Provided information coherent with (1) I can divide vector $\boldsymbol{\mu}^{(t)}$ calculation into two separated subsets:

$$\begin{aligned}\boldsymbol{\pi}_{(\boldsymbol{\mu})}^{(t)} &= \left\{\pi_i^{(t)} = \left\{\begin{matrix}\sum_{i=1}^{\rho} \boldsymbol{\mu}^* \Big/ \sum_{i=1}^{\rho} \boldsymbol{\kappa}^{(t)} & \forall i = 1, \cdots \rho\\ \sum_{i=\rho+1}^{k} \boldsymbol{\mu}^* \Big/ \sum_{i=\rho+1}^{k} \boldsymbol{\kappa}^{(t)} & \forall i = \rho + 1, \cdots k\end{matrix}\right\}\right\}\\ \boldsymbol{\pi}_{(\boldsymbol{\upsilon})}^{(t)} &= \left\{\pi_j^{(t)} = \sum_{j=1}^{l} \boldsymbol{\upsilon}^* \Big/ \sum_{j=1}^{l} \boldsymbol{\lambda}^{(t)} \quad \forall j = 1, \cdots, l\right\}\end{aligned} \tag{23}$$

Because both row subsets have been appropriately scaled, I can split $\boldsymbol{\mu}^{(\mathrm{t})}$ calculation into two separated processes while preserving macroeconomic aggregates. Formally:

$$\begin{aligned}\widehat{\boldsymbol{\alpha}}^{(t)} &= \operatorname{diag}\left\{\begin{matrix}\operatorname{Min}_{i=1}^{\rho}\left[{\alpha_i}^{(t)}\right] \otimes \mathbf{i} & \forall i = 1, \cdots \rho\\ \operatorname{Min}_{i=\rho+1}^{k}\left[1, \left|{\alpha_i}^{(t)}\right|\right] \otimes \mathbf{i} & \forall i = \rho + 1, \cdots k\end{matrix}\right.\\ \widehat{\boldsymbol{\beta}}^{(t)} &= \operatorname{diag}\left[\operatorname{Min}_j\left[\beta_j^{(t)}\right] \otimes \mathbf{i}\right] \quad \forall j = 1, \cdots, l\end{aligned} \tag{24}$$

Additional information can allow the least conflicting rows and columns to adjust considering constraints much closer to $\boldsymbol{\mu}^*$ and $\boldsymbol{\upsilon}^*$. In my example, if $\sum_{i=1}^{\rho} \boldsymbol{\mu}^* + \sum_{i=\rho+1}^{k} \boldsymbol{\mu}^* = \sum_{j=1}^{l} \boldsymbol{\upsilon}^*$ then:

$$\sum_{i=1}^{\rho} \boldsymbol{\mu}^* + \sum_{i=\rho+1}^{k} \boldsymbol{\mu}^* = \sum_{i=1}^{\rho} \Sigma\widetilde{\boldsymbol{\mu}}^{(t)} + \sum_{i=\rho+1}^{k} \Sigma\widetilde{\boldsymbol{\mu}}^{(t)} = \sum_{j=1}^{l} \boldsymbol{\upsilon}^* \tag{25}$$

Hence, any combination — $\boldsymbol{\mu}^{(t)}$, $\boldsymbol{\upsilon}^{(t)}$ — between the two pairs of alternatives will present the same overall sum.

3.2.5 Step-by-step workflow

I now present a step-by-step description of my methodological proposal.

Step 1. In every iteration, I calculate vectors $\widetilde{\boldsymbol{\mu}}^{(t)}$ and $\widetilde{\boldsymbol{\upsilon}}^{(t)}$ as explained in section 3.2.2.

Step 2. Following the developments in section 3.2.3, I calculate $\alpha_i^{(t)}$ and $\beta_j^{(t)}$ for each row i, column j and iteration t implementing equation (26)

$$
\alpha_i^{(t)} = \begin{cases}
1 & \text{if} \quad \left\{\begin{array}{l}
\exists\, z_{ij}^{(t)} \neq 0 \;/ \sum_j r_i^{(t)} p_{ij}^{(t)} - \sum_j \left[r_i^{(t)}\right]^{-1} n_{ij}^{(t)} = \mu_i^* \\
\exists\, p_{ij}^{(t)} \neq 0 \;/ \sum_j r_i^{(t)} p_{ij}^{(t)} = \mu_i^* \quad \text{and} \quad \bar{\mu}_i{}^{(t)} \leq \mu_i^* \\
\exists\, n_{ij}^{(t)} \neq 0 \;/ \sum_j \left[r_i^{(t)}\right]^{-1} n_{ij}^{(t)} = \mu_i^* \quad \text{and} \quad \bar{\mu}_i{}^{(t)} \leq \mu_i^*
\end{array}\right. \\
\dfrac{\bar{\mu}_i{}^{(t)} - \kappa_i^{(t)}}{\mu_i^* - \kappa_i^{(t)}} & \text{if} \quad \left\{\begin{array}{l}
\exists\, p_{ij}^{(t)} \neq 0 \;/ \sum_j r_i^{(t)} p_{ij}^{(t)} = \mu_i^* \quad \text{and} \quad \bar{\mu}_i{}^{(t)} > \mu_i^* \\
\exists\, n_{ij}^{(t)} \neq 0 \;/ \sum_j \left[r_i^{(t)}\right]^{-1} n_{ij}^{(t)} = \mu_i^* \quad \text{and} \quad \bar{\mu}_i{}^{(t)} > \mu_i^*
\end{array}\right. \\
0 & \text{if} \quad \nexists\, z_{ij}^{(t)} \neq 0 \;/ \sum_j r_i^{(t)} p_{ij}^{(t)} - \sum_j \left[r_i^{(t)}\right]^{-1} n_{ij}^{(t)} = \mu_i^*
\end{cases}
$$

$$
\beta_j^{(t)} = \begin{cases}
1 & \text{if} \quad \left\{\begin{array}{l}
\exists\, z_{ij}^{(t)} \neq 0 \;/ \sum_j r_i^{(t)} p_{ij}^{(t)} - \sum_j \left[r_i^{(t)}\right]^{-1} n_{ij}^{(t)} = \upsilon_j^* \\
\exists\, p_{ij}^{(t)} \neq 0 \;/ \sum_j s_j^{(t)} p_{ij}^{(t)} = \upsilon_j^* \quad \text{and} \quad \bar{\upsilon}_j{}^{(t)} \leq \upsilon_j^* \\
\exists\, n_{ij}^{(t)} \neq 0 \;/ \sum_j \left[s_j^{(t)}\right]^{-1} n_{ij}^{(t)} = \upsilon_j^* \quad \text{and} \quad \bar{\upsilon}_j{}^{(t)} \leq \upsilon_j^*
\end{array}\right. \\
\dfrac{\bar{\upsilon}_j{}^{(t)} - \lambda_j^{(t)}}{\upsilon_j^* - \lambda_j^{(t)}} & \text{if} \quad \left\{\begin{array}{l}
\exists\, p_{ij}^{(t)} \neq 0 \;/ \sum_j s_j^{(t)} p_{ij}^{(t)} = \upsilon_j^* \quad \text{and} \quad \bar{\upsilon}_j{}^{(t)} > \upsilon_j^* \\
\exists\, n_{ij}^{(t)} \neq 0 \;/ \sum_j \left[s_j^{(t)}\right]^{-1} n_{ij}^{(t)} = \upsilon_j^* \quad \text{and} \quad \bar{\upsilon}_j{}^{(t)} > \upsilon_j^*
\end{array}\right. \\
0 & \text{if} \quad \exists\, z_{ij}^{(t)} \neq 0 \;/ \sum_i p_{ij}^{(t)} s_j^{(t)} - \sum_i n_{ij}^{(t)} \left[s_j^{(t)}\right]^{-1} = \upsilon_j^*
\end{cases}
\tag{26}
$$

For each row and column, the algorithm chooses $\alpha_i^{(t)} = 1$ and $\beta_j^{(t)} = 1$ if they are no strict or economic infeasibility problems. This includes the case were positive and negative entries coexist and the cases where they are only positive or negative entries. I use equations (21) to address economic infeasibilities. Finally, I use $\alpha_i^{(t)} = 0$ and $\beta_j^{(t)} = 0$ for the extreme case where every entry different from zero in a row (column) is fixed or column (row) underconstrained.

Step 3. For each iteration t, I choose the $\boldsymbol{\alpha}^{(t)}$ and $\boldsymbol{\beta}^{(t)}$ values according to equation (22). As noted earlier, $\boldsymbol{\alpha}^{(t)}$ and $\boldsymbol{\beta}^{(t)}$ value assignment can be partitioned if additional information is available as shown in (23)-(24). After doing so, calculating the vectors $\boldsymbol{\mu}^{(t)}$ and $\boldsymbol{\upsilon}^{(t)}$ is straightforward using equation (19).

Step 4. After setting the row or column targets for iteration t, I calculate matrix $\mathbf{Z}^{(t+1)}$ using GRAS.

Step 5. Steps 1 to 4 are repeated until (15) is fulfilled for a small enough ε tolerance error. The process concludes with vectors $\boldsymbol{\mu}^{(T)}$ and $\boldsymbol{\upsilon}^{(T)}$ as consolidated targets.

3.3 EMPIRICAL APPLICATION

3.3.1 Data and methods

In this section I provide a modest empirical application solving conflicting information cases. I run two different experiments to illustrate how does my methodological proposal address the improvement opportunities spotted in section 0. Essentially, I propose two experiments based on a real supply-use table that is modified to generate conflicting information problems. I am aware this is not a robustness test. Therefore, all results must be interpreted with appropriate precaution. I use the 2011 and 2016 SUTs of Galicia (NW Spain) at purchasers' prices[11]. Both SUTs are reported to be survey-based (IGE, 2015, 2019). Experiment I reflects a situation reported in literature as in one-side RAS. A similar situation arises when double deflation

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[11] All data can be retrieved from: https://www.ige.eu/web/mostrar_actividade_estatistica.jsp?idioma=gl&codigo=0307007003

methods are used to get IO data in constant prices. Experiment II illustrates a situation where superior data is introduced in the balancing process. Therefore, I simulate a more common situation faced by IO data producers and users. Experiment II can also be regarded as a particular situation in experiment I.

	Products	Industries	Final demand	$\boldsymbol{\kappa}$
Products		$\mathbf{U}$	$\mathbf{F}$	$\mathbf{q}$
Value-added		$\mathbf{W}$		$\mathbf{w}$
Industries	$\mathbf{V}$			$\mathbf{g}$
Imports	$\mathbf{M}$			$\mathbf{m}$
Trade margins	$\mathbf{B}$			$\mathbf{b}$
$\boldsymbol{\lambda}'$	$\mathbf{q}'$	$\mathbf{g}'$	$\mathbf{f}'$	

Table 2. Supply and use table at purchasers' prices.
Source: own elaboration.

Table 2 provides a schematic overview for the SUT structure. Matrix $\mathbf{U}$ represents intermediate consumptions of products $(i = 1, \cdots, k)$ by industries $(j = 1, \cdots, l)$. Matrix $\mathbf{F}$ represents commodity shipments to final demand. $\mathbf{F}$ has dimensions $(k \times \varphi)$ where φ represents the number of final demand components. Matrix $\mathbf{W}$ stands for value added and has dimensions $(\psi \times l)$ where ψ stands for the number of value-added components. Matrix $\mathbf{V}$ represents the supply that each industry provides for each commodity and has dimensions $(l \times k)$. Matrix $\mathbf{M}$ stands for the commodity flows imported from different origins and has dimensions $(o \times k)$ where o denotes the number of import origins. Matrix $\mathbf{B}$ is the bridge matrix between basic and purchasers' prices and has dimensions $(\gamma \times k)$ where γ denotes trade margin components. In addition, vectors $\mathbf{q}$ denote total supply and total use by commodity. Vector $\mathbf{g}$ represents gross output by industry. Vectors $\mathbf{f}$ and $\mathbf{w}$ stand for the sum of each component of final demand and value-added matrices. Vector $\mathbf{m}$ contains total imports by origin. Vector $\mathbf{b}$ contains the sum of each bridge matrix component.

In my dataset, matrices $\mathbf{U}$ and $\mathbf{V}$ account for $k = 110$ products and $l = 72$ industries. Final demand matrix $\mathbf{F}$ has $\varphi = 8$ components: (i) household consumption, (ii) government spending, (iii) collective consumption, (iv) gross fixed capital formation, (v) inventory variations, (vi) export to the rest of Spain, (vii) exports to EU member states and (viii) exports to non-member of the EU. Matrix $\mathbf{W}$ has $\psi = 3$ different rows: (a) compensation of employees, (b) gross operating surplus and (c) other net taxes on production. Import matrix $\mathbf{M}$ has $o = 3$ import origins: imports from the rest of Spain, from EU member states and from non-member of the EU. Finally, bridge matrix **B** has $\gamma = 3$ rows: trade and transport margins, value-added tax, and other taxes less subsidies on products. Galicia´s SUTs for 2011 and 2016 are sparse, namely matrix **V**. They also contain negative entries in matrices **F**, **W** and **B**. Figure 1 illustrates these features.

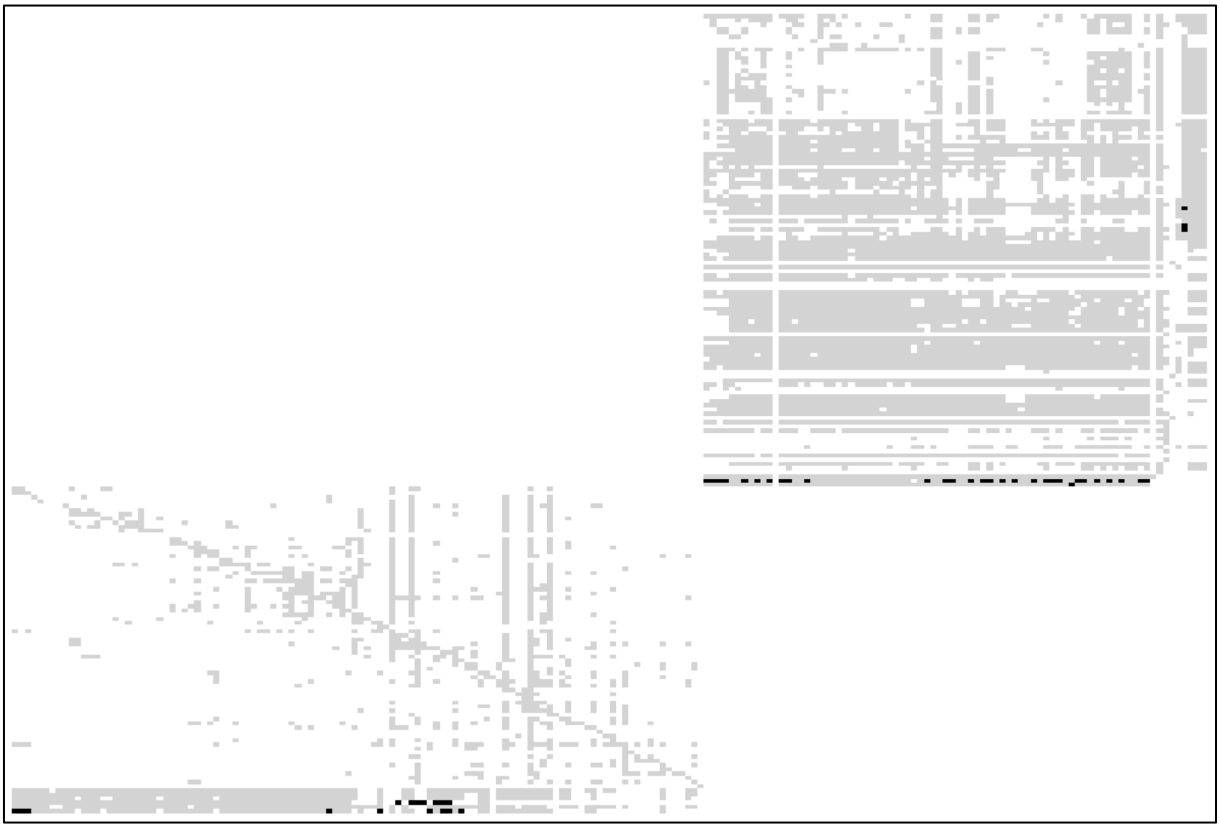

Figure 1. Distribution of positive (grey) and negative (black) entries. 2011 SUT of Galicia.
Source: own elaboration.

To measure how much matrix $\mathbf{Z}^{(T)}$ differs from $\mathbf{Z}^{*}$, I use a Weighted Average Percentage Error (WAPE) measure suggested by Mínguez et al. (2009) and slightly modified by Temursho et al. (2011, p. 109). Let $x_{ij}^{(T)}$ refer to an element of matrix $\mathbf{Z}^{(T)}$. Let x_{ij}^{*} refer to an element of matrix $\mathbf{Z}^{*}$. WAPE is defined as follows:

$$\text{WAPE} = \sum_{i=1}^{m} \sum_{j=1}^{n} \left(\frac{\left| x_{ij}^{*} \right|}{\sum_i \sum_j x_{ij}^{*}} \right) \frac{\left| x_{ij}^{(T)} - x_{ij}^{*} \right|}{\left| x_{ij}^{*} \right|} \cdot 100 \tag{27}$$

The true matrices will be the published ones, albeit neglecting the modifications introduced to run both experiments.

3.3.2 Experiment I: underconstrained entries

I underconstrain matrix $\mathbf{M}$ assuming we only know its row margins $\mathbf{m}^*$ and do not have any data on imports by commodity. I use a one-side balancing procedure for this matrix. Thus, I reproduce a situation as described in section 3.1.2.2. Given the initial targets, underconstrained entries generate an economic infeasibility problem. In the use matrix, I underconstrain column $j = 3$ in matrix $\mathbf{F}$, corresponding to collective consumption assuming we only know its row margins too. The three non-zero entries of this column are the only entries of their corresponding rows. Given the initial targets, I generate a strict infeasibility problem. Therefore, speed of convergence is likely to be affected because of the few degrees of freedom in this part of the matrix. This constraint setting is discretionary. However, it replicates problems that might be faced by IO statistics' users when balancing a SUT. Figure 2 illustrates how underconstrained entries are distributed.

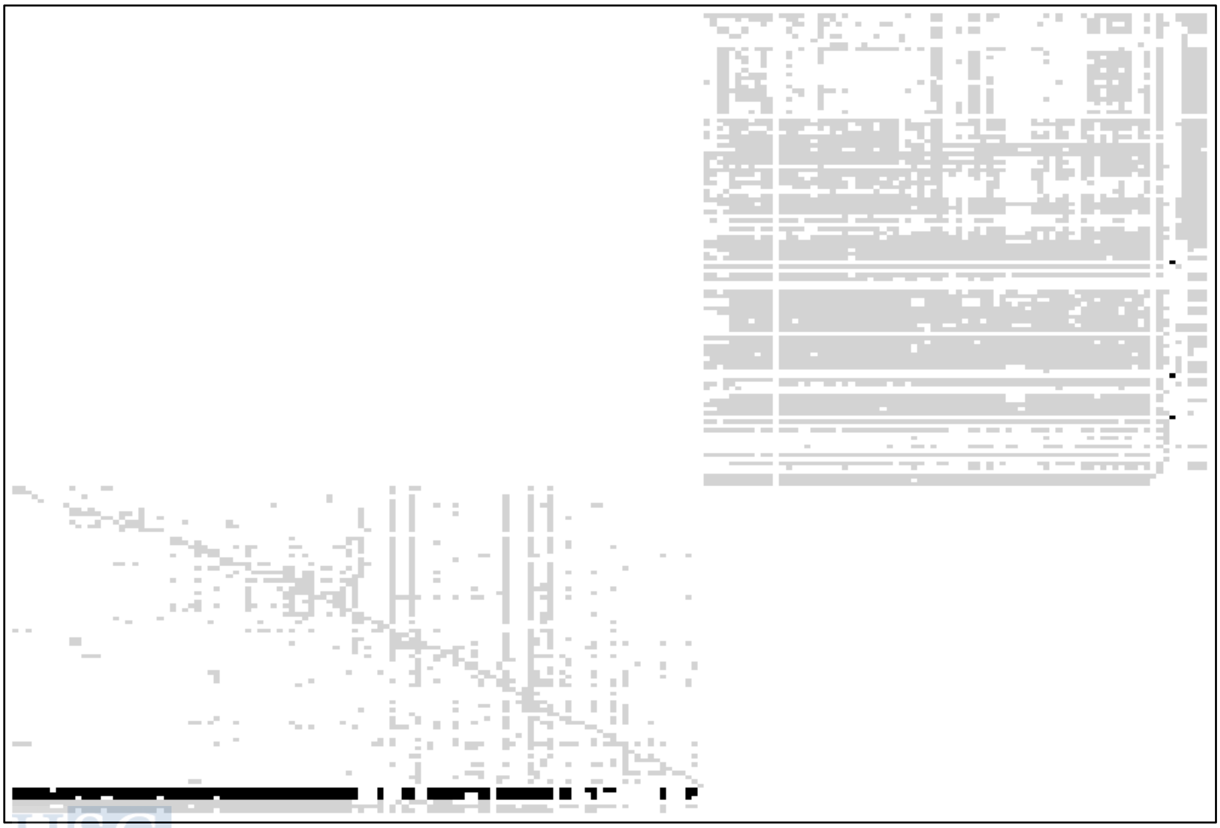

Figure 2. Underconstrained entries (black) in experiment I. 2011 SUT of Galicia.
Source: own elaboration.

I use KRAS and my modified KRAS (MKRAS) to balance the 2011 SUT according to the 2016 SUT margins. KRAS was programmed taking $\alpha\sigma = 0.10$ for all targets. After an initial test, an exception was made for vector **f** elements ($\alpha\sigma = 10$) to achieve a solution within a reasonable number of iterations. Following Wood´s (2011) KRAS application for SUT balancing, I introduce a subset constraint so that $\mathbf{q}_{\bullet\bullet}^{(t)} = \mathbf{g}_{\bullet\bullet}^{(t)}$. As for MKRAS I first program the algorithm for a minimum information scenario (MKRAS-1). In this scenario, the following information is considered:

- $\mathbf{q}_{\bullet\bullet}^{*} = \mathbf{g}_{\bullet\bullet}^{*} =$ overall sum of vectors $\mathbf{q}$ and $\mathbf{g}$, total supply/use by products and inputs/outputs by industry.
- $\mathbf{w}_{\bullet\bullet}^{*} =$ overall sum of gross value-added.
- $\mathbf{m}_{\bullet\bullet}^{*} =$ overall sum of imports.
- $\mathbf{b}_{\bullet\bullet}^{*} =$ overall sum of trade margins.

In a SUT, vectors $\mathbf{q}$ and $\mathbf{g}$ must be equal in both supply and use sides. My setting chooses combinations for $\mathbf{q}^{(t)}$ and $\mathbf{g}^{(t)}$, according to Min $\left[\boldsymbol{\alpha}_{(\mathbf{q})}^{(t)}, \boldsymbol{\beta}_{(\mathbf{q})}^{(t)}\right]$ and Min $\left[\boldsymbol{\alpha}_{(\mathbf{g})}^{(t)}, \boldsymbol{\beta}_{(\mathbf{g})}^{(t)}\right]$. This is, I use supply side or use side combinations according to which solves the larger information conflict.

I also test whether the inclusion of additional information improves results (MKRAS-2). To do so, I further break down $\boldsymbol{\mu}^{(t)}$ and $\boldsymbol{\upsilon}^{(t)}$ calculation. I consider additional information to calculate specific $\boldsymbol{\alpha}_{(\mathbf{q})}^{(t)}$ and $\boldsymbol{\beta}_{(\mathbf{q})}^{(t)}$ for primary, industry and services commodities' supply/use. I also calculate specific $\boldsymbol{\alpha}_{(\mathbf{g})}^{(t)}$ and $\boldsymbol{\beta}_{(\mathbf{g})}^{(t)}$ for primary, industry and services industries' inputs/outputs. Finally, I calculate specific $\boldsymbol{\beta}_{(\mathbf{f})}^{(t)}$ values for consumption, gross capital formation and export components.

	V	M	B	U	F	W	T	*Δ* GDP	Sign flips
MKRAS-1	9.58	28.76	15.95	32.41	17.59	11.78	29	0.0000%	No
MKRAS-2	7.54	28.76	16.51	32.27	16.58	11.70	2067	0.0000%	No
KRAS	7.38	28.76	24.55	30.94	15.73	11.42	9289	0.0048%	Yes

Table 3. WAPE, iterations, GDP distortion and sign flips. MKRAS-1, MKRAS-2 and KRAS in experiment I.
Source: own elaboration.

Table 3 summarises the results I obtain in my first experiment. In the minimum information scenario, MKRAS appears to yield errors in line with those derived from using KRAS. These figures, however, are achieved in less iterations, respect target aggregates (e.g., GDP) and avoid negative scaling coefficients. When additional information is introduced (MKRAS-2), we slightly reduce the error in all SUT matrices while preserving more original targets.

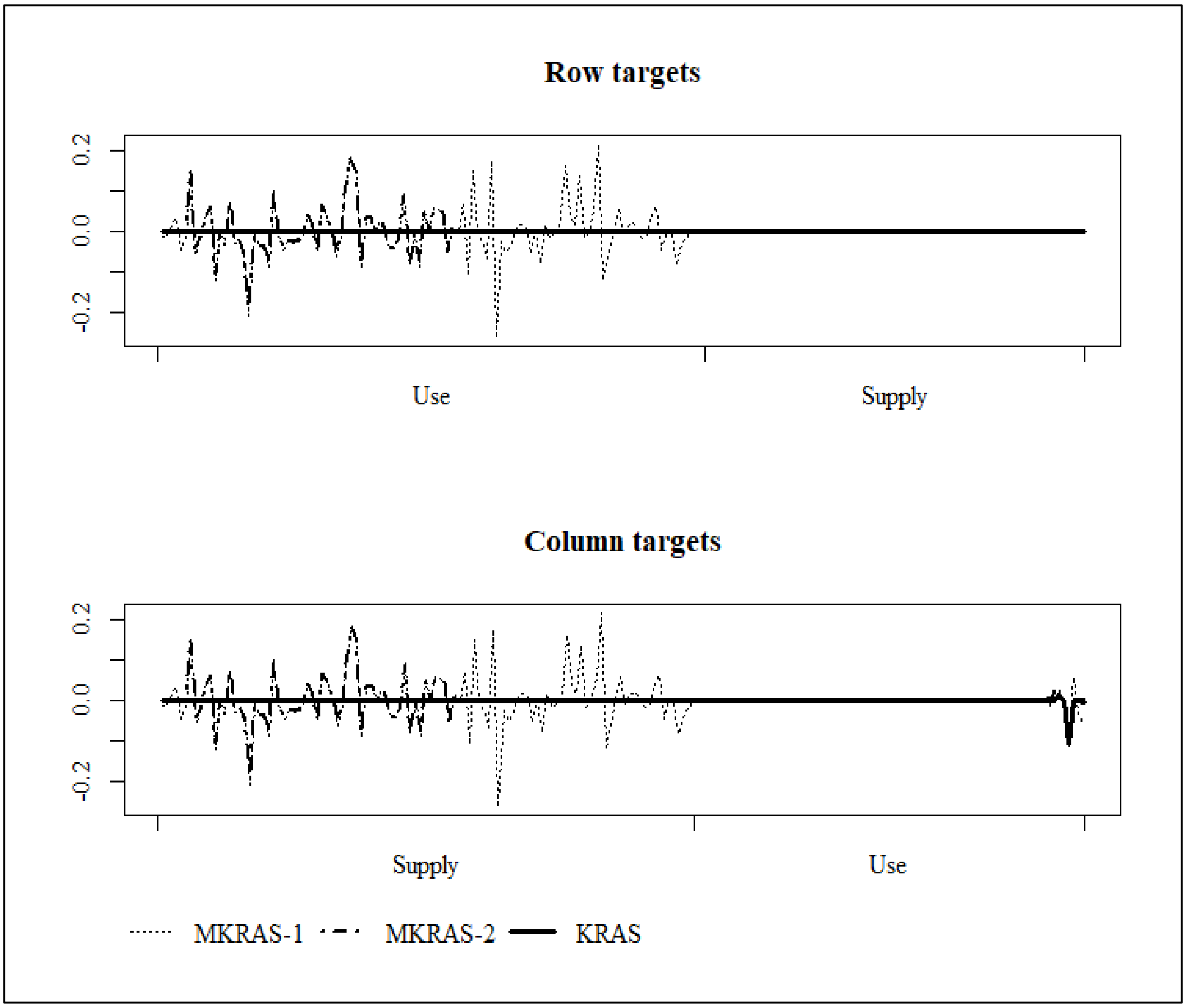

Figure 3. Row and column target modifications in experiment I, logarithmic scale. MKRAS-1, MKRAS-2 and KRAS.
Source: own elaboration.

MKRAS introduces greater distortions in target vectors and preserves the non-conflicting ones. This is captured in Figure 3, in which the horizontal axes account for SUT rows and columns. Introducing additional information (MKRAS-2), I further reduce the number of altered row and column targets. KRAS introduces much smaller modifications across all row and column targets. Again, we can observe a trade-off between target distortion and speed of convergence. However, these modifications seem not to compromise the estimate´s accuracy.

3.3.3 Experiment II: introducing superior information

Suppose we are given exogenous information about primary and manufactured imports. To introduce a conflicting information problem, we multiply part of matrix $\mathbf{M}^*$ by a scalar $\Delta = 1.05$. For some columns in the supply table, the value of the fixed cells is set to be greater than their correspondent targets. Therefore, I generate a situation as described in equations (6)-(8). Underconstrained entries in matrix **F** remain as in experiment I. Figure 4 illustrates how the superior information is distributed.

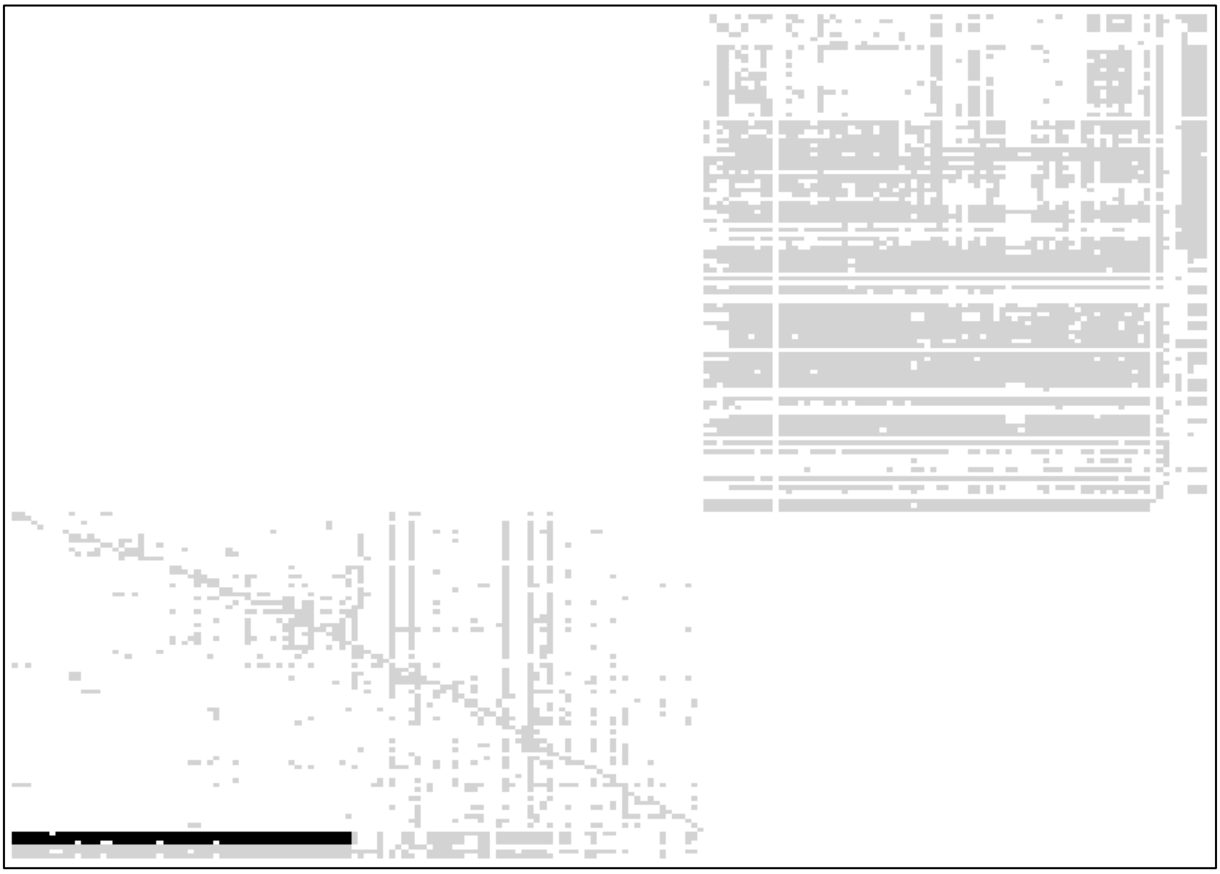

Figure 4. Fixed entries (black) in experiment II. 2011 SUT of Galicia**.**
Source: own elaboration.

As in the previous section, I contrast results between two different information scenarios for MKRAS (MKRAS-1 and MKRAS-2) and KRAS. KRAS was programmed considering $\alpha\sigma = 0.10$ for all targets. After running a trial, an exception was made for vectors **f** and **o** ($\alpha\sigma = 10$) to achieve a solution within a reasonable number of iterations. Table 4 summarises the results I obtain.

	V	M	B	U	F	W	T	Δ GDP	Sign flips
MKRAS-1	8.62	6.51	15.28	31.20	16.90	11.61	33	0.0000%	No
MKRAS-2	9.33	5.82	18.90	32.07	17.17	11.59	2066	0.0000%	No
KRAS	6.50	5.66	14.96	30.95	15.73	11.43	9286	0.0051%	Yes

Table 4. WAPE, iterations, GDP distortion and sign flips. MKRAS-1, MKRAS-2 and KRAS in experiment II.
Source: own elaboration.

Again, MKRAS-1 yields a solution with less iterations, respecting target GDP figure and without negative scaling coefficients. However, it is interesting to see how introducing additional constraints (MKRAS-2) does not lead to substantially lower errors. Results only improve slightly in certain SUT matrices (**M** and **W**). Nevertheless, results do not worsen more than 2% except in the case of matrix **B**. Anyhow, it seems that introducing restrictions in target modification might not be a straightforward decision to make. If we concentrate our distortions in certain targets, we might be inducing a higher overall error in our estimates.

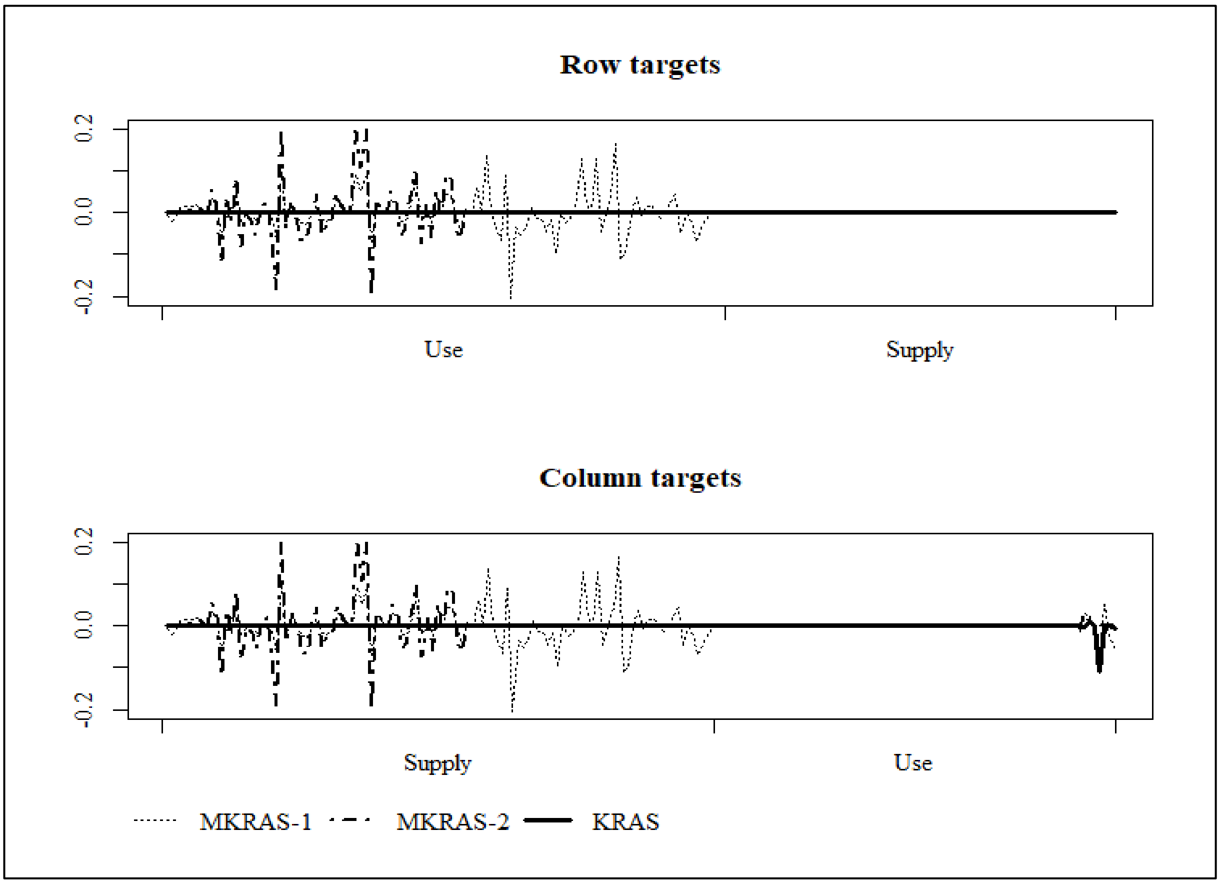

Figure 5. Row and column target modifications in experiment II, logarithmic scale. MKRAS-1, MKRAS-2 and KRAS.
Source: own elaboration.

3.4 DISCUSSION

First, MKRAS yields solutions respecting aggregate target figures. In experiments I and II this feature was probed through GDP. In contrast, KRAS achieved solutions introducing distortions in these figures. Modifications are slight in relative terms. Still, if official data is to be strictly observed, this outcome can be considered problematic. Figure 3 and Figure 5 illustrate how additional information can be included in MKRAS so that to preserve certain targets while allowing others to change. By doing so, I induce greater distortions in the remaining targets. Nevertheless, this generally yields no bigger errors in my example. I believe my results to be promising since they suggest that our alternative target modifications do not affect estimates' accuracy substantially.

More interestingly, my tests provide an example of how MKRAS can deal with strict and economic infeasibilities without introducing undesired sign flips. In both cases KRAS does not account for the magnitude of additional constraints. As a consequence, negative scaling coefficients are derived. In doing so, the economic meaning of some results is compromised.

In all three cases, we observe a trade-off between constraint modifications and speed of convergence. This seems logical since the more constraints are allowed to change, the faster an algorithm can reach a solution. MKRAS dynamically uses information contained in the matrix, skipping KRAS trial-error dynamics, and thus reducing the number of iterations needed. This last result might not be as significant, given the increasing computational capacity available. Nonetheless, this feature can facilitate certain balancing tasks in large matrices (e.g., multiregional models).

3.5 CONCLUSIONS

In this chapter I introduce an alternative way to manage conflicting information. The main novelty is the way constraint modifications are calculated when strict or economic infeasibility situations appear. I calculate the frontier point in which every row/column balancing problem turns strictly or economically infeasible. This information is used to modify the constraint set to circumvent possible conflicting information problems in each iteration. Therefore, I dynamically redefine balancing problems so that standard procedures can be implemented without undesired outcomes. As main features, my methodological proposal yields balancing solutions which preserve aggregate figures and prevent undesired sign flips. Results presented in the third section of this chapter suggest that these methodological improvements can be implemented without compromising the accuracy of the estimates.

The present work suggests several avenues for future research. First, we need a more systematic identification of the convergence problems, related with incoherent constraint structures and sparse matrices. Analysing how matrix decomposability (Bilbao Terol et al., 1994; Quiñoá López, 2013) interacts with conflicting constraints would be beneficial. Second, introducing and discussing other balancing features not addressed could constitute a valuable extension. In addition, combining our approach with other RAS variants might be an interesting way forward. Our algorithm could be used in more generalised contexts, considering possible sign reversals in some cells (Lenzen, Moran, et al., 2014) or including more dimensions as part of the constraint set (Valderas Jaramillo & Rueda Cantuche, 2021). It would also be interesting to explore if our methodology could be used when less information is available as in Euro Method (Valderas Jaramillo, Rueda Cantuche, Olmedo, & Beutel, 2019), SUT-RAS (Temursho & Timmer, 2011) or Path-RAS (Pereira López et al., 2013).

My main limitation is the empirical testing. In this regard, the results I report must be taken with appropriate precaution since they might be based on peculiar data. However, I provide detailed description of our experiment in section 3.3 to ensure it is reproducible, transparent and to facilitate further evaluations. Admittedly, the algorithm here presented should be predicated upon more real-world IO tables or SUTs, systematically contrasting its performance. This could be done for single region and multiregional models. Performing a sensitivity analysis regarding ε tolerance errors could also be considered as a way forward.

4 A PATH FOR REGIONAL SUPPLY-USE TABLES IN CONSTANT PRICES[12]

Abstract. Supply and use tables (SUTs) in constant prices are needed to appropriately measure technological change, connect physical and monetary models, and ensure coherent volume and price information across economic accounts. To estimate SUTs in constant prices, researchers normally apply commodity-specific deflators to SUTs. From an economic perspective, deflators are undoubtedly cell-specific since exchanges of a commodity occur in different markets and institutional contexts. RAS can be used to calculate such cell-specific deflators. But deflating SUTs via RAS can become impossible due to excessive information requirements. This chapter revisits Path-RAS (Pereira López et al., 2013) and applies it to build SUTs in constant prices. My proposal lowers information requirements, enables cell-specific deflators, and avoids ad hoc adjustments. Additional information about specific industries, products or aggregated published figures can be included if existing and non-conflicting. I provide an empirical application based on the current 27 European Union (EU) countries to explore the accuracy of our estimations considering different information scenarios.

4.1 SUPPLY-USE TABLES: CORE OF THE SYSTEM OF NATIONAL AND REGIONAL ACCOUNTS

SUTs play a central role in the United Nations' (2009) system of national accounts (SNA). They provide the basis for the construction of input-output (IO) tables. As a framework, they ensure (i) systematic bookkeeping of aggregated and disaggregated macroeconomic data, (ii) consistency between the production of goods and services, as well as income accounts, and (iii) coherent gross domestic product (GDP) figures, not only within a nation from both production and expenditure perspectives but also across nations.

Since they report linkages from commodities to industries and vice versa, SUTs enable links between other economic datasets that report information either by commodity or industry. In this vein, SUTs can be used to relate national accounts to jobs and occupations, land use, energy

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[12] This chapter partially reproduces Pereira López, X. and de la Torre Cuevas, F. (2022). An alternative for tracing the path between supply and use tables in current and constant prices. *Proceedings of the 28th International Input-Output Association Conference*. https://www.iioa.org/conferences/28th/papers.html

consumption, pollution, waste generation, water usage, among a wider range of possibilities**.** They can also be used as foundational information in the construction of social accounting matrices (SAMs). As SAMs, SUTs are frequently linked to various dimensions of social life (J. Round, 2003) as well as flows of funds (Tsujimura & Mizoshita, 2003).

In most countries, a full SUT framework consists of a supply table at basic prices combined with a transformation matrix to purchaser's prices. A SUT also includes a use table measured in both basic and purchaser's prices. Gross value added (GVA) is measured at basic prices to complete the accounting framework. For the purposes of this chapter, the SUT framework only considers the supply and use tables at basic prices. For k products and l industries a SUT can be summarised as in Table 5[13].

	Products	Industries	Final demand	Σ
Products		$\mathbf{U}^d$	$\mathbf{F}^d$	$\mathbf{q}$
Products		$\mathbf{U}^m$	$\mathbf{F}^m$	$\mathbf{m}$
Value added		$\mathbf{W}$		$\mathbf{w}$
Industries	$\mathbf{V}$			$\mathbf{g}$
Imports	$\mathbf{M}$			$\mathbf{o}$
Σ	$\mathbf{q}' + \mathbf{m}'$	$\mathbf{g}'$	$\mathbf{f}'$	

Table 5. Supply and use table with disaggregated domestic and imported flows.
Source: own elaboration.

Matrices $\mathbf{U}^d$ and $\mathbf{U}_{\mathbf{ij}}^m$ represent intermediate product consumption by industries, domestically produced (d) and imported (m) respectively. Both have dimension $(k \times l)$. Matrices $\mathbf{F}^d$ and $\mathbf{F}^m$ represent domestically produced and imported commodity shipments to final demand. They have dimensions $(k \times \varphi)$ where φ represents the number of final demand components. Matrix $\mathbf{W}$ stands for value added and has dimensions $(l \times p)$ where p stands for the number of value-added components. Matrix $\mathbf{V}$ represents the supply that each industry provides for each commodity and has dimensions $(l \times k)$. Matrix $\mathbf{M}$ stands for the commodity flows imported from different origins and has dimensions $(k \times o)$ where o denotes the number of import origins.

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[13] Matrices are denoted in upper-case bold font; vectors in lower-case bold font; and scalars are denoted in italic font. Vectors are columns by definition. Superscript $'$ indicates transposition. A bar above the variable, $\bar{\mathbf{x}}$, denotes constant prices. A circumflex, $\hat{\mathbf{x}}$, indicates that the vector has been transformed into a square diagonal matrix, i.e., one with elements on the main diagonal and zeros elsewhere. A summation vector of ones is denoted by $\mathbf{i}$.

In addition, vectors $\mathbf{q}$ and $\mathbf{m}$ denote total supply and total use (domestic and imported) by commodity. Vector **g** represents gross output by industry. Vectors **f** and **w** stand for the sum of each component of final demand and value-added matrices. Finally, **o** contains total imports by origin.

The following basic accounting equalities must hold for the SUT to be balanced:

$$\begin{gathered}\mathbf{q} = \mathbf{U}^{d}\mathbf{i} + \mathbf{F}^{d}\mathbf{i} = \mathbf{V}'\mathbf{i} = \mathbf{q} \\ \mathbf{m} = \mathbf{U}^{m}\mathbf{i} + \mathbf{F}^{m}\mathbf{i} = \mathbf{M}'\mathbf{i} = \mathbf{m} \\ \mathbf{g} = \mathbf{U}^{d'}\mathbf{i} + \mathbf{U}^{m'}\mathbf{i} + \mathbf{W}'\mathbf{i} = \mathbf{V}\mathbf{i} = \mathbf{g}\end{gathered} \tag{28}$$

Total commodity supply, both domestically produced and imported, must equal total use of each commodity. Total inputs by industry must equal total outputs by industry.

4.2 WHY SHOULD SUPPLY-USE TABLES BE MEASURED IN CONSTANT PRICES?

According to de Boer and Rodrigues (2020), interest in price deflation can be traced back as far as the 18th century. Dutot (1738) was a pioneer in calculating indexes, when he did so for several commodities by accounting for price variations as far back as 1515. Since then, a vast literature on indexes has emerged that suggests economists consider both price and quantity changes (Balk, 2008).

IO models are no exception (Duchin, 2009; Oosterhaven, 2023). According to Leontief (1951), they were initially conceived from both a physical and a monetary perspective. In fact, the first precedent of an IO price model (Leontief, 1937b) appeared soon after the first IO table was published (Leontief, 1936). The extant literature identifies three main reasons why IO frameworks should be measured also in constant prices. They are discussed in following paragraphs. Please note that the motivations listed are neither exhaustive nor mutually exclusive.

4.2.1 Measuring impacts and structural change

There has been a bit of a debate about the suitability and utility of using IO frameworks in constant prices for measuring structural change. Arto et al. (2015) suggest that some trade analysis related with global value chains can yield misleading results if performed in constant prices. Dietzenbacher and Termursho (2012) assess the extent to which impact analyses differ in current versus constant prices. Using Danish IO tables from years 2001 to 2007, at a somewhat aggregate level they find that deflated and non-deflated IO tables yield quite similar results. They point, however, that (i) sector-level differences are notable and (ii) their test used potentially peculiar data and, thus, should be taken with some caution. An alternative study focused on India by Tandon and Ahmed (2016) shows substantial differences in impacts over time by industry. When covering time periods with significant inflation rates, using data in constant prices has been reported as relevant too (Sánchez Chóliz & Duarte, 2006).

Within IO economics, structural decomposition analysis (SDA) is arguably one of the most widely used family of techniques for measuring structural change and its drivers. See Rose & Casler (1996) and Miller & Shao (1994) for historical overviews and Oosterhaven (2021) for more recent comments and insights. Nowadays, most empirical SDA analyses use deflated IO data (Savona & Ciarli, 2019). The rationale behind this choice follows. Structural change consists of the relocation of economic activity across sectors (Herrendorf et al., 2014). If we consider current prices only, relative price changes could relocate value while the distribution of the volume of output follows a different path as shown, among many others, by Herrendorf, Rogerson, & Valentinyi (2013). Several studies show that differences can be quite substantial if researchers use either current or constant prices. For example, Kander (2005) and Henriques & Kander (2010) evaluate the global transition towards the service economy using both possibilities, as many others have since then (Fix, 2019). They suggest that, to some extent, the spread of Baumol’s (1967) disease within an economy is an illusion once real output changes are considered.

4.2.2 Linking physical and monetary IO models

Since exchanges in an economy involve both a physical and a monetary dimension, two parallel IO models can be derived based on physical input-output (PIOT) and a monetary input-output (MIOT) tables (Miller & Blair, 2022, pp. 43–44). Economic-environmental analysis can be traced further back in IO literature (Isard et al., 1968; Leontief, 1970) as discussed briefly in section 2.1.3.2. Pioneering work on PIOT models include Isard, Chougill, Kissin, Seyfarth and Tatlock (1972) and Szyrmer and Ulanowicz (1987). However, it was not until the decade of 1990 when PIOT models started to be compiled in more regular basis (Giljum & Hubacek, 2004). Nowadays much of the information needed for PIOT construction is systematically collected with that for economic national accounts (United Nations, 2003).

Hubacek and Giljum (2003) and Giljum, Hubacek, & Sun (2004) initiated a debate on whether PIOT or MIOT should be used. They argued that PIOTs yield different and more accurate results since they better capture the physical reality of economic exchanges. In a reply, Suh (2004) argued that PIOT results might only tell us that some products are less expensive and others more costly per unit of physical measurement. He also pointed that PIOTs suffer from operational issues including statistical bias that attaches to sectoral aggregation as well as problems that arise from sectoral inconsistencies across tables over time. Hoen (2002) makes a similar point in defence of MIOT models in constant prices instead of PIOT. For all industries producing physical commodities, a bridge between the two models should exist and should not be hard to calculate since value equals mass multiplied by price per unit mass (Hoekstra & Van Den Bergh, 2006).

Establishing the equivalence between physical and monetary flows requires prices, either actual or estimated (Többen, 2017a). Despite this straightforward relationship, Weisz and Duchin (2006) suggest that PIOT and MIOT tables cannot be translated from one to another using a single price for all deliveries of an industry or commodity. Cell-specific deflators are needed. Dietzenbacher (2005), however, notes that this is not the only issue one faces when linking PIOT and MIOT models. Appropriate waste treatment has also found to be fundamental when one links the two model types (Towa et al., 2020).

4.2.3 Institutional requirements

SUTs compiled in both current and constant prices ensure that both volume and price information contained in an SNA are coherent and consistent. The calculation of price and volume changes for the transactions of commodities is ideally supported through the use of SUT frameworks (Mahajan et al., 2018). In addition to statistical criteria, some policy decisions necessarily require perspectives in constant prices too. For example, the EU's Stability and Growth Pact (SGP) suggests using volume growth rates, which require national accounts in constant prices (Eurostat, 2008). In any case, it should be clear by now that transparent and systematic approaches are needed during policy making, and this means one should place figures in constant prices avoiding *ad hoc* procedures as much as possible.

4.3 ALTERNATIVES FOR SUT DEFLATION

4.3.1 Double deflation

Initially conceived to estimate real GDP (United Nations, 1973), the double-deflation method (DD) is still highly recommended for obtaining IO data in constant prices (Li & Kuroko, 2016). In fact, widely used global IO models such as the World Input-Output Dataset (WIOD), use double deflation to obtain matrices measured in previous year prices (Dietzenbacher, Los, Stehrer, et al., 2013). Double deflation is based on the idea that it is difficult, if not impossible, to obtain price indices for the different GVA components (Ahmad, 1999). In contrast, some economic measures like gross output, imports or final demand are often published officially in both volume and monetary terms.

	Products	Industries	Final demand	Σ
Products		$\bar{\mathbf{U}}^{d} = \hat{\boldsymbol{\pi}}^{\mathbf{q}}\mathbf{U}^{d}$	$\bar{\mathbf{F}}^{d} = \hat{\boldsymbol{\pi}}^{\mathbf{q}}\mathbf{F}^{d}\hat{\boldsymbol{\pi}}^{\mathbf{f}}$	$\bar{\mathbf{q}}$
Products		$\bar{\mathbf{U}}^{m} = \hat{\boldsymbol{\pi}}^{\mathbf{m}}\mathbf{U}^{m}$	$\bar{\mathbf{F}}^{\mathbf{m}} = \hat{\boldsymbol{\pi}}^{\mathbf{m}}\mathbf{F}^{m}\hat{\boldsymbol{\pi}}^{\mathbf{f}}$	$\bar{\mathbf{m}}$
Value added		$\bar{\mathbf{W}} = \mathbf{W}\hat{\boldsymbol{\pi}}^{\mathbf{w}}$		$\mathbf{w}$
Industries	$\bar{\mathbf{V}} = \hat{\boldsymbol{\pi}}^{\mathbf{g}}\mathbf{V}\hat{\boldsymbol{\pi}}^{\mathbf{q}}$			$\bar{\mathbf{g}} = \hat{\boldsymbol{\pi}}^{\mathbf{g}}\mathbf{g}$
Imports	$\bar{\mathbf{M}} = \mathbf{M}\hat{\boldsymbol{\pi}}^{\mathbf{m}}$			$\bar{\mathbf{o}}$
Σ	$\bar{\mathbf{q}}' + \bar{\mathbf{m}}'$	$\bar{\mathbf{g}}' = \mathbf{g}\hat{\boldsymbol{\pi}}^{\mathbf{g}}$	$\bar{\mathbf{f}}'$	

Table 6. Supply and use table in constant prices using double deflation.
Source: own elaboration.

Given the SUT framework in Table 6, let $\boldsymbol{\pi}^{\mathbf{q}}$, $\boldsymbol{\pi}^{\mathbf{m}}$, $\boldsymbol{\pi}^{\mathbf{g}}$ and $\boldsymbol{\pi}^{\mathbf{f}}$ be the deflators associated with vectors $\mathbf{q}$, $\mathbf{m}$, $\mathbf{g}$ and $\mathbf{f}$, respectively. Elements of vectors $\boldsymbol{\pi}^{\mathbf{q}}$ and $\boldsymbol{\pi}^{\mathbf{m}}$ are defined as $1/p_i$ where p_i denotes the ratio of current (domestic and imports) price and the base year price for commodity i. Each element of $\boldsymbol{\pi}^{\mathbf{g}}$ is defined as $1/p_j$ where p_j denotes the ratio of current price and the base year price for industry j. Analogously, element of $\boldsymbol{\pi}^{\mathbf{f}}$ is defined as $1/p_j$ where p_j denotes the ratio of current price and the base year price for final demand component. Table 6 illustrates how these deflators can be applied to deflate a SUT by means of double deflation.

If coherent deflators can be derived from price information, matrices $\bar{\mathbf{V}}$ and $\bar{\mathbf{M}}$ remain balanced. Through balancing equations in (28), total GVA in constant prices by industry can be derived as a residual:

$$\bar{\mathbf{W}}'\mathbf{i} = \bar{\mathbf{g}} - \bar{\mathbf{U}}^{d\prime}\mathbf{i} - \bar{\mathbf{U}}^{m\prime}\mathbf{i} \tag{29}$$

To obtain a full GVA matrix $\overline{\mathbf{W}}$, a vector of implicit GVA deflators $\boldsymbol{\pi}^{\mathbf{w}}$ can be calculated. Each element of $\boldsymbol{\pi}^{\mathbf{w}}$ is a ratio. The difference between an industry's deflated gross output and its deflated intermediated consumption is divided by GVA in current prices:

$$\boldsymbol{\pi}^{\mathbf{w}} = \left(\bar{\mathbf{g}} - \bar{\mathbf{u}}_{\bullet\mathbf{j}}^{d} - \bar{\mathbf{u}}_{\bullet\mathbf{j}}^{m}\right)\left(\widehat{\mathbf{W}'\boldsymbol{\imath}}\right)^{-\mathbf{1}} \tag{30}$$

Double deflation is theoretically sound and preferred to single-deflation methods since it yields a balanced SUT and thus balanced real GDP figures from both income and spending perspectives (Oulton et al., 2018). But it does have some pitfalls. These are particularly related with intermediate transactions, which are the core of IO models. First, this method implicitly assumes that an industry or commodity category is linked to a single commodity that corresponds to the price index applied. The reality, however, is that any given element of a SUT presents a composite commodity that embodies a mix unique to that specific industry and/or commodity transaction. Thus, double deflation necessarily induces some degree of aggregation bias (Dietzenbacher & Hoen, 1999). Double deflation also assumes that all exchanges of an industry or commodity have the same price dynamics; this neglects the fact that different market and institutional contexts undoubtedly affect price changes of the composite commodity differently (Folloni & Miglierina, 1994). GVA estimates are particularly sensitive to the manner in which they are deflated, due to measurement errors inherent in $\bar{\mathbf{q}}$, $\bar{\mathbf{g}}$, $\overline{\mathbf{m}}$ and $\bar{\mathbf{f}}$ (Wolff, 1994). Moreover, from (29) and (30) one can readily see that double deflation can induce a sign flip in an industry if its deflated intermediate consumption exceeds its deflated gross output. In such cases *ad hoc* adjustments are required.

4.3.2 Biproportional techniques

Dietzenbacher and Hoen (1998) suggest that deflating via RAS ultimately applies cell-specific deflators. They focus on the intermediate transaction matrix given a set of industry output, final demand and import vectors in constant prices. Within IO analysis, basic RAS is a popular technique, if not the most popular, for matrix updating and balancing (Lahr & de Mesnard, 2004). Note that several other approaches exist that can deal with problems to which RAS is typically applied (Jackson & Murray, 2004). Some have been used to balance SUTs (Nicolardi, 2013; Rampa, 2008). Temursho, Webb and Yamano (2011), however, suggest that GRAS (Günlük-Şenesen & Bates, 1988; Junius & Oosterhaven, 2003) presents the best balance between accuracy and speed/simplicity. Thus, in what remains of this paper, we consider GRAS to be the *status quo* of the state of the art in matrix balancing[14]. While originally developed for balancing and updating symmetric IO tables, GRAS and other biproportional techniques can also be applied to SUTs (Serpell, 2018).

To implement GRAS[15], we split a benchmark matrix $\mathbf{Z}_{(0)}$ into matrices $\mathbf{Z}^{+}_{(0)}$ and $\mathbf{Z}^{-}_{(0)}$. On the one hand, matrix $\mathbf{Z}^{+}_{(0)}$ contains only the positive elements of $\mathbf{Z}_{(0)}$. On the other, matrix $\mathbf{Z}^{-}_{(0)}$ contains the absolute values of all negative elements. Therefore, we have $\mathbf{Z}_{(0)} = \mathbf{Z}^{+}_{(0)} - \mathbf{Z}^{-}_{(0)}$. Vectors $\boldsymbol{\mu}$ and $\boldsymbol{\upsilon}$ are the row and column sum targets for the balanced matrix $\mathbf{Z}^{*}$. GRAS derivation arrives at a second-order equation. For rows and columns with positive and negative elements, the definition of coefficients r_i and s_j considers the positive root of the second-order equations. For the cases where no positive or negative elements are in a row or column, scalars are defined as in standard RAS (Temursho et al., 2013). The algorithm runs iteratively until the conditions:

$$\begin{array}{c} \left|\left[\hat{\mathbf{r}}\mathbf{Z}^{+}\hat{\mathbf{s}} - (\hat{\mathbf{r}})^{-1}\mathbf{Z}^{-}(\hat{\mathbf{s}})^{-1}\right]\mathbf{i} - \boldsymbol{\mu}\right| < \varepsilon \\ \left|\left[\hat{\mathbf{r}}\mathbf{Z}^{+}\hat{\mathbf{s}} - (\hat{\mathbf{r}})^{-1}\mathbf{Z}^{-}(\hat{\mathbf{s}})^{-1}\right]'\mathbf{i} - \boldsymbol{\upsilon}\right| < \varepsilon \end{array} \tag{31}$$

are fulfilled for a sufficiently small value of ε—a pre-determined level of tolerated error.

The biggest obstacle for GRAS implementation is that data on commodity vectors, $\mathbf{q}$ and $\mathbf{m}$, are rarely available. The same problem appears when it comes to price deflation: we might lack a complete set of deflators for each row and column in the SUT. To overcome this issue, a first balancing alternative appeared when Beutel´s (2002, pp. 114–118) “Euro method” algorithm was adapted for a SUT framework (SUT-Euro). SUT-RAS proposed by Temursho and Timmer (2011) solves some SUT-Euro limitations. It uses SUT balancing equations (1) to endogenously derive targets for $\mathbf{q}$ and $\mathbf{m}$, provided an industry output target data ($\mathbf{g}$). Further, it can be applied

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[14] For the sake of simplicity, we do not consider subsequent GRAS extensions (Lenzen et al., 2009; Lenzen, Moran, Geschke, & Kanemoto, 2014; among others).

[15] At the risk of being slightly reiterative, we introduce GRAS again to make sure there is no confusion due to changes in notation across chapters.

to rectangular matrices and manages negative values just like GRAS. SUT-RAS also can adopt additional information as long as constraints do not conflict (Valderas Jaramillo, Rueda Cantuche, Olmedo, & Beutel, 2019). In fact, SUT-RAS and GRAS are apparently equivalent as long as **q** and **m** are exogenously set (Temursho, 2021).

Despite the solid theoretical foundation and promising empirical results, the scarcity of price indices has tended to prevent the use of RAS-based deflation approaches from the user´s point of view. SUT-RAS data requirements—gross output by industry— are reasonable when updating via current prices. Admittedly, many developed countries can estimate gross output by industry in constant prices. They can even give deflated estimates for a number of commodities, final demand components and trade. But data on industry output (either in current or constant prices) are often not available for many developing countries. At the regional level, data scarcity can become an even more acute problem. Furthermore, SUT-RAS cannot assign different reliability measures to supply and use tables separately.

4.3.3 An alternative path between SUTs in current and constant prices

Data on prices and volumes are increasingly published at higher levels of disaggregation in developed countries. But data availability for developing nations and regions remains a prime constraint for the compilation of official IO statistics in constant prices (Tandon & Ahmed, 2016). The aim of this chapter is to present a methodological alternative for SUT deflation. I intend to address some improvement opportunities spotted in double-deflation and biproportional techniques. Particularly I focus on:

a) Relaxing information requirements to enable SUT deflation where data are scarce and yet permit the application of additional information if available and non-conflicting.
b) Obtaining cell-specific deflators, as opposed to the one-price-fits-all approach implicit in double deflation.
c) Transparently managing possible incoherencies that can arise during the deflation process to avoid *ad hoc* solutions.

To such ends, I revisit the Path-RAS approach introducing major modifications in the original algorithm (Pereira López, Carrascal Incera, & Fernández Fernández, 2013; Pereira López & Rueda Cantuche, 2013). This is the prime contribution of this chapter. As such, I detail it in section 0. Still, it essentially remains a modification of Path-RAS. In section 4.5 we present an empirical application based on the EU-27 countries. Section 4.6 concludes, states the limitations and points to possible future research avenues.

4.4 METHODOLOGICAL PROPOSAL: THE MODIFIED PATH-RAS

4.4.1 Minimum information requirements

My method resembles GRAS. A benchmark matrix $\mathbf{Z}_{(0)}$ is modified to obtain a new matrix $\mathbf{Z}^*$ using targets up-to-date margins $\boldsymbol{\mu}$ and $\boldsymbol{\upsilon}$. Different from GRAS, row and column targets are endogenously calculated during each iteration. There is, however, a minimum set of data needed to start the balancing process:

- $\mathbf{q}^*_{\bullet\bullet}$ = overall supply and use by products.
- $\mathbf{g}^*_{\bullet\bullet}$ = overall input and output by industries.
- $\mathbf{f}^*_{\bullet\bullet}$ = overall final demand.
- $\mathbf{m}^*_{\bullet\bullet}$ = overall imports.
- $\mathbf{w}^*_{\bullet\bullet} = \mathbf{f}^*_{\bullet\bullet} - \mathbf{m}^*_{\bullet\bullet}$ = overall gross value added.

Note, requirements can be further simplified using national accounts' identities.

4.4.2 Workflow

To facilitate comprehension of this section, I explicitly specify the industry and commodity structures for both purchases and sales in a SUT and relate them to balancing equations (28). Four matrices can be defined. On the one hand, taking industry structures, consider matrices $\mathbf{A}^d = \mathbf{U}^d(\hat{\mathbf{g}})^{-1}$, $\mathbf{A}^m = \mathbf{U}^m(\hat{\mathbf{g}})^{-1}$ and $\mathbf{C} = \mathbf{V}'(\hat{\mathbf{g}})^{-1}$. On the other hand, regarding commodity structures, we get matrices $\mathbf{B}^d = (\hat{\mathbf{q}})^{-1}\mathbf{U}^d$, $\mathbf{B}^m = (\hat{\mathbf{m}})^{-1}\mathbf{U}^m$ and $\mathbf{D} = \mathbf{V}(\hat{\mathbf{q}})^{-1}$. Substituting $\mathbf{A}^d$, $\mathbf{A}^m$, $\mathbf{C}$, $\mathbf{B}^d$, $\mathbf{B}^m$ and $\mathbf{D}$ in (28) I get:

$$\begin{gathered}\mathbf{q} = \mathbf{A}^d\mathbf{g} + \mathbf{F}^d\mathbf{i} = \mathbf{C}'\mathbf{g} = \mathbf{q} \\ \mathbf{m} = \mathbf{A}^m\mathbf{g} + \mathbf{F}^m\mathbf{i} = \mathbf{M}'\mathbf{i} = \mathbf{m} \\ \mathbf{g} = \mathbf{B}^{d\prime}\mathbf{q} + \mathbf{B}^{m\prime}\mathbf{m} + \mathbf{W}'\mathbf{i} = \mathbf{D}\mathbf{q} = \mathbf{g}\end{gathered} \tag{32}$$

As in (28), total commodity supply, both domestically produced and imported, must equal total use by commodity. Total inputs by industry must equal total industry outputs. In this way, SUTs remain balanced.

4.4.2.1 Step 0. Defining a starting point

Let iterations $n = 0, 1, \cdots, N$ be indicated by subscript (n) associated with matrices and vectors. Superscripts A, C, B, D in vectors refer to the structures or paths followed by the algorithm to estimate new target vectors after every iteration. Superscript 0 indicates the starting point.

The process initiates with the obtention of output by industry $\mathbf{g}_{(1)}^{(0)}$, final demand components $\mathbf{f}_{(1)}^{(0)}$ and total imports by origin $\mathbf{m}_{(1)}^{(0)}$ estimates that will be considered as the starting point. To do so, let me define a diagonal matrix $\hat{\boldsymbol{\pi}}_{(1)}^{(0)}$ with dimensions $(l + \varphi + o) \times (l + \varphi + o)$. This matrix contains deflators defined as ratios between the given pieces of information in constant prices and their counterparts in matrix $\mathbf{Z}_{(0)}$. As an example, for the minimum information scenario[16]:

$$\boldsymbol{\pi}_{(1)}^{(0)} = \left[\operatorname{diag}\begin{bmatrix}\sum \mathbf{g}_{(0)} \\ \sum \mathbf{f}_{(0)} \\ \sum \mathbf{o}_{(0)}\end{bmatrix}\right]^{-1} \begin{bmatrix}\mathbf{g}_{\bullet\bullet}^{*} \\ \mathbf{f}_{\bullet\bullet}^{*} \\ \mathbf{m}_{\bullet\bullet}^{*}\end{bmatrix} \tag{33}$$

The starting point of the balancing process is defined as:

$$\begin{bmatrix}\bar{\mathbf{g}}_{(1)}^{(0)} \\ \bar{\mathbf{f}}_{(1)}^{(0)} \\ \bar{\mathbf{o}}_{(1)}^{(0)}\end{bmatrix} = \hat{\boldsymbol{\pi}}_{(1)}^{(0)} \begin{bmatrix}\mathbf{g}_{(0)} \\ \mathbf{f}_{(0)} \\ \mathbf{o}_{(0)}\end{bmatrix} \tag{34}$$

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[16] We use *diag* as equivalent to our prior use of a circumflex. We apply it to composite vectors for notational clarity.

Deflators can be specific for some industries, products, final demand components, import origins or calculated according to aggregated information. Once calculated, deflators are expanded (if needed) to achieve vectors with the appropriate dimensions.

4.4.2.2 Step 1. Path AC

The first step balances industries using the starting-point targets in equation (34). For the supply matrix, row targets $\boldsymbol{\mu}_{(1)}^{(0)}$; for the use matrix, column targets $\boldsymbol{\upsilon}_{(1)}^{(0)}$:

$$\boldsymbol{\mu}_{(1)}^{(0)} = \begin{bmatrix}\bar{\mathbf{g}}_{(1)}^{(0)}\\ \bar{\mathbf{o}}_{(1)}^{(0)}\end{bmatrix} \quad \boldsymbol{\upsilon}_{(1)}^{(0)} = \begin{bmatrix}\bar{\mathbf{g}}_{(1)}^{(0)}\\ \bar{\mathbf{f}}_{(1)}^{(0)}\end{bmatrix} \tag{35}$$

By industry balancing, we mean that matrices **V** and **M** are row-scaled. Conversely, matrices $\mathbf{U}^d$, $\mathbf{U}^m$ and **W** are column-scaled. Formally:

$$\begin{gathered}\begin{bmatrix}\mathbf{V}_{(1)}\\ \mathbf{M}_{(1)}\end{bmatrix} = \hat{\mathbf{r}}\begin{bmatrix}\mathbf{V}_{(0)}^{+}\\ \mathbf{M}_{(0)}^{+}\end{bmatrix} + (\hat{\mathbf{r}})^{-1}\begin{bmatrix}\mathbf{V}_{(0)}^{-}\\ \mathbf{M}_{(0)}^{-}\end{bmatrix}\\ \begin{bmatrix}\mathbf{U}_{(1)}^{d}\\ \mathbf{U}_{(1)}^{m}\\ \mathbf{W}_{(1)}\end{bmatrix} = \begin{bmatrix}[\mathbf{U}_{(0)}^{d}]^{+}\\ [\mathbf{U}_{(0)}^{m}]^{+}\\ \mathbf{W}_{(0)}^{+}\end{bmatrix}\hat{\mathbf{s}} + \begin{bmatrix}[\mathbf{U}_{(0)}^{d}]^{-}\\ [\mathbf{U}_{(0)}^{m}]^{-}\\ \mathbf{W}_{(0)}^{-}\end{bmatrix}(\hat{\mathbf{s}})^{-1}\end{gathered} \tag{36}$$

Coefficients vectors **r** and **s** are calculated using the GRAS algorithm.

To conclude step 1, the algorithm endogenously calculates targets for **q**, **m** and **w**. Substituting $\bar{\mathbf{g}}_{(1)}^{(0)}$ in (32) I get:

$$\begin{gathered}\mathbf{q}_{(2)}^{(A)} = \mathbf{A}_{(1)}^{d}\bar{\mathbf{g}}_{(1)}^{(0)} + \mathbf{F}_{(1)}^{d}\mathbf{i} = \mathbf{U}_{(1)}^{d}\mathbf{i} + \mathbf{F}_{(1)}^{d}\mathbf{i}\\ \mathbf{m}_{(2)}^{(A)} = \mathbf{A}_{(1)}^{m}\bar{\mathbf{g}}_{(1)}^{(0)} + \mathbf{F}_{(1)}^{m}\mathbf{i} = \mathbf{U}_{(1)}^{m}\mathbf{i} + \mathbf{F}_{(1)}^{m}\mathbf{i}\\ \mathbf{q}_{(2)}^{(C)} = \mathbf{C}_{(1)}'\bar{\mathbf{g}}_{(1)}^{(0)} = \mathbf{V}_{(1)}'\mathbf{i}\\ \mathbf{m}_{(2)}^{(C)} = \mathbf{M}_{(1)}'\mathbf{i}\\ \mathbf{w}_{(2)}^{(A)} = \mathbf{W}_{(1)}\mathbf{i}\end{gathered} \tag{37}$$

Since $\bar{\mathbf{g}}_{(1)}^{(0)}$ has been substituted in different structural equations, it is most likely that $\mathbf{q}_{(2)}^{(A)} \neq \mathbf{q}_{(2)}^{(C)}$ and $\mathbf{m}_{(2)}^{(A)} \neq \mathbf{m}_{(2)}^{(C)}$. Target vectors for $\mathbf{q}$ and $\mathbf{m}$ are derived as convex combination between vectors obtained through paths A and C. Formally:

$$\begin{gathered}
\mathbf{q}_{(2)}^{(AC)} = \alpha \mathbf{q}_{(2)}^{(A)} + (1-\alpha)\mathbf{q}_{(2)}^{(C)} \\
\mathbf{m}_{(2)}^{(AC)} = \alpha \mathbf{m}_{(2)}^{(A)} + (1-\alpha)\mathbf{m}_{(2)}^{(C)} \\
\text{with} \quad 0 \leq \alpha \leq 1
\end{gathered} \tag{38}$$

I suggest interpreting values for α can as the degree of reliability assigned to the information contained in the $\mathbf{A}^d$, $\mathbf{A}^m$ and $\mathbf{C}$ matrices.

Vectors $\mathbf{q}_{(2)}^{(AC)}$, $\mathbf{m}_{(2)}^{(AC)}$ and $\mathbf{w}_{(2)}^{(A)}$ might need to be corrected to ensure balances defined in equation (28). If additional information is available, this correction can require the introduction of subset constraints to be applied to the target vectors during the next iteration. Following the example given in step 0, new deflators can be calculated:

$$\begin{gathered}
\boldsymbol{\pi}_{(2\boldsymbol{\upsilon})}^{(AC)} = \frac{\mathbf{q}_{\bullet\bullet}^{*} + \mathbf{m}_{\bullet\bullet}^{*}}{\sum \mathbf{q}_{(2)}^{(AC)} + \sum \mathbf{m}_{(2)}^{(AC)}} \\
\boldsymbol{\pi}_{(2\boldsymbol{\mu})}^{(AC)} = \left[\operatorname{diag} \begin{bmatrix} \sum \mathbf{q}_{(2)}^{(AC)} \\ \sum \mathbf{m}_{(2)}^{(AC)} \\ \sum \mathbf{w}_{(2)}^{(A)} \end{bmatrix} \right]^{-1} \begin{bmatrix} \mathbf{q}_{\bullet\bullet}^{*} \\ \mathbf{m}_{\bullet\bullet}^{*} \\ \mathbf{w}_{\bullet\bullet}^{*} \end{bmatrix}
\end{gathered} \tag{39}$$

Finally, targets for iteration $n = 2$ are derived. For the supply table, column targets $\boldsymbol{\upsilon}_{(2)}^{(AC)}$; for the use table, row targets $\boldsymbol{\mu}_{(2)}^{(AC)}$:

$$\begin{gathered}
\boldsymbol{\upsilon}_{(2)}^{(AC)} = \left[\bar{\mathbf{q}}_{(2)}^{(AC)} + \bar{\mathbf{m}}_{(2)}^{(AC)} \right] = \hat{\boldsymbol{\pi}}_{(2\boldsymbol{\upsilon})}^{(AC)} \left[\mathbf{q}_{(2)}^{(AC)} + \mathbf{m}_{(2)}^{(AC)} \right] \\
\boldsymbol{\mu}_{(2)}^{(AC)} = \begin{bmatrix} \bar{\mathbf{q}}_{(2)}^{(AC)} \\ \bar{\mathbf{m}}_{(2)}^{(AC)} \\ \bar{\mathbf{w}}_{(2)}^{(A)} \end{bmatrix} = \hat{\boldsymbol{\pi}}_{(2\boldsymbol{\mu})}^{(AC)} \begin{bmatrix} \mathbf{q}_{(2)}^{(AC)} \\ \mathbf{m}_{(2)}^{(AC)} \\ \mathbf{w}_{(2)}^{(A)} \end{bmatrix}
\end{gathered} \tag{40}$$

These vectors combine information contained in the $\mathbf{A}^d$, $\mathbf{A}^m$ and **C** matrices. They also ensure balance in the SUT framework. In addition, subset constraints can be included.

4.4.2.3 Step 2. Path BD

By commodity balancing we mean that matrices **V** and **M** are column-scaled. Conversely, matrices $\mathbf{U}^d$, $\mathbf{U}^m$ and **W** are row-scaled. Formally:

$$\begin{gathered}
\begin{bmatrix} \mathbf{V}_{(2)} \\ \mathbf{M}_{(2)} \end{bmatrix} = \begin{bmatrix} \mathbf{V}^+_{(1)} \\ \mathbf{M}^+_{(1)} \end{bmatrix} \hat{\mathbf{s}} + \begin{bmatrix} \mathbf{V}^-_{(1)} \\ \mathbf{M}^-_{(1)} \end{bmatrix} (\hat{\mathbf{s}})^{-1} \\
\begin{bmatrix} \mathbf{U}^d_{(2)} \\ \mathbf{U}^m_{(2)} \\ \mathbf{W}_{(2)} \end{bmatrix} = \hat{\mathbf{r}} \begin{bmatrix} [\mathbf{U}^d_{(1)}]^+ \\ [\mathbf{U}^m_{(1)}]^+ \\ \mathbf{W}^+_{(1)} \end{bmatrix} + (\hat{\mathbf{r}})^{-1} \begin{bmatrix} [\mathbf{U}^d_{(1)}]^- \\ [\mathbf{U}^m_{(1)}]^- \\ \mathbf{W}^-_{(1)} \end{bmatrix}
\end{gathered} \tag{41}$$

Coefficients vectors **r** and **s** are calculated using the GRAS algorithm.

To conclude step 2, targets for **g**, **f** and **o** are calculated endogenously. Substituting $\overline{\mathbf{q}}^{(AC)}_{(2)}$ and $\overline{\mathbf{m}}^{(AC)}_{(2)}$ in (32) I get:

$$\begin{gathered}
\mathbf{g}^{(B)}_{(3)} = \mathbf{B}^{d'}_{(2)} \overline{\mathbf{q}}^{(AC)}_{(2)} + \mathbf{B}^{m'}_{(2)} \overline{\mathbf{m}}^{(AC)}_{(2)} + \mathbf{W}'_{(2)} \mathbf{i} \\
\mathbf{g}^{(D)}_{(3)} = \mathbf{D}_{(2)} \overline{\mathbf{q}}^{(AC)}_{(2)} \\
\mathbf{f}^{(B)}_{(3)} = {\mathbf{F}^{d'}}_{(2)} \mathbf{i} + {\mathbf{F}^{m'}}_{(2)} \mathbf{i} \\
\mathbf{o}^{(D)}_{(3)} = \mathbf{M}_{(2)} \mathbf{i}
\end{gathered} \tag{42}$$

Since $\overline{\mathbf{q}}^{(AC)}_{(2)}$ and $\overline{\mathbf{m}}^{(AC)}_{(2)}$ have been substituted in different structural equations, it is most likely that $\mathbf{g}^{(B)}_{(3)} \neq \mathbf{g}^{(D)}_{(3)}$. Target vector for **g** is derived as convex combination between vectors obtained through paths B and D. Formally:

$$\begin{gathered}
\mathbf{g}^{(BD)}_{(3)} = \beta \mathbf{g}^{(B)}_{(3)} + (1 - \beta) \mathbf{g}^{(D)}_{(3)} \\
\text{with} \quad 0 \leq \beta \leq 1
\end{gathered} \tag{43}$$

I suggest interpreting values for β as the degree of reliability assigned to the information contained to the information in the $\mathbf{B}^d$, $\mathbf{B}^m$ and **D** matrices.

Vectors $\mathbf{g}_{(3)}^{(BD)}$, $\mathbf{f}_{(3)}^{(B)}$ and $\mathbf{o}_{(3)}^{(D)}$ might need to be rectified to ensure balances defined in equation (28). If additional information is available, this rectification can be used to introduce subset constraints for next iteration.

Following the example given in step 0, new deflators can be calculated:

$$\begin{aligned}
\boldsymbol{\pi}_{(3\boldsymbol{\mu})}^{(BD)} &= \left[\operatorname{diag}\begin{bmatrix}\sum\mathbf{g}_{(3)}^{(BD)}\\ \sum\mathbf{o}_{(3)}^{(D)}\end{bmatrix}\right]^{\mathbf{-1}}\begin{bmatrix}\mathbf{g}_{\bullet\bullet}^{*}\\ \mathbf{m}_{\bullet\bullet}^{*}\end{bmatrix}\\
\boldsymbol{\pi}_{(3\boldsymbol{\upsilon})}^{(BD)} &= \left[\operatorname{diag}\begin{bmatrix}\sum\mathbf{g}_{(3)}^{(BD)}\\ \sum\mathbf{f}_{(3)}^{(B)}\end{bmatrix}\right]^{-1}\begin{bmatrix}\mathbf{g}_{\bullet\bullet}^{*}\\ \mathbf{f}_{\bullet\bullet}^{*}\end{bmatrix}
\end{aligned} \tag{44}$$

Subsequently, targets for iteration $n = 3$ are derived. For the supply table, we define row targets $\boldsymbol{\mu}_{(3)}^{(BD)}$; for the use table, column targets $\mathbf{v}_{(3)}^{(BD)}$:

$$\begin{aligned}
\boldsymbol{\mu}_{(3)}^{(BD)} &= \begin{bmatrix}\bar{\mathbf{g}}_{(3)}^{(BD)}\\ \bar{\mathbf{o}}_{(3)}^{(D)}\end{bmatrix} = \widehat{\boldsymbol{\pi}}_{(3\boldsymbol{\mu})}^{(BD)}\begin{bmatrix}\mathbf{g}_{(3)}^{(BD)}\\ \mathbf{o}_{(3)}^{(D)}\end{bmatrix}\\
\boldsymbol{\upsilon}_{(3)}^{(BD)} &= \begin{bmatrix}\bar{\mathbf{g}}_{(3)}^{(BD)}\\ \bar{\mathbf{f}}_{(3)}^{(B)}\end{bmatrix} = \widehat{\boldsymbol{\pi}}_{(3\boldsymbol{\upsilon})}^{(BD)}\begin{bmatrix}\mathbf{g}_{(3)}^{(BD)}\\ \mathbf{f}_{(3)}^{(B)}\end{bmatrix}
\end{aligned} \tag{45}$$

These vectors combine information contained in the $\mathbf{B}^{d}$, $\mathbf{B}^{m}$ and $\mathbf{D}$ matrices. They also ensure balance in the SUT framework. In addition, subset constraints can be included.

4.4.2.4 The iterative process

In each iteration, let $\mathbf{z}_{i\bullet}$ and $\mathbf{z}_{\bullet j}$ stand for the SUT row and column sum vectors. In addition, let vectors $\boldsymbol{\mu}_{(n)}$ and $\boldsymbol{\upsilon}_{(n)}$ be defined as:

$$\boldsymbol{\mu}_{(n)} = \begin{bmatrix}\boldsymbol{\mu}_{(n)}^{(AC)}\\ \boldsymbol{\mu}_{(n)}^{(BD)}\end{bmatrix} \quad \boldsymbol{\upsilon}_{(n)} = \begin{bmatrix}\boldsymbol{\upsilon}_{(n)}^{(AC)}\\ \boldsymbol{\upsilon}_{(n)}^{(BD)}\end{bmatrix} \tag{46}$$

To achieve a unique solution, steps 1 and 2 are repeated iteratively until $n = N$ when:

$$\begin{aligned} \max\left|\boldsymbol{\mu}_{(N)} - \mathbf{z}_{i\bullet}\right| < \varepsilon \\ \max\left|\boldsymbol{\upsilon}_{(N)} - \mathbf{z}_{\bullet j}\right| < \varepsilon \end{aligned} \tag{47}$$

is fulfilled for a sufficiently small ε.

4.5 EMPIRICAL APPLICATION

4.5.1 Methods and data

The main challenge faced when empirically testing deflation alternatives is the absence of "true" IO data measured in constant prices. In this chapter, I circumvent this difficulty using inter-temporal survey-based data in current prices. The rationale for this choice follows. If a balancing method can accurately update a matrix $\mathbf{Z}_{(0)}$ to obtain matrix $\mathbf{Z}^*$ given a set of marginal totals, we can expect the result to be as accurate as if this same information is given in constant prices. In other words, we can assume if a method is good for updating, it will be good for deflating. I understand this is a strong assumption since no full set of IO data in current prices are ever available based on a complete census of establishments. Purebred survey-based IO data is never cost-effective (Lahr, 1993), not even in the case of national statistical agencies[17]. I understand that my findings are imperfect from this perspective, but it is the best that one can do, given the resources at hand. Thus, my findings in this section should be taken with appropriate caution.

My dataset includes 2010 and 2015 SUTs for current 27 European Union countries retrieved from the FIGARO model[18]. See Remond-Tiedrez & Rueda Cantuche (2019) for a description of this model. Supply $\mathbf{V}$, and use $\mathbf{U}^d, \mathbf{U}^m$ matrices account for $k = l = 64$ products and industries. Import matrix $\mathbf{M}$ has $o = 1$ import origins. Therefore $\mathbf{M} = \mathbf{m}$ according to our

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[17] Governments interpolate information for firms that do not reply and answer to some questions that establishments fail to supply. Published government data are far from perfect, despite our hopes and beliefs.

[18] All data used in this paper was retrieved from: https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/data/database

notation. Final demand matrices $\mathbf{F}^d, \mathbf{F}^m$ have $\varphi = 6$ components: (i) household consumption, (ii) collective consumption, (iii) government spending, (iv) gross fixed capital formation, (v) inventory variations, (vi) exports. Matrix $\mathbf{W}$ has $p = 4$ different rows: (a) taxes less subsidies on products, (b) gross operating surplus (c) compensation of employees and (d) other net taxes on production. To simplify how results are reported, let:

$$\mathbf{U} = \begin{bmatrix} \mathbf{U}^d \\ \mathbf{U}^m \end{bmatrix} \quad \mathbf{F} = \begin{bmatrix} \mathbf{F}^d \\ \mathbf{F}^m \end{bmatrix} \tag{48}$$

SUTs in basic prices are organised following the scheme depicted in Table 5. I use the 2010 and 2015 data since those are years in which EU member countries must report symmetric IO tables alongside SUTs (Eurostat, 2014).

To measure the accuracy of our estimates, I use the weighted average percentage error (WAPE) by Mínguez et al. (2009) which was further refined by Temursho et al. (2011) as in chapter 3. Recall, this measure is defined as follows. Let $\mathbf{X}^* = \{x_{ij}^*\}$ be a subset of target matrix $\mathbf{Z}^*$ (e.g., $\mathbf{X}^* = \mathbf{V}^*$). Let t stand for a specific deflation alternative (e.g., double deflation). To facilitate comparisons between methodologies across countries, we consider the initial distance $\mathrm{WAPE}^{(0)}$ defined as the WAPE between $\mathbf{Z}_{(0)}$ and $\mathbf{Z}^*$ matrices. The accuracy gains (denoted by Δ) for each deflation alternative t with respect to the initial distance is defined as:

$$\Delta^{(t)} = \frac{\mathrm{WAPE}^{(0)} - \mathrm{WAPE}^{(t)}}{\mathrm{WAPE}^{(0)}} \times 100 \tag{49}$$

Hence, the closer we get to 100%, the better the result will be.

4.5.2 Deflation alternatives: two Path-RAS settings, double deflation, and GRAS

I evaluate my methodological proposal for two different information settings. The first (Path-RAS-1) makes use of the minimum information requirements as stated in section 4.4.1. For the second setting (Path-RAS-2), I assume output by industry to be fully known. In both cases I arbitrarily set $\alpha = \beta = 0.5$.

To contrast Path-RAS' performance, I applied double deflation to our dataset following the developments of section 4.3.1. In addition, I approximately reproduce the "column-row-column" deflation practice reported by Eurostat (2008, pp. 247–250). To do so, we use GRAS. This situation (deflation using standard GRAS) is hardly reproducible from the user´s point of view, especially for countries/regions with less available data. Nevertheless, using GRAS, I simulate a reference scenario and observe how close one can using less information.

	$\mathbf{g}^*$	$\mathbf{o}^*$	$\mathbf{q}^*$	$\mathbf{m}^*$	$\mathbf{f}^*$	$\mathbf{w}^*$
Path-RAS-1	Sum	Sum	Sum	Sum	Sum	Sum
Path-RAS-2	Vector	Vector	Sum	Sum	Sum	Sum
DD	Vector	Vector	Vector	Vector	Vector	Sum
GRAS	Vector	Vector	Vector	Vector	Vector	Vector

Table 7. Information used for each deflation alternative.
Source: own elaboration.

Table 7 summarises the information sets used by each deflation alternative. All target information is from 2015 SUTs. On the one hand, label "Sum" is used when only the overall sum of a vector is known. On the other hand, label "Vector" means that all elements of that vector are considered.

4.5.3 Empirical outcomes

Figure 6 and Figure 7 illustrate the results. Two clarifying comments must be made before we start discussing our findings. First, double deflation yields, by definition, the same results as GRAS for the $\mathbf{M}$ and $\mathbf{V}$ matrices. This is because a set of consistent targets is imposed for all products, industries and for total imports by origin (see section 4.3.1). Second. in the case of Romania, the supply matrix $\mathbf{V}$ is a diagonal matrix with no secondary production. Therefore, all alternatives that consider exogenously given $\mathbf{g}^*$ targets (Path-RAS-2, DD, and GRAS) precisely generate the 2015 matrix.

On the one hand, Path-RAS-1 yields the poorest performance for matrices $\mathbf{V}, \mathbf{M}, \mathbf{U}$ and $\mathbf{F}$ as expected. Using only the minimum information requirements, this alternative ensures that estimated tables respect the limited set of targets. Accuracy gains are generally modest compared to those obtained with the remaining alternatives. In some cases, the overall error is even slightly greater after balancing than before.

Figure 6. Accuracy gains for each deflation alternative. Matrices **V, M, U** and **F**.
Source: own elaboration.

On the other hand, Path-RAS-2 generally performs as well as double deflation and GRAS. Thus, results suggest, despite fewer information requirements, that Path-RAS is as accurate as alternatives that are more data-demanding. Moreover, Path-RAS-2 seems to perform better for **V** and **U** matrices. This is in line with Dietzenbacher and Hoen's (1998) findings that intermediate transactions with cell-specific deflation would be substantially better. Overall results are likely to improve as additional information constrains matrices **M** and **F**. Note that volume data on final demand and imports tend to be more widely available than are data for intermediate demand or intermediate inputs.

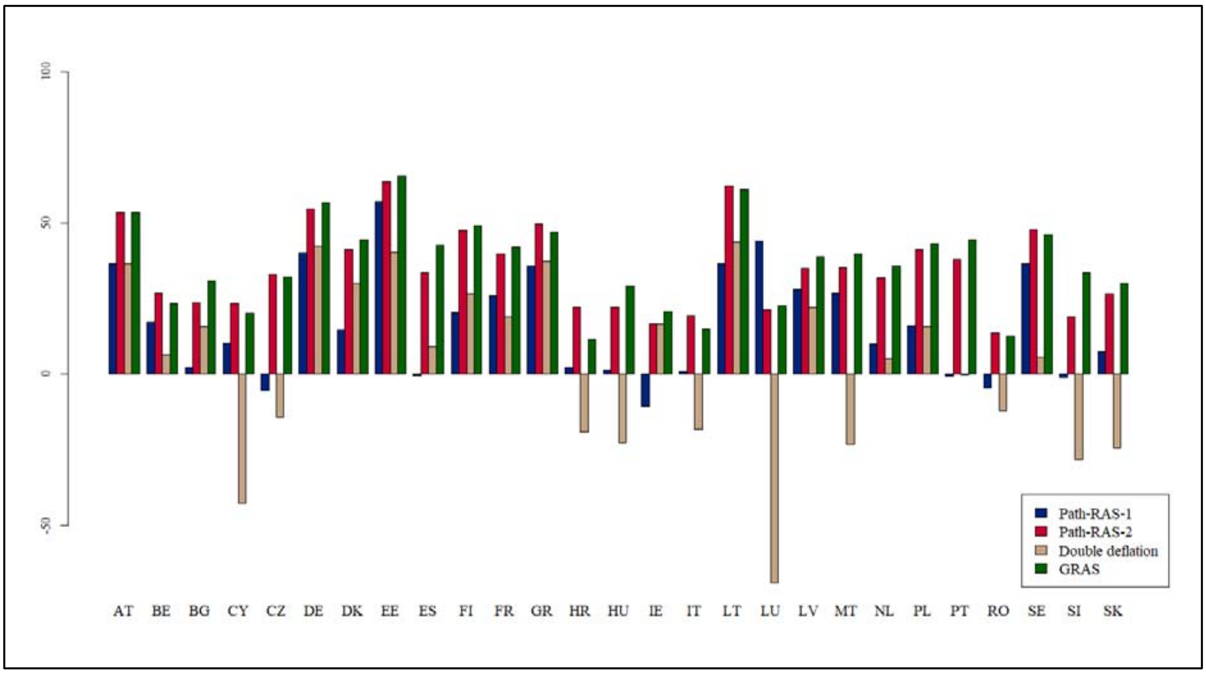

Figure 7. Accuracy gains for each deflation alternative. Value-added matrix (**W**).
Source: own elaboration.

GVA estimates deserve a separate comment. For eighteen out of twenty-seven countries that we analysed, Path-RAS-1 outperformed double deflation in estimating GVA. Double deflation, making use of more information, yields relatively smaller accuracy gains. In ten cases, accuracy gains for GVA using double deflation were negative. Indeed, Path-RAS-2 yielded better results in all cases; accuracy gains are in line with those via GRAS. This result is highlighted since GRAS requires total GVA components to be established exogenously. While the exogenous specification of GVA is reasonable when updating matrices in current prices, it is nigh unto impossible for matrix price deflation. Thus, the Path-RAS modification appears to be a truly viable innovation in this regard.

4.6 CONCLUSIONS

In this chapter, I develop an alternative way to estimate SUTs in constant prices. My proposal modifies the Path-RAS approach for SUT updating. It requires less information than do known predecessor approaches. Most importantly, I reduce needs for GVA price indexes. I believe these features can facilitate SUT deflation in regions and nations where data is relatively scarce. The approach yields cell-specific deflators, capturing IO price dynamics more realistically. Therefore, it could be used to circumvent some issues related with physical and monetary IO models. Moreover, the algorithm does not introduce *ad hoc* adjustments, given that constraints are non-conflicting. Hence, I provide a transparent and reproducible method both from the user´s and the producer´s point of view.

Even though Path-RAS demands comparatively modest amounts of data, it yields promising results. Admittedly, when available information is minimal, Path-RAS performs no better than its “competition.” But it appears to outshine double deflation when it comes to estimating GVA. Moreover, when industry output is constrained, Path-RAS performs in line with GRAS, which requires GVA to be exogenously defined. This suggests our modification to Path-RAS yields results that are sufficiently accurate despite using less information. Estimates for $\mathbf{V}$ and $\mathbf{U}$ appear to be relatively more accurate. This could be confirming the appropriateness of cell-specific deflators to measure intermediate transactions in constant prices.

The prime limitation of my work is the empirical test. Thus, this approach needs further empirical assessments. A broader coverage of countries could reduce biases associated with the use of peculiar data. Alternatively, accuracy could be evaluated using random SUTs as in Bonfiglio & Chelli (2008). We also hope to extend our analysis by deriving IO tables from the deflated SUTs. We, thus, should be able to analyse how different deflation methods relate to such standard work as, for example, impact analysis or multiplier analysis. A possible extension of the research presented here could be the inclusion of techniques that systematically manage conflicting information. Finally, we hope future research will identify optimal reliability values (α, β) associated with the supply and use matrices.

5 LINKING REGIONS TO THE WORLD[19]

Abstract. Multiregional input-output (MRIO) models provide better maps of economic structure. But a lack of viable trade data within nations deters the inclusion of subnational regional economies in global MRIO models. To facilitate more-ready development of such multiscale MRIO models, I identify a gravity model simplification with minimal data requirements that generates reasonable estimates of region-to-abroad trade. In this chapter, I illustrate the approach by spatially disaggregating two hypothetically constructed countries and embedding their regions within the FIGARO global MRIO model. The results suggest that it is possible to reduce information requirements and still produce relatively accurate multiscale MRIO models.

5.1 INTRODUCTION

5.1.1 Multiregional input-output models: maps for possible new discoveries

Multiregional[20] input-output (MRIO) models have had a notable development over the past decade (see Dietzenbacher, Los, Lenzen, et al., 2013; Lahr, Dietzenbacher, et al., 2020; Miller & Blair, 2022, pp. 70–107 for some overviews). They yield detailed mappings of structural relationships among different industries and economies than do single-region models. If models can be considered a sort of mapping of reality, then it follows that we should be able to attain better findings as our models better reflect actual human and environmental interaction across space and sectors (our maps become more accurate).

Table 8 schematically describes an MRIO model composed by $o, d = 1, \cdots, g$ regions where the pair of superscripts o, d denote, respectively, the origin and destination of economic transactions. Note, I use “region” to refer to both national and subnational territorial units. Each matrix $\mathbf{T}^{od} = \{t_{ij}^{od}\}$ represents commodity shipments ($i = 1, \dots, m$) across industries ($j =$

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[19] This chapter partially reproduces: de la Torre Cuevas, F. and Lahr, M. L. (2023). Simplifying gravity equations to embed regions within world input-output models. *Proceedings of the 29th International Input-Output Association Conference.*

[20] For the sake of simplicity, in this chapter I use the expressions “multiregional” and “interregional” indistinctively. Alternatively, Miller and Blair (2022) refer to MRIO and IRIO models as “many-region” models.

$1, \dots n$) for each of the g regions. Regional direct requirements matrices show shipments among firms in the same region ($o = d$). I consider a symmetric model, where $m = n$ for a given region. But m and n may vary across the different types of model regions (province, nation, and rest of world).

	Intermediate transactions			Final demand			
	1	⋯	g	1	⋯	g	Σ
1	$\mathbf{T}^{11}$	⋯	$\mathbf{T}^{1g}$	$\mathbf{F}^{11}$	⋯	$\mathbf{F}^{1g}$	$\mathbf{x}^{1\bullet}$
⋮	⋮	⋱	⋮	⋮	⋱	⋮	⋮
g	$\mathbf{T}^{g1}$	⋯	$\mathbf{T}^{gg}$	$\mathbf{F}^{g1}$	⋯	$\mathbf{F}^{gg}$	$\mathbf{x}^{g\bullet}$
GVA	$\mathbf{W}^{\bullet 1}$	⋯	$\mathbf{W}^{\bullet g}$	–	⋯	–	$\mathbf{w}^{\bullet\bullet}$
Σ	$\mathbf{x}^{\bullet 1}$	⋯	$\mathbf{x}^{\bullet g}$	$\mathbf{f}^{\bullet 1}$	⋯	$\mathbf{f}^{\bullet g}$	

Table 8. Description of a symmetric MRIO model.
Source: own elaboration.

Analogously, matrices $\mathbf{F}^{od} = \{f_{ij}^{od}\}$ represent commodity shipments to final demand across regions and have dimensions $(m \times q)$, $where$ q denotes the number of final demand sectors (e.g., household consumption, government spending, capital investment, etc.), excluding exports. Matrices $\mathbf{W}^{\bullet o} = \{w_{ij}^{\bullet o}\}$ correspond to each region´s gross value added (GVA) with $(p \times n)$ dimensions, where p stands for the number of GVA components (e.g., compensation of employees, indirect business taxes, property-type income, etc.). Because GVA is not tradeable, only its origin is considered. In addition, vectors $\mathbf{x}^{\bullet d}$, $\mathbf{x}^{o\bullet}$ and $\mathbf{f}^{\bullet d}$ represent gross output, total final use, and sum of final demand components for each region. The symbol • denotes a sum across the specified matrix dimension.

5.1.2 Global MRIO models: what about regions?

MRIO models were initially conceived by Isard (1951) to account for linkages among subnational units of a single country. His pioneering work on space economy was followed-up by some extended insights and an application by Leontief (1953a) and Isard (1953b). These pioneering approaches considered models in which a true or "ideal" pattern of trade is specified (Riefler, 1973). That is, the $\mathbf{T}^{od}$ matrices in Table 8 are fully available from statistical offices. Unfortunately, we know that they are not. So, Chenery (1953) and Moses (1955) were the first to circumvent the problem by developing models in which trade coefficients are represented only via the main diagonal elements of each $\mathbf{T}^{od}$ matrix. Riefler and Tiebout (1970) elaborated these approaches by fully specifying the $\mathbf{T}^{od}$ matrices in which $o = d$. They let interregional trade coefficients to be specified à la Chenery-Moses.

During the initial decades of (inter)regional IO analysis a number of multiregional models were developed on the basis of survey or semi-survey data. For instance, Polenske (1980) compiled state-level national MRIO tables of the United States. But because of the expense of their compilation; because the trade matrices were computationally difficult to develop and implement; and because Miller (1966, 1969) suggested interregional spillover and feedback effects tend to be small, interest in producing MRIO accounts dwindled. Even Leontief's (1980) enthusiasm about the possible policy implications derived from MRIOs and an early call by Duchin (1983) to pursue a well-calibrated world MRIO model did not generate much fresh momentum.

The perceived value of MRIOs has improved substantially over the last two decades. In part, the costs of producing them has declined substantially; the computational intractability of large MRIO models has become a non-issue as computational power is now more or less ubiquitous. Meanwhile, the demand for international MRIOs, at least, has risen as economies have become more globally integrated[21]. That is, producers (firm and nation's alike) have become increasingly interested in the implications of the rising global dispersion of the different stages of production of each finished good (Gereffi & Korzeniewicz, 1994; Sachs et al., 1995). There is a new-found interest in research on the integration of what had been, for nearly a century, largely national markets, and value chains. The international nature of climate change also has enhanced the demand for GMRIO models considerably. Somehow ironically, global MRIO (GMRIO) models linking countries worldwide are now more common than those linking subnational units within a nation.

Some trends might motivate the (re)introduction of a regional scale in MRIO models. Brenner (1999) notes that globalisation has not only heightened territorial heterogeneity within countries, but it also has somewhat decoupled regional economic performance from national economic performance. More recently, Bolea et al. (2022) have shown how, not only national

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[21] Global MRIO (GMRIO) datasets are now available, thanks to systematized data collection undertaken by various international institutions (Eurostat, 2008; Mahajan et al., 2018). Tukker and Dietzenbacher (2013) identify academic and political interest on environmental issues related with international trade as a main reason GMRIO models have been developed. Indeed, a cadre of GMRIO datasets now exists, each has a unique geographic focus, detail in terms of industries and products, and span of time coverage. See Huo et al. (2022) and Miller and Blair (2022) for recent reviews.

trends, but region-to-region relationships affect a territory`s position in global value chains for the European Union (EU) case. Such trends seem to have accelerated since the 2008 financial crisis (Monfort, 2020). In addition, the nature of globalisation appears to be (re)forming supranational country blocks (Xiao et al., 2020; Zhang et al., 2022). Tracing the links across regions and nations is not just a continuation of MRIO original goals, but also an inevitable path to follow for those trying to understand how the world economy currently works. Moreover, perhaps we should be using MRIO models for subnational research as well as international research.

5.2 LINKING REGIONS WITH THE WORLD: LOOKING FOR NON-SURVEY SOLUTIONS

Meng et al. (2013) and Feng et al. (2013) were among the first to link regional and national input-output (IO) tables. Thissen et al. (2018) were able to link 256 EU regions to a number of non-EU countries relying on a specific trade database (Thissen et al., 2013). More recently, Towa, Zeller, Merciai, Schmidt and Achten (2022) implemented a hybrid approach to generate multiscale MRIO models. None of these efforts, however, link survey-based regional information to national and international IO tables using regularly published data at the regional level.

The lack of viable regional IO tables has encouraged scholars and practitioners to produce clever solutions to ameliorate the usual problem of data scarcity (Lahr, 2018). Our present case is no exception. The literature identifies three main tools that deal with this problem: (i) import/export weights, (ii) gravity models and (iii) RAS balancing techniques. This set of tools is by no means an exhaustive list of all alternative approaches that have been applied, nor are they mutually exclusive; indeed, they are often used in concert with each other.

5.2.1 Import/export weights

Fry et al. (2022) review multiscale MRIO models that have been produced over the last decade. They replace national data for a country (Australia) with an MRIO that they estimate with techniques applied by Lenzen et al. (2014) and insert into a GMRIO. The authors then focus on estimating each subnational region’s share of the nation’s international trade flows using techniques in Wang, Geschke and Lenzen (2017) and applying import (μ) and export (ξ) weights to generate those shares.

Let a country c in a MRIO such as illustrated in table 1 be divided into $1,\cdots,r$ subnational regions. According to our notation, import and export weights for region r are defined as:

$$\mu_j^{or} = \frac{t_{\bullet j}^{or}}{t_{\bullet j}^{oc}} \quad \forall o \not\subset c \quad \xi_i^{rd} = \frac{t_{i\bullet}^{rd}}{t_{i\bullet}^{cd}} \quad \forall d \not\subset c \tag{50}$$

Numerators $t_{\bullet j}^{or}$ and $t_{i\bullet}^{rd}$ represent commodity j (i) imports (exports) related to region r from (to) country o (d) situated outside country c. Denominators $t_{\bullet j}^{oc}$ and $t_{i\bullet}^{cd}$ are the corresponding national totals for the regional shipments. While denominators can always be retrieved from the GMRIO to which the region is to be linked, numerators are rarely available with industry and country detail. As an example, Tian et al. (2022) rely on detailed data on provincial imports/exports by sector and country origin/destination to link a Chinese MRIO to a GMRIO. Regional trade databases hardly ever meet such detail standards.

Supporting information section S1-2 of Fry et al. (2022) provides a way for reducing information requirements. First, they estimate the share of commodity j (i) demanded (supplied) by each region. And second, the share of commodity j (i) shipped from (to) Australian ports is estimated using the inverse of the distance between regions (represented by their geographical centre) and ports—essentially applying a gravity model. Finally, the two ratios are combined to estimate the trade potential, which is subsequently normalised so their shares sum to unity. Applying these shares to total international trade by commodity then yields each region's international flows by commodity:

$$\begin{aligned} t_{ij}^{or} &= \mu_j^{or} t_{ij}^{oc} \quad \forall i \\ t_{ij}^{rd} &= \xi_i^{rd} t_{ij}^{cd} \quad \forall j \end{aligned} \tag{51}$$

While the approach requires little information, it does not exploit some information that can generally be known—the distances among regions and to countries that trade with the nation.

5.2.2 Gravity models

Gravity models are among the most popular models within social physics, a field first developed by Quetelet (1835). Reilly (1931) is generally credited with being the first to apply a gravity model, in his case, like ours, to estimate trade flows[22]. In his treatise, he applies Newton´s universal law of gravitation, which states that the force of attraction Φ between two bodies i and j is directly proportional to their masses (m_i and m_j) and inversely proportional to the square of the distance l that separates them. Formally:

$$\Phi_{ij} = k\frac{m_i m_j}{\left(l_{ij}\right)^2} \tag{52}$$

where k is the so-called gravity constant.

Following Batten and Martellato (1985), Sargento et al (2012) show how data limitations can affect gravity equations when estimating a country's interregional trade. Haddad (2014) even applies the gravity model to extreme cases of regional data scarcity to simultaneously calculate interregional and intraregional trade flows. But Yamada (2015) appears to be the first to apply gravity equation to produce a multiscale MRIO model. He breaks regional accounts of each Japanese prefecture into those for several metropolitan areas. In so doing, Yamada derives initial estimates for intra-Japan flows by combining import/export weights with an adapted generalised version of the gravity model shown in equation (52). Following our own notation, for an area r contained in a prefecture c trading with another area d outside the prefecture:

$$t_{ij}^{rd} = k^{rd}\frac{\left(t_{i\bullet}^{r\bullet}\right)^{\alpha}\left(t_{\bullet j}^{\bullet d}\right)^{\beta}}{\left(l^{rd}\right)^{\gamma}} \quad \begin{matrix} \forall i = j \\ \forall d \not\subset c \end{matrix} \tag{53}$$

where $t_{i\bullet}^{r\bullet}$ stands for total supply of commodity $i = j$ shipped from r, $t_{\bullet j}^{\bullet d}$ stands for total demand of commodity $i = j$ by region d and l^{rd} is an employment-weighed distance[23] measure between regions. He applies a Chenery-Moses' type model, so all off-diagonal t_{ij} are zeros. Taking the natural logarithm of both sides in equation (53), Yamada next estimates parameters

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[22] Batten and Boyce (1986) provide a comprehensive literature review on estimating trade flows.

[23] See footnote 8 in Yamada (2015, p. 17) for greater detail.

α, β, γ via regression analysis predicated upon data in Japan's 2005 survey-based MRIO model elaborated by METI (2010). Zheng et al. (2019) apply this same approach in China.

Gravity models are one way to estimate trade flows when information on freight shipments by transportation modes are minimally available (if at all) and distance (or travel time) is an important consideration (i.e., a nation is sufficiently large, e.g., say, at least larger than Liechtenstein). They can use aggregate import/export data, which is generally more accessible, as well as data by commodity, like value/weight ratios. Most importantly, they use distance (or travel time) between regions to explain trade flows, just as freight providers do when allocating shipping costs to their customers. Unfortunately, precise gravity model parameters (α, β, γ) must be identified, and are virtually impossible to established a priori (Boero et al., 2018; Lahr et al., 2020). But use of posteriori parameters from existing survey-based models is a legitimate way to estimates trade estimates using gravity models.

5.2.3 RAS balancing

Both import/export weights and gravity models are often combined with RAS balancing (Bacharach, 1970; Stone & Brown, 1962)[24]. More recent developments inform how model builders handle negative trade flows (Günlük-Şenesen & Bates, 1988; Junius & Oosterhaven, 2003), make use of known interior constraints (Gilchrist & St. Louis, 1999; Valderas Jaramillo & Rueda Cantuche, 2021) and manage problems of conflicting information (Lenzen et al., 2009). Temursho, Oosterhaven and Cardenete (2020) apply these developments when balancing an MRIO model.

Three goals justify the use of RAS when building a MRIO model. First, RAS straightforwardly assures interregional accounts respect "known" data (e.g., regional gross output). Second, it ensures coherence between the production and the consumption aspects of interregional accounts. And third, the introduction of additional, superior information constrains RAS, forcing more accurate solutions to emerge (if they, in fact, can emerge at all).

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[24] Once again, see Lahr and De Mesnard (2004) for an overview.

As Jackson and Murray (2004) show, a matrix obtained after RAS balancing is just one of many that could result from the constraints inherent to the balancing problem to be solved—albeit one that as close as possible to the prior matrix (McDougall, 1999) to which RAS is applied. RAS techniques cannot compensate for bad initial MRIO estimates (Fournier Gabela, 2020; Wiebe & Lenzen, 2016). RAS ensures coherence but not accuracy, at least as far as MRIO data are concerned.

5.2.4 Improving trade-offs between information requirements and accuracy

Herein, I suggest an improvement opportunity that considers both import/export weights and gravity approaches for estimating a region's international trade flows. The idea is to make use of widely available data to exploit as much as possible any trade-off between information requirements and accuracy to produce MRIO accounts that are as precise as possible. These accounts are subjected to biproportional balancing only to ensure their coherence.

5.3 METHODOLOGICAL PROPOSAL

I start by considering a generalised gravity model equation in a similar fashion to equation (53):

$$\tilde{t}_{ij}^{od} = k\frac{(t_{i\bullet}^{o\bullet})^{\alpha}\left(t_{\bullet j}^{\bullet d}\right)^{\beta}}{(l^{od})^{\gamma}} \quad \forall i,j \tag{54}$$

A tilde (~) indicates hypothetical, as opposed to estimated, behaviour.

For region r contained in country c and import flows with foreign origin o between industries i and j can be expected to behave as:

$$\tilde{t}_{ij}^{or} = k\frac{(t_{i\bullet}^{o\bullet})^{\alpha}\left(t_{\bullet j}^{\bullet r}\right)^{\beta}}{(l^{or})^{\gamma}} \quad \begin{array}{c} \forall i,j \\ \forall o \not\subset c \end{array} \tag{55}$$

where $t_{i\bullet}^{o\bullet}$ denotes total exports of commodity i from o; $t_{\bullet j}^{\bullet r}$ denotes total imports needed to fulfil region r's demand for commodity j; and l^{or} is the distance (or total travel cost) between o and r.

Similarly, equation (55) can describe country c import trade with the rest of countries in the World:

$$\tilde{t}_{ij}^{oc} = k\frac{(t_{i\bullet}^{o\bullet})^{\alpha}\left(t_{\bullet j}^{\bullet c}\right)^{\beta}}{(l^{oc})^{\gamma}} \quad \begin{array}{c}\forall i,j\\ \forall o \not\subset c\end{array} \tag{56}$$

This leads to a set of simplifications, the novelty of my work in this chapter. Let´s assume that β and γ parameters are the same for region r and country c. In doing so, we assume that a given GMRIO model has a unique gravity equation related to its trade specification[25]. I calculate import shares by dividing (55) by (56):

$$\mu_{ij}^{or} = k\frac{\left(t_{\bullet j}^{\bullet r}/t_{\bullet j}^{\bullet c}\right)^{\beta}}{(\lambda^{rc})^{\gamma}} \quad \forall t_{ij} \subset \mathbf{T}^{o\neq c,r} \tag{57}$$

where $(\lambda^{rc})^{\gamma} = (l^{or})^{\gamma}/(l^{oc})^{\gamma}$ is a fixed measure of relative distance between region r, country c and origin o whereas parameter κ is considered as a normalisation factor that ensures:

$$\sum_{r} \mu_{ij}^{or} = 1 \quad \forall o \not\subset c \tag{58}$$

By making use of (58), we can find that region r's international imports are, thus, simply shares of the nation's international imports:

$$t_{ij}^{or} = \mu_{ij}^{or} t_{ij}^{oc} \quad \forall t_{ij} \subset \mathbf{T}^{o\neq c,r} \tag{59}$$

---

[25] If more exhaustive data on imports and exports are available, specific α, β and γ parameters can be calculated for region r. In our context of limited information requirements, however, this is not possible.

Analogously, for region r in country c and a foreign destination d, export flows between industries i and j can be expected to be:

$$\tilde{t}_{ij}^{rd} = k\,\frac{(t_{i\bullet}^{r\bullet})^{\alpha}\left(t_{\bullet j}^{\bullet d}\right)^{\beta}}{(l^{rd})^{\gamma}} \quad \begin{matrix} \forall i,j \\ \forall d \not\subset c \end{matrix} \tag{60}$$

where $t_{i\bullet}^{r\bullet}$ denotes r's total international exports of commodity i, $t_{\bullet j}^{\bullet d}$ denotes total international imports by d of commodity j, and l^{rd} denotes the distance between r and d.

The same equation can be written to describe country c exports to the rest of countries in the World:

$$\tilde{t}_{ij}^{cd} = k\,\frac{(t_{i\bullet}^{c\bullet})^{\alpha}\left(t_{\bullet j}^{\bullet d}\right)^{\beta}}{(l^{cd})^{\gamma}} \quad \begin{matrix} \forall i,j \\ \forall d \not\subset c \end{matrix} \tag{61}$$

Like in equation (57), I assume α and γ parameters are the same for region r and country c. Thus, export shares can now be calculated by dividing (60) by (61):

$$\xi_{ij}^{rd} = k\,\frac{(t_{i\bullet}^{r\bullet}/t_{i\bullet}^{c\bullet})^{\alpha}}{(\lambda^{rc})^{\gamma}} \quad \forall t_{ij} \subset \mathbf{T}^{r,d\neq c} \tag{62}$$

where $(\lambda^{rc})^{\gamma} = (l^{rd})^{\gamma}/(l^{rc})^{\gamma}$ is the fixed relative distance between r, c, and destination d, whereas parameter κ is a normalisation factor that ensures:

$$\sum_{r} \xi_{ij}^{rd} = 1 \quad \forall d \not\subset c \tag{63}$$

A region's international imports are, thus, a share of the nation international imports making use of (63):

$$t_{ij}^{rd} = \xi_{ij}^{rd} t_{ij}^{cd} \quad \forall t_{ij} \subset \mathbf{T}^{r,d\neq c} \tag{64}$$

Taking the logarithm on both sides of equation (53) parameters α, β and γ can be estimated from the transaction data contained in the original GMRIO where region r is to be nested. Such a solution has already been tested by Riddington, Gibson, and Anderson (2006), Yamada (2015) and (2019), among others, yielding promising results.

5.4 HARMONIZING BENELUX AND THE BIG THREE WITHIN THE FIGARO WORLD MODEL

I now illustrate our proposal's usefulness via a modest empirical application. I aggregate Belgium (BE), Luxembourg (LU) and Netherlands (NL), on the one hand, and Germany (DE), France (FR) and Italy (IT), on the other, into two hypothetical countries: Benelux (BNL) and The Big Three (BIG3). I then disaggregate these countries and embed them into a GMRIO model using my methodological proposal, comparing the estimates against available published data. I evaluate two different concepts of accuracy as for Jensen (1980). Section 5.4.4.1 is devoted to evaluate "partitive" accuracy (i.e., cell-by-cell errors). In sections 5.4.4.2 and 5.4.4.3 I address "holistic" accuracy using interregional feedback effects and spillovers as proxies. The scope of this empirical assessment is limited. Therefore, results must be taken with appropriate precaution.

5.4.1 Benelux and The Big Three: national economies, different regional features

My country choice is not a random one. First, I pick national economies that have strong and long-lasting historical, geographical, and societal ties. Some of these countries started economic integration talks as early as in the 1920s (Mikesell, 1958; Walsh, 2008). Second, cultural, and economic linkages induced these countries to partially cede their sovereignty in favour of supranational authorities (Baldwin & Venables, 1995). Namely, all countries adopted the Euro as their currency (Krugman et al., 2009, pp. 559–566). Therefore, they no longer have control over monetary policy. These two features make these countries more likely to behave as regional economies within a supranational framework.

Third, my choice includes two different types of countries. On the one hand, we have three relatively small economies (Belgium, Luxemburg, and Netherlands). As expected, they present greater openness to trade (Figure 8). Trade openness is defined as the sum of imports and exports over gross domestic product (GDP). On the other hand, I also selected three relatively big economies (Germany, France, and Italy). In these cases, foreign trade is somewhat less relevant. Hence, one can contrast some regularities described in literature regarding bigger and smaller regions in the context of the estimation accuracy of MRIO models.

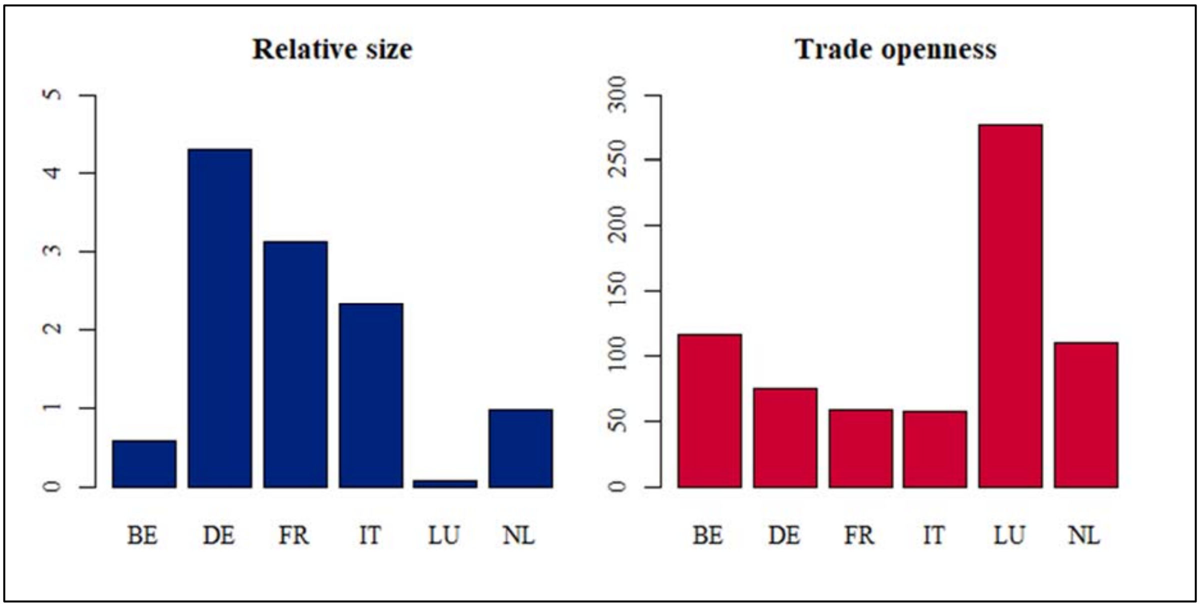

Figure 8. Relative size (share of global GDP) and trade openness. Year 2015.
Source: own elaboration.

5.4.2 FIGARO, global MRIO focused on Europe

FIGARO is my choice of data for a GMRIO model[26]. See Remond-Tiedrez and Rueda Cantuche (2019) for an overview of this dataset. It has a good balance of country and industry detail for all European Union (EU-28) countries[27]. This is relevant since BNL's and BIG3's trade concentrates with fellow EU member countries, as shown in Figure 9.

FIGARO is also fairly up-to-date compared with other GMRIOs available; it has fully comparable accounts from 2010 and all of the way through to 2020 (Piñero et al., 2022). We use the 2015 product-by-product model data as a benchmark. FIGARO product-by-product tables disaggregate all national economies into $i = j = 64$ commodities and industries. It accounts for $g = 45$ countries plus a "rest of the World" region (FIG).

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[26] FIGARO database is available for public access: https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/data/database

[27] The United Kingdom (UK) is included since it formally remained in the EU until January 31st, 2020.

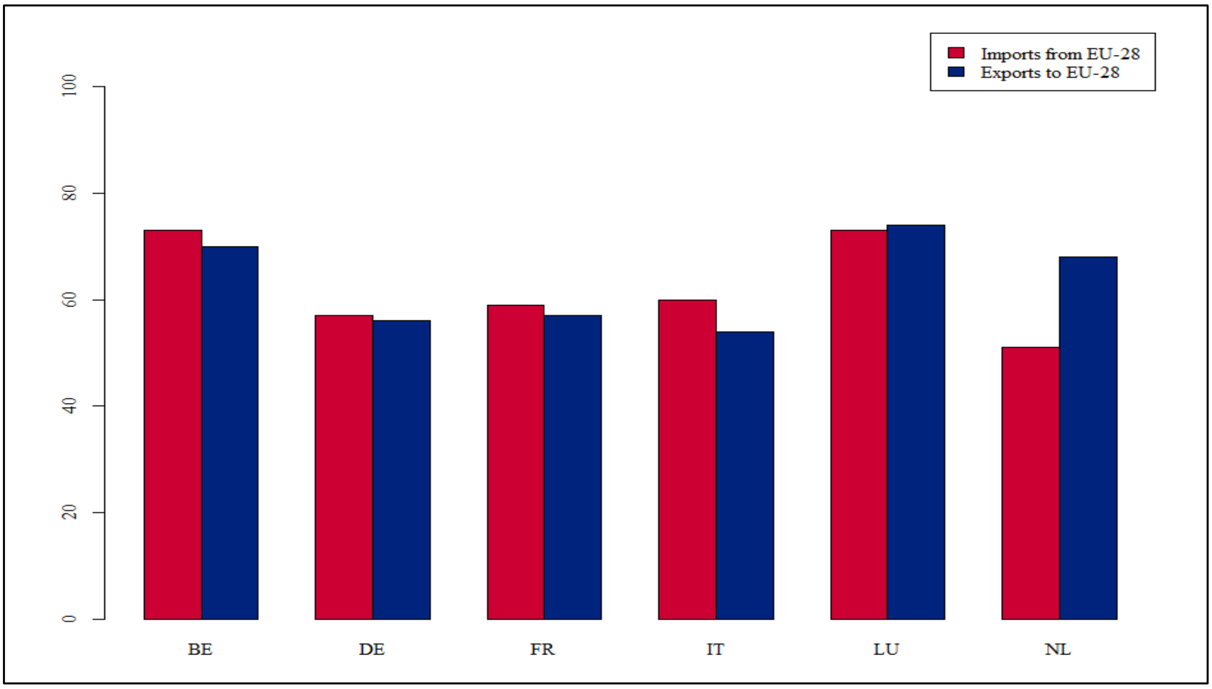

Figure 9. Trade proportion with EU-28, year 2015.
Source: own elaboration using Eurostat, exports, and imports by Member States of the EU/third countries.

To place the "rest of the World" region (FIG), I calculate a centroid considering BNL and BIG3 trade data with countries not included in FIGARO[28] and their main ports' coordinates. Let h stand for any given country not included in FIGARO. According to the notation I have followed in this chapter:

$$\begin{aligned} lat^{FIG} &= \frac{\sum_h (t_{\bullet j}^{\bullet h} + t_{i\bullet}^{h\bullet}) lat^h}{\sum_h (t_{\bullet j}^{\bullet h} + t_{i\bullet}^{h\bullet})} \\ long^{FIG} &= \frac{\sum_h (t_{\bullet j}^{\bullet h} + t_{i\bullet}^{h\bullet})\, long^h \cos\left(lat^h \pi/180\right)}{\sum_h (t_{\bullet j}^{\bullet h} + t_{i\bullet}^{h\bullet}) \cos\left(lat^h \pi/180\right)} \end{aligned} \tag{65}$$

Analogously, I calculate BNL and BIG3 centroids using GDP data retrieved from FIGARO dataset. If we let r be a given country and let c stand for BNL or BIG3.

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[28] Data are public and available in the TiVA database, OECD: https://www.oecd.org/sti/ind/measuring-trade-in-value-added.htm

According to our notation we get:

$$
\begin{aligned}
lat^c &= \frac{\sum_r (i'\mathbf{W}^{\bullet r} i) lat^r}{\sum_r (i'\mathbf{W}^{\bullet r} i)} \\
long^c &= \frac{\sum_r (i'\mathbf{W}^{\bullet r} i)\, long^r \cos\left(lat^r \pi/180\right)}{\sum_r (i'\mathbf{W}^{\bullet r} i) \cos\left(lat^r \pi/180\right)}
\end{aligned}
\tag{66}
$$

BNL is assigned to the port of Rotterdam and BIG3 to the port of Hamburg for the remaining calculations.

5.4.3 Region-to-abroad trade flows: implementing three different alternatives

5.4.3.1 Import/export weights

I first estimate international trade flows using import/export weights (hereafter MXW) as in equations (50) and (51). I calculate differentiated μ_j^{or} and ξ_i^{rd} for matrices **T** and **F** using the published FIGARO model. Formally:

$$\mu_j^{\mathbf{T}or} = \frac{t_{\bullet j}^{or}}{t_{\bullet j}^{oc}} \quad \text{and} \quad \mu_j^{\mathbf{F}or} = \frac{f_{\bullet j}^{or}}{f_{\bullet j}^{oc}} \quad \forall o \not\subset c \tag{67}$$

$$\xi_i^{\mathbf{T}rd} = \frac{t_{i\bullet}^{rd}}{t_{i\bullet}^{cd}} \quad \text{and} \quad \xi_i^{\mathbf{F}rd} = \frac{f_{i\bullet}^{rd}}{f_{i\bullet}^{cd}} \quad \forall d \not\subset c \tag{68}$$

As discussed in section 5.2, this information is rarely available for regional cases. However, import/export weights provide an ideal scenario that can help to assess the relative accuracy of other approaches.

5.4.3.2 Gravity model

Alternatively, I estimate international trade flows using a gravity model for a full trade specification. I follow Sargento et al (2012) and their standard gravity model (hereafter, SGM). Consider a region r contained in country c.

According to our notation I rewrite their gravity equation for imports and exports as:

$$
\begin{aligned}
t_{ij}^{or} &= k_i^{o\bullet} \cdot \left\{ \frac{(t_{i\bullet}^{o\bullet})^{\alpha} \left(t_{\bullet j}^{\bullet r}\right)^{\beta}}{(l^{or})^{\gamma}} \right\} \cdot \left\{ \frac{t_{\bullet j}^{\bullet r} / t_{\bullet\bullet}^{\bullet r}}{t_{\bullet j}^{\bullet c} / t_{\bullet\bullet}^{\bullet c}} \right\} \quad \forall o \not\subset c \\
t_{ij}^{rd} &= k_i^{o\bullet} \cdot \left\{ \frac{(t_{i\bullet}^{r\bullet})^{\alpha} \left(t_{\bullet j}^{\bullet d}\right)^{\beta}}{(l^{rd})^{\gamma}} \right\} \cdot \left\{ \frac{t_{i\bullet}^{r\bullet} / t_{\bullet\bullet}^{r\bullet}}{t_{i\bullet}^{c\bullet} / t_{\bullet\bullet}^{c\bullet}} \right\} \quad \forall d \not\subset c
\end{aligned}
\tag{69}
$$

Estimates for final demand imports and exports are derived analogously.

Two differences with respect to equation (54) are to be highlighted. The second term in brackets is the degree of specialization as defined by Sargento (2009) which equals a simple location quotient. Numerator accounts for regional import and export shares of a product. The national counterpart is given in the denominator. In addition, $k_i^{o\bullet}$ is a proportionality constant ensuring row sums of our estimated model equals known values of vector $\mathbf{x^{o\bullet}}$.

I obtain parameters α, β and γ taking the natural logarithm in both sides of equation (6). The regression analysis is predicated upon data within FIGARO. I only consider aggregate trade in goods by countries following a preponderance of empirical literature on gravity models (Head & Mayer, 2014; Ivanova, 2014). First, I run an ordinary least squares (OLS) regression to measure the significance of the explanatory variables and goodness of fit. After that, I apply generalised least squares (GLS) as per Chaney (2018). I thereby circumvent problems of heteroskedasticity.

	BNL	BIG3
Exports — α	1.044*** (0.023)	1.050*** (0.025)
Imports — β	0.988*** (0.022)	1.032*** (0.024)
Distance — γ	0.500*** (0.026)	0.484*** (0.027)
Observations	686	683
Akaike Inf. Crit.	1928.367	2042.608
Bayesian Inf. Crit.	2004.992	2065.211
R^2 (OLS)	0.844	0.834
Note	$* p < 0.1$, $** p < 0.05$, $*** p < 0.01$	

Table 9. Regression-based parameter estimation, summary of results.
Source: own elaboration.

I estimate travel times for all countries connected via road using minimum highway-travel times between capital cities. For the remaining countries I estimate travel times taking the shortest path through the sea between biggest freight ports[29]. I exclude trade flows coming from and bounded to the FIG artificial region. Furthermore, I assume a 40 km/h average speed for ships. Note that more refined distance measures are available for all countries in the world (Mayer & Zignago, 2011). However, no comparable dataset is likely to be available in the regional case.

Table 9 summarises the results derived from the regression analysis. In both models, all variables are statistically significant with p-values smaller than 0.01. OLS regression suggests an acceptable goodness of fit through R^2. Parameters α, β in our GLS regressions are close to unity, as is often found in literature (e.g., Hillberry & Hummels, 2003; Martínez San Román et al., 2012). Values for distance elasticity γ are relatively close to what Yamada (2015, p. 15) reports, albeit using a different model.

5.4.3.3 Gravity-based import export weights

I now can assess our methodological proposal (hereafter, GBW). As with the preceding methods, I distinguish between intermediate and final demand imports. I do not differentiate between intermediate and exports in final demand, however. As for distance, I use the same data as in the gravity model.

Formally, I specify equations (58) and (63) as:

$$\begin{aligned} \mu_{ij}^{\mathbf{T}^{or}} &= \kappa \frac{\left(t_{\bullet j}^{\bullet r}/t_{\bullet j}^{\bullet c}\right)^{\beta}}{(\lambda^{rc})^{\gamma}} \quad \forall t_{ij} \subset \mathbf{T}^{o\neq c,r} \\ \mu_{ij}^{\mathbf{F}^{or}} &= \kappa \frac{\left(f_{\bullet j}^{\bullet r}/f_{\bullet j}^{\bullet c}\right)^{\beta}}{(\lambda^{rc})^{\gamma}} \quad \forall f_{ij} \subset \mathbf{F}^{o\neq c,r} \end{aligned} \tag{70}$$

$$\xi_{ij}^{\mathbf{T}^{rd}} = \xi_{ij}^{\mathbf{F}^{rd}} = \kappa \frac{(t_{i\bullet}^{r\bullet} + f_{i\bullet}^{r\bullet}/t_{i\bullet}^{c\bullet} + f_{i\bullet}^{c\bullet})^{\alpha}}{(\lambda^{rc})^{\gamma}} \quad \begin{array}{l} \forall t_{ij} \subset \mathbf{T}^{r,d\neq c} \\ \forall f_{ij} \subset \mathbf{F}^{r,d\neq c} \end{array} \tag{71}$$

I use the same parameters as in the standard gravity models too. Therefore, I use just as much information as a gravity model does.

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[29] Coordinates for ports are available in the World Port Index dataset: https://msi.nga.mil/Publications/WPI

5.4.3.4 Final merging and balancing

Next step is to assemble the different estimated blocks, following the scheme depicted in Table 8. I take all remaining data on trade and value added from the published FIGARO data. As for trade flows of third countries ($g \neq c$), they are always available in the GMRIO model to be taken as benchmark. I also assume regional value added for $r \subset c$ to be available too. Finally, literature suggest a variety of methods to estimate intraregional and interregional trade flows in an IO context. I introduce published data so that our estimates do not get distorted by a discretional choice between methodological alternatives.

I apply a final balancing step to achieve a region/country-wise coherent model using GRAS. Two reasons justify this final adjustment for all rows and columns. First, incomplete information results in slight mismatches countries' row/column sums with their correspondent total outputs, which we assume are known. Second, FIGARO accounts retain inherent minor mismatches in row and column sums due to disclosure issues.

5.4.4 Results

5.4.4.1 Cell-by-cell accuracy

To evaluate my proposal´s performance I first measure the estimate's accuracy cell by cell. I focus on international trade flows among regions (Belgium, Luxembourg, and Netherlands; Germany, France and Italy) with other countries. Once again, I use the weighted average percentage error (WAPE) measure suggested by Mínguez et al. (2009) and refined by Temursho, Webb, & Yamano (2011)[30].

Table 10 illustrates the results obtained. As expected, import/export weights yields the most accurate estimates in all cases. These results are logical since this alternative uses much more information to split aggregated trade flows. Conversely, estimates generated via the gravity model require less information and consistently perform worse. Results from the proposal here presented lie somewhere in between, yet far closer to results using import/export weights than

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[30] This measure has already been described in previous chapters.

those from the gravity model. The only exception to this regularity is Luxembourg´s imports used to meet final demand.

Across submatrices and approaches, errors generally correlate inversly with country size. In our empirical application see the Netherlands and Germany examples. This result aligns with what we know about the spatial aggregation and disaggregation of IO tables; that is, it is more difficult to capture the economic structure of smaller economies (Pereira López et al., 2020). A final note on our results attaches. Our estimates using import/export weights for exports in both **T** and **F** matrices almost perfectly reproduce FIGARO. This result might be suggesting that FIGARO uses similar techniques to build their tables.

			BNL			BIG3		
			BE	LU	NL	DE	FR	IT
T	Imports	MXW	37.46	47.53	26.61	29.79	42.47	47.85
		SGM	127.61	157.89	114.84	122.66	124.34	132.19
		GBW	51.79	64.84	37.36	38.19	55.31	58.30
	Exports	MXW	0.04	0.28	0.13	0.07	0.11	0.08
		SGM	109.38	104.93	115.44	124.07	122.10	129.15
		GBW	30.06	32.67	18.87	20.23	30.52	34.58
F	Imports	MXW	38.27	70.81	22.67	27.74	44.30	41.59
		SGM	93.07	97.44	89.10	83.80	88.83	79.28
		GBW	59.96	117.76	35.94	31.77	51.34	46.96
	Exports	MXW	1.59	6.43	2.00	0.50	0.54	0.69
		SGM	106.37	98.93	98.33	92.96	99.41	100.16
		GBW	30.48	40.28	17.53	16.11	28.26	28.90

Table 10. Weighted average percentage error for international trade estimates.
Source: own elaboration.

5.4.4.2 Interregional feedbacks

Feedback effects are the impacts that a demand stimulus has on a region´s own output through trade linkages with other regions. Following Miller and Blair (2022, p. 79) we calculate the overall percentage error (OPE) to measure the relative contribution of interregional feedback effects over an entire economy. We also consider indirect impacts separately (as suggested by Oosterhaven, 1981) to obtain the net overall percentage error (Net OPE).

Figure 10 summarises our results. As suggested in literature (Miller, 1986), smallest feedback effects are observed in the smallest countries: Luxembourg and Italy, respectively. On the other hand, biggest effects are observed for the Netherlands and Germany. Therefore, it appears our methodological alternative captures this observed regularity. Netting out direct final demand effects leads to substantially greater effects as commented by Oosterhaven and Hewings (2014).

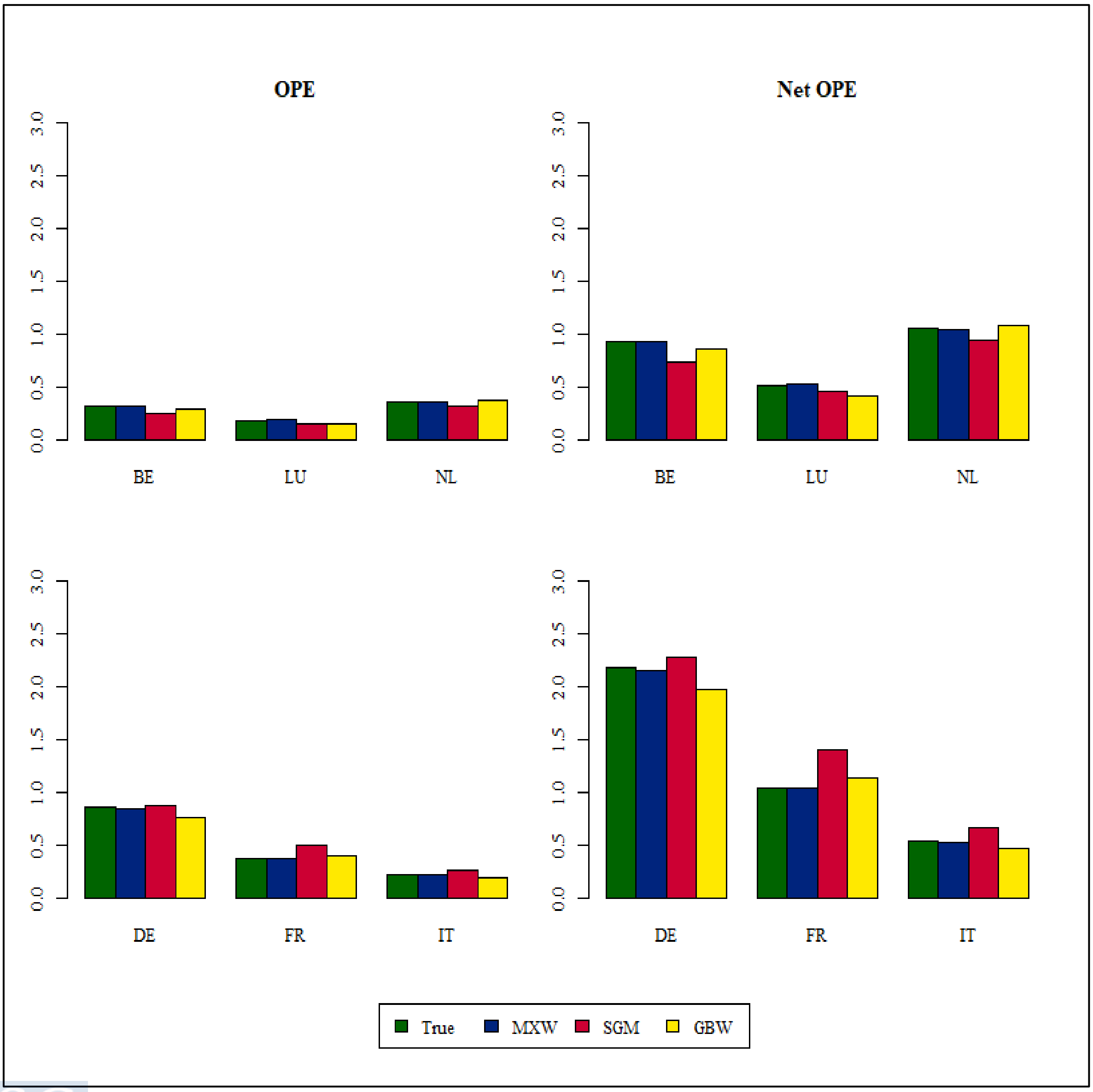

Figure 10. OPE and Net OPE. BNL and BIG3 countries.
Source: own elaboration.

As for accuracy, a model based on import/export weights yields results closer to the true values. Interestingly, estimates using the gravity-based weights are closer to reality in this case than when measured cell-by-cell. Despite the effects been relatively reduced, our methodological proposal captures them as accurately as more data-demanding alternatives. In addition, our proposed method outperforms the gravity model in 4 out of 6 cases. Differences between models are, however, relatively small.

5.4.4.3 Measuring spillovers to the rest of EU-28

We need MRIO models to properly address a variety of questions beyond feedback effects (Round, 2001). At an industry-specific level, interregional spillover effects identify the economy-wide output elasticity for an additional unit of regional final demand. Formally, this is equivalent to the column sum of the Leontief inverse matrix excluding the entries of the region to be analysed (Miller & Blair, 2022, pp. 257–261). Moreover, we can measure spillovers to specific regions or groups of regions with column summation across correspondent rows.

Note, spillovers are relevant from a normative point of view. Public and policymakers in a region might be interested in knowing where the money for public purchases finally ends up. As an example, results for a similar regional policy can vary substantially across regions in a country. Pérez, Dones and Llanos (2009) show different impacts of EU structural funds in the Spanish regions. Patandianan and Shibusawa (2020) apply this approach to assess tourism policies in Japan.

Figure 11 reports how each tested alternative underestimates/overestimates BNL/BIG3 spillovers to the remaining EU-28 countries. The closer to the unit, the better the estimate. Each point in the graph represents an industry (i.e., a column in the GMRIO models). As in previous sections, detailed import/export weights capture spillover effects more precisely across countries and industries. On the opposite side, the standard gravity model induces the greater distortions. The model based on the gravity-based weights appears to follow a similar trend as the standard gravity model regarding underestimations and overestimations. Nevertheless, errors are reduced in 153 out of 192 cases (80%) for BNL and 137 out of 192 cases (71%) for BIG3 models. This result suggests that it is possible to capture the structure of interregional trade with the same amount of information in a more precise way.

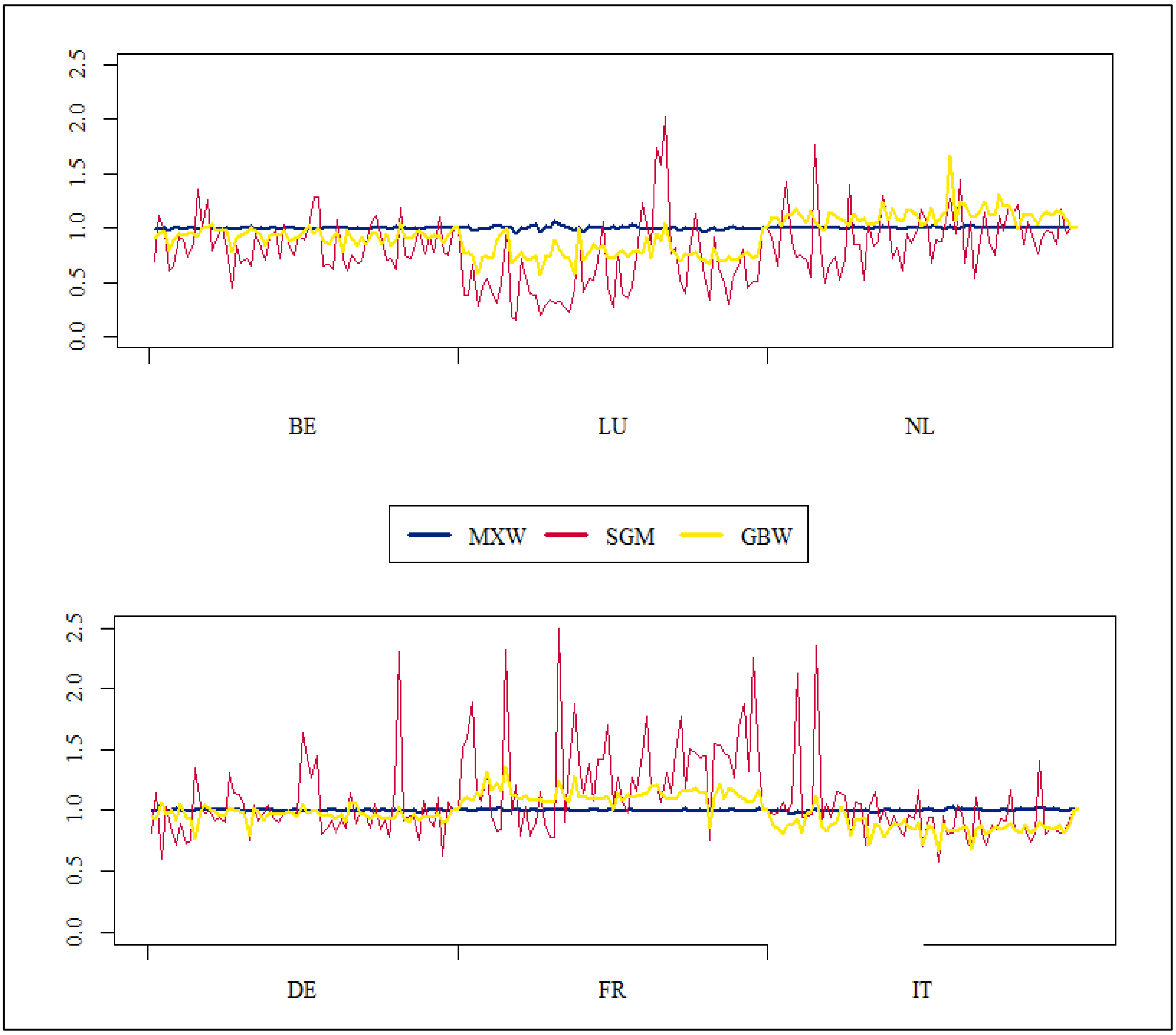

Figure 11. Spillovers to EU-28: underestimation and overestimation.
Source: own elaboration.

5.5 CONCLUSIONS

In the present chapter I suggest an alternative way to nest input-output (IO) regional models into global multiregional input-output (MRIO) models. The purpose in doing so is to make it easier to assess current global challenges from regional perspectives. My approach estimates import/export weights via a gravity formulation, thus taking distance into account. Information and computational requirements are the same as in gravity models. I use data that is normally available, provided that an input-output model already covers regions to be nested.

Despite the approach's modest demands, it yields some promising empirical findings. Cell-by-cell accuracy of its estimates certainly could be improved upon. But the approach appears not to fall too far behind other alternatives with greater data demands. Its estimates also outperform those from a standard gravity model approach that employs the same information. In fact, when measuring feedback effects and spillovers effects, I found its estimates are closer to “reality”, i.e., those in FIGARO. Findings from section 5.4 not only appear coherent but also seem quite reasonable relative to similar approaches discussed within related literature.

As for the implications of this work, knowing the way a region or a region´s industries affect another region´s output also enables more-accurate calculations of matter like jobs, transboundary income flows, energy use, and pollution. I show it is possible to extend this kind of analyses into a multi-scale framework combining consolidated techniques to produce national MRIO models with a method that nest such models into global MRIO models. This might enable a more-informed discussion within the different levels of governmental jurisdiction involved in regional policy and also with the general public.

Despite this chapter been focused on methods, the proposal could be useful in expanding applied regional economic research in two complementary directions. First, the less information required to produce fairly accurate multiscale MRIO models, the more research questions could be addressed using this kind of tools. Second, the geographical scope of these possible analysis can also be positively affected. If we can produce MRIO models using widely available data, then research does not need to be circumscribed to regions and countries providing detailed trade statistics.

A main limitation of my work is the narrow scope of the empirical application. Thus, the results could suffer from bias peculiar to the GMRIO data we use. I look forward to further empirical assessments of MRIO approaches. I also hope to see the development of more-sophisticated techniques to generate the gravity parameters. This research avenue includes the use of better geographical measures as in Anderson and van Wincoop (2003). The implementation of panel data with sectoral or regional fixed-effects also could yield more precise parameters as suggested by Redding and Venables (2004). Fixed-effects to account for cross-hauling might lead to superior outcomes as well. Enhanced balancing procedures with (Valderas Jaramillo & Rueda Cantuche, 2021) is yet another set of possible extensions. These tasks, however, go beyond the purpose of the present chapter.

6 CONCLUDING REMARKS, IMPLICATIONS AND LIMITATIONS

Chapters 3, 4 and 0 are the core of the present dissertation. All three chapters include specific conclusions related to the topic they cover. Alongside those concluding remarks, I also state the limitations and implications of my work as well as comments on possible future research avenues. In this final chapter, my first aim is to derive a general conclusion for this thesis. It is also my intention to briefly discuss what my findings might imply in future research related to regional input-output (IO) analysis. Finally, I state the common limitations of chapters 3, 4 and 0.

It is my hope to have contributed adding some more points in the continuum ranging between pure survey based and pure non-survey (West, 1990). In other words, I hope I have expanded, even if just slightly, the toolbox of regional input-output analysis. Despite being devoted to different challenges, conclusions in chapters 3, 4 and 0 share some common features that relate with my thesis' leitmotiv. In the three cases, I present alternative methodologies that can be applied in a wide range of information scenarios. The balancing algorithm in chapter 3 can handle conflicting information problems using only information endogenous to the prior matrix. If expert judgement or other superior information is available it can be introduced, letting the unknown parts of the matrix adjust according to what is given as certain. In chapter 4, my price deflation alternative for supply and use tables reduces information requirements compared to known predecessor approaches within iterative balancing methods. As in chapter 3, additional information can be further included. My results suggest that the more data is used, the more accurate estimates we get. Finally, in chapter 0 I provide a feasible way to nest a single-region subnational model into a global multiregional input-output table. To calculate estimates, I use data that is normally included in regional input-output models — international imports and exports — as well as a distance measure. If available, data on trade for specific industries and countries can be included in the last balancing step.

Admittedly, my findings are incremental to the field. Nevertheless, the strand of literature that I expand has some relevant implications. From an academic perspective, a larger and more flexible toolbox can reduce possible biases towards research conducted upon more developed regions and countries. As pointed by Batten (1982), Hewings and Romanos (1981), and others, one driver for this predisposition could be the fact that developed regions and nations tend to publish detailed and good quality input-output data on a regular basis. The more flexible our methods are regarding information requirements, the easier it will be to expand the geographical coverage of our research towards territories with less information available. Considering a practical point of view, expanding hybrid approaches for (inter)regional IO modelling should facilitate less developed regions to build their own models according to their financial constraints. This way, regional IO models, with their subsequent extensions, might be able to provide further insights and useful guidance for regional policy where it is needed the most.

6.1.1 To conclude, we must point out some general limitations of our work.

First, my inquiries can most certainly benefit from further empirical testing. In chapters 3, 4 and 0, I provide empirical applications that are designed to be transparent and reproducible. But we possible biases can be inherent to the peculiar nature of the data to which the approaches are applied. Nonetheless, they withstood some robustness checks in the form of peer reviews and expert comments at specialised conferences, workshops and other forums.

In second place, I point to several future research avenues that could extend my methodological proposals. Most relate to the field of input-output (IO) analysis. Nevertheless, hybrid approaches to construct regional IO models can still benefit from closer collaboration with other techniques, even outside the economics field. Until now, synthesis with location theory (Isard & Kuenne, 1953), gravity models (Leontief & Strout, 1963), econometrics (Stevens et al., 1983), and entropy (Golan et al., 1994) among many other techniques seems to have been fertile. In the future, more channels of synthesis (Isard, 1960) might appear. For instance, they might be related to the use of radiation models (Alis et al., 2021; Fernández Vázquez & Carrascal Incera, 2022; Simini et al., 2012), big data from the internet (Tranos et al., 2023) or artificial intelligence (Pakizeh & Kashani, 2022). Let us conclude by saying: there is still plenty to be done.

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8 ANNEX I: PUBLICATIONS PARTIALLY REPRODUCED IN THIS THESIS

Chapter 3 — Jumping over conflicting information

- **Journal article:**

  de la Torre Cuevas, F., Pereira López, X. and López Iglesias, E. (2023). A new alternative for matrix balancing under conflicting information. *Economic Systems Research*, 1-27. https://doi.org/10.1080/09535314.2023.2170217

- **Affiliations:**
  - Fernando de la Torre Cuevas. Departamento de Economía Aplicada, Universidade de Santiago de Compostela.
  - Xesús Pereira López. Departamento de Economía Cuantitativa, Universidade de Santiago de Compostela.
  - Edelmiro López Iglesias. Departamento de Economía Aplicada, Universidade de Santiago de Compostela.
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- **Contribution by the Ph.D. student:**

  All the authors in this article have done relevant contributions. The Ph.D. student has been actively involved in the design and development of all sections: literature review, methodological proposal, empirical application, discussion and conclusions. In particular, the Ph.D. student has had a decisive contribution in elaborating the methodological proposal, which is the main novelty presented in the article.

Chapter 4 — A path for regional supply-use tables in constant prices

- **Conference proceeding:**

  Pereira López, X. and de la Torre Cuevas, F. (2022). An alternative for tracing the path between supply and use tables in current and constant prices. *Proceedings of the 28th International Input-Output Association Conference*. https://www.iioa.org/conferences/28th/papers.html

Chapter 0 — Linking regions to the World

- **Conference proceedings:**

de la Torre Cuevas, F. and Lahr, M. L. (2022). Harmonising Galicia within FIGARO and measuring feedback: Simplifying gravity equations to embed a region within world in input-output models. *Proceedings of the XLVII Reunión de Estudios Regionales. https://reunionesdeestudiosregionales.org/granada2022/en/conference-proceedings/*

de la Torre Cuevas, F. and Lahr, M. L. (2023). Simplifying gravity equations to embed regions within world input-output models. *Proceedings of the 29th International Input-Output Association Conference.*

9 ANNEX II: PUBLICATIONS DERIVED FROM THIS THESIS

Journal articles:

de la Torre Cuevas, F. (2020). Mudanzas e continuidades na estrutura económica de Galicia tras a crise financeira. Unha análise a través de táboas input-output (TIO) dos anos 2008 e 2016 *Revista Galega de Economía*, *29*(3), 1–27. https://doi.org/10.15304/rge.29.3.7126

de la Torre Cuevas, F., Pereira López, X. and López Iglesias, E. (2023). A new alternative for matrix balancing under conflicting information. *Economic Systems Research*, 1-27. https://doi.org/10.1080/09535314.2023.2170217

Conference proceedings:

de la Torre Cuevas, F. and Pereira López (2021). Propuesta metodológica para la desagregación de marcos contables basada en el Three-Steps RAS. Una aplicación para las tablas de origen y destino de Galicia. *Proceedings of the XLVI Reunión de Estudios Regionales*. https://reunionesdeestudiosregionales.org/madrid2021/en/conference-proceedings/

Pereira López, X. and de la Torre Cuevas, F. (2022). An alternative for tracing the path between supply and use tables in current and constant prices. Proceedings of the 28th International Input-Output Association Conference. https://www.iioa.org/conferences/28th/papers.html

de la Torre Cuevas, F. and Lahr, M. L. (2022). Harmonising Galicia within FIGARO and measuring feedback: Simplifying gravity equations to embed a region within world in input-output models. *Proceedings of the XLVII Reunión de Estudios Regionales*. https://reunionesdeestudiosregionales.org/granada2022/en/conference-proceedings/

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de la Torre Cuevas, F. and Lahr, M. L. (2023). A space-industry econometric filter: the A matrix as a measure of industry proximity. *Proceedings of the 29th International Input-Output Association Conference.*

Flegg, A. T., Pereira López, X., Sánchez Chóez, N., Tohmo, T. and de la Torre Cuevas, F. (2023). Curve shapes and parameters in FLQ regional modelling: some alternative approaches. *Proceedings of the 29th International Input-Output Association Conference.*

Sargento, A. L. M., Lahr, M. L., Ferreira, J. P. and de la Torre Cuevas, F. (2023). Revisiting Methods for Estimating Interregional Input-Output Accounts: It's Not Just About Trade Flows. *Proceedings of the 29th International Input-Output Association Conference.*

Regional input-output analysis is a widely used tool for regional scientists to study economic, social and environmental phenomena. Ever since its first steps, regional input-output analysis has suffered from the lack of adequate and detailed data at different subnational levels. The problem becomes particularly acute in less developed regions, where resources to gather information are seldom available. Scholars agree in that hybrid approaches to construct regional input-output models are the most cost-effective alternative. The aim of this thesis is to expand the toolbox that regional input-output modellers have in hand with new hybrid techniques. In this vein, I introduce three methodological alternatives that relax information requirements to solve certain modelling challenges.