Micro-Macro simulations for wellbeing, Version 1.0

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Abstract

We explain the object and development of the UK Wellbeing Simulator. The primarily version supports the evaluation of large interventions in the UK amongst adults in the areas of mental health, physical health, and work. We embed direct effects of psychiatric help for 25% of the depressed population into a larger model that includes spillovers and general equilibrium effects, to arrive at a cost-per-wellbeing. We show how effects change over time and differ by subgroup and region. The model is a stepping stone towards a larger model that would be able to evaluate childhood interventions and investments in the areas of art, sport, and culture.

Keywords:

JEL Classification:

1 General Introduction

"The journey of a 1000 miles starts with a single step"

— Lao Tzu

In this booklet we describe the development and main points of a Micro-Macro simulation model as developed by the wellbeing team at the LSE in 2017. The general aim is a simulation model for the UK with which to evaluate the cost-effectiveness of different large policy interventions in terms of pounds-per-unit-of-wellbeing.

We eventually want to be able to look at interventions in childhood, interventions in specific markets (housing, crime), interventions in the tax-and-subsidy mix, and interventions in the culture of organisations. We start much more modestly though by building a model that is useful for interventions in health amongst adults. Our first example intervention is the hypothetical treatment of 1 in 4 depressed individuals in 2010, as if the Improved Access to Psychiatric Therapies program that has been rolled out nationwide from 2010-2016 had all taken place in 2010 on a very particular group. We work out how the lives of those hypothetical patients and the rest of the UK would have looked like from 2010-2015 compared to their actual lives.

The micro-simulation model tracks the changes in the main outcomes of relevance to a wellbeing-oriented polity: the wellbeing of the population, the public purse, length of life, and key mediating factors (employment, relationships, physical health, education, crime). Throughout, we but incorporate the findings from the best studies into a single simulation model, and as such we try to reflect the scientific consensus of this moment. The model can support decisions at the higher levels of government, such as Treasuries, budget offices, large metropolitan areas, international organisations, large philantropic organisations, and macro research units.

The main strength of the June 2017 Mental Health version is that it incorporates many feedback effects of an improvement in mental health: we have worked out how the increased labour supply of those with improved mental health affects the employment and wages of others; we have allowed for spillovers within the family; we have accounted for improved physical health and concomitant reductions in health costs due to the improved mental health; we have allowed for a gradual phasing out of mental health improvements as people revert to baseline; we have allowed for reference-feedback effects such that those not directly affected lose out a little because their situations have reduced in relative terms; and we have costed all changes in terms of their effects on taxes and benefits.

There are three preliminary findings regarding the IAPT-style intervention according to our current calculations: i) after 5 years, a hypothetical IAPT happening in 2010 has recouped no more than about 20% of the public investments in terms of increased taxation and reduced benefit take-up; ii) the largest effect on the public system would come from a demand shift for physical health care, though not due to an improvement in the physical health of those out of depression but rather a strongly reduced tendency to demand NHS services. That reduced demand shift would pay back the intervention in about 2 years if it were monetised (ie if the size of the physical health part of the NHS was reduced); and iii) that the costs per unit of well-being (a 1 point shift on a 0-10 scale for 1 year) is around +300 pounds if we do not monetise the shift in physical health demand, and -380 pounds if we monetise the physical health demand shift.

The key 'believability' weakness of the June 2017 IAPT application is that we cannot yet allow for adjustments in the general price of (mental) health due to changes in the market for (mental) health, simply because there is no available research on that issue anywhere in the literature at the moment: the field has so far presumed the absence of general equilibrium effects in mental health, but it seems intuitively likely that the competition within workplaces and communities provide stresses, so that recuperated patients who can re-enter these competitions increase the pressures on others.

The main wider points to come from the June 2017 model are that interventions in adult (mental) health are relatively easy to evaluate because there is a lot of work on key mechanisms to base it on, and limiting the analysis to a 5-year window comes at little cost. Modelling interventions over a whole life-cycle will be much harder. Modelling effects of 'cultural' interventions, such as a wholesale adoption of mindfulness programs or a tilting of the tax and subsidy mix towards flatter organisations, would seem to require expanded national statistics that actually pick up the intermediary stock variables that cultural interventions supposedly affect (like levels of community cohesion, or the ability to withstand mental stressors without succumbing to mental health episodes[1]).

1.1 Overview of this booklet

This booklet has three main parts. In the first part, we give a general (mainly non-mathematical) description of the Simulation model as it stands in June 2017. In the second part we apply the model to a hypothetical IAPT intervention in 2010. In Part III we explain the methodology in full and that is explicitly based on the idea that the object of public policy is to maximise the wellbeing of the UK population as a whole.

[1] Frijters and Foster (2013) discuss the ways in which community cohesian depends on long-run economic circumstances.

Part I

The June 2017 UKWBS

In the simplest terms, our model consists of mapping changes to a known baseline scenario, including as many areas of life as we have reasonable literature information on. The baseline scenario is what happened in the UK in the period 2010-2015 in terms of our key outcomes of health, life satisfaction, longevity, and net public expenditures. The changed scenario is the hypothetical effect of a large intervention on a particular target population in 2010. We have in mind an improvement in the mental health of a subset of the UK population, but the methodology is geared towards many different types of interventions on adults, primarily via major public services (the health system, the education system, the welfare system, the criminal justice system, etc.).

1.2 A quick description of the broad methodology in individual terms

Our immediate objective is to see how outcomes of interest for individual i at time t depend on the choice of specific public policies and programmes, hereafter simply referred to as interventions, in the area of public health, especially mental health:

$$Y_{it} = Y(X_{it}, INT_{it})$$

where X_{it} is a vector of intermediary outcomes x_{it} from the past up until the present, hence allowing the past to affect current outcomes, for instance via savings or adaptation; INT_{it} is a vector of interventions; and Y_{it} is an outcome of interest, including mental health and wellbeing, physical health and longevity, and net use of the public purse.

At the societal level, the evaluation of an intervention in a T year interval then depends the changes an intervention makes:

$$\Delta U = \sum_{t=0}^{T} \sum_{i} w_{it} Y(X_{it}, INT_{it}) - \sum_{t=0}^{T} \sum_{i} w_{it} Y(X_{it}, 0)$$

where w_{it} denotes the weight given in the social welfare function to individual i at time t (which could, for instance, depend on discounting, citizenship, and whether someone is still alive); and $Y(X_{it}, 0)$ is the outcome without the intervention. The effect of an intervention is then a vector of outcomes ΔU which sum up the changes at the individual level and which can be used to further describe the effect of the intervention, such as by comparing the changes in the use of the public purse with the changes in health outcomes as in cost-benefit analyses (see Part II).

1.2.1 Target Population and Business-as-Usual

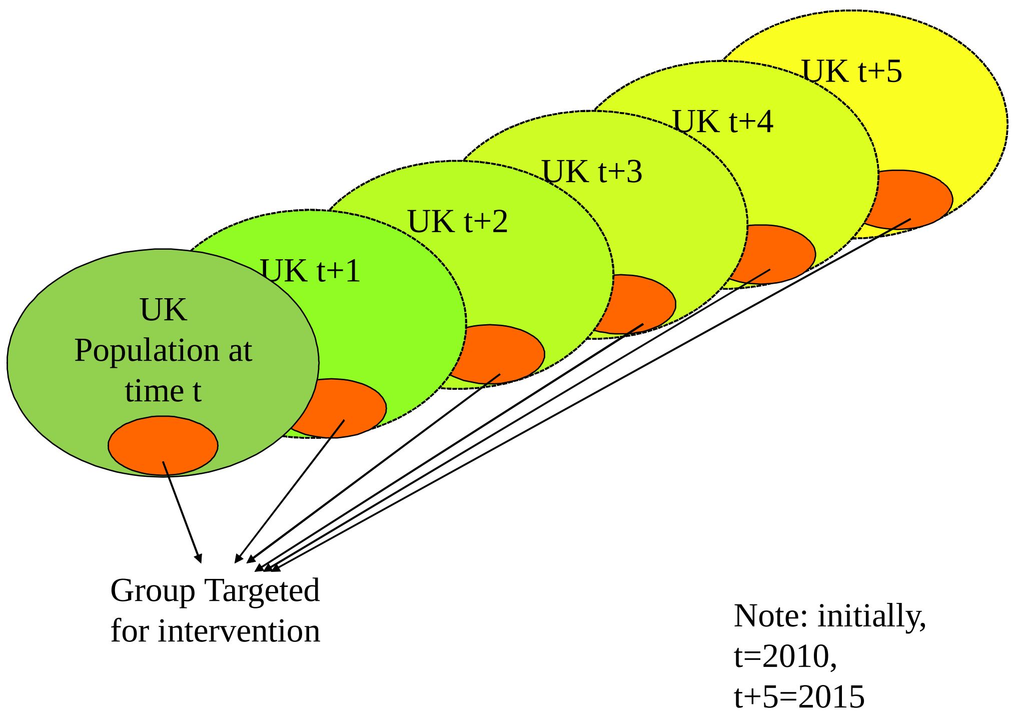
We need to populate the model with a nationally representative sample of the whole UK population and a business-as-usual scenario in order to give us a good idea of how individuals and communities normally behave over time, and which also includes information on the key outcomes and behaviours of interest.

We use the Understanding Society panel dataset, formerly known as the British Household Panel Survey (BHPS), which has followed over 20,000 citizens yearly since the early 1990s. This panel has information on education, employment, income, taxation, relationships, mental health, wellbeing, and so on. Moreover, it has extensive information on social structures, including information on other household members and the environment in which people live, allowing to match community characteristics to individuals over time.

For this target population, we want to define a business-as-usual scenario for five years for the main outcomes of interest. We do so by going back five years in time from the most recently available wave (2015) and simply taking what happened between then (2010) and now as the baseline scenario, implying that our hypothesised intervention relates to what could have happened to the UK population under a particular intervention. This greatly simplifies the problem as we do not need to model all forms of behaviour but only behavioural changes that there is sufficient information on.

Figure 1 illustrates how we focus on 6 years, definining a target intervention group as a sub-set of the whole population (t=2010).

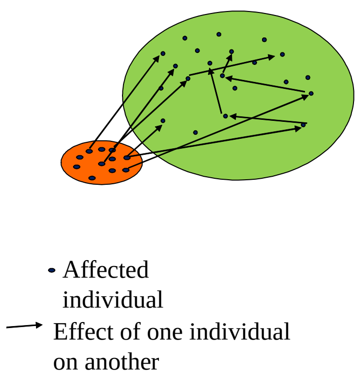
Figure 1: Trajectory of (Target) Population over Observation Period



1.2.2 Intervention Methodology: the Macro-Environment

The business-as-usual scenario needs to be compared to an intervention scenario, and one key issue to consider is just whose behaviour is 'allowed' to change due to interventions: if every person's behaviour can change, then we would need to model all the behavioural choices made by everyone in the panel over time, a task that is beyond current capabilities. This potential complexity is illustrated in Figure 2.

Figure 2: Complexity of Behavioural Spillovers



A key innovation of our methodology is to split the impacts of interventions into two categories: behavioural changes for those immediately affected by interventions, who personally undergo changes in employment, relationships, etc., and macro-behavioural changes for those not immediately affected. These macro-behavioural changes will include changes in markets via prices (supply, demand), reference effects of changes to local and national averages (relative income, relative health), and will in the future also include levels of community cohesion and social capital to capture the effects of cultural change..

We thus plan to set up a simple macro-model that captures the behaviour of those not immediately affected in a way that treats their individual characteristics as unaffected, but the sum of those characteristics as the outcome of a macro-model perturbed by the intervention on the patient group.

Formally, this means modelling changes as

$$\begin{aligned}\Delta W &= \sum_{t=0}^{T}\sum_{i}^{N_a} w_{it}\Delta Y(X_{it}, INT_{it}) + f(Z_t, \Delta_a Y_t) \\ &= \Delta_a Y_t + f(Z_t, \Delta_a Y_t)\end{aligned}$$

where N_a is the number of people immediately affected by interventions, a (small) subset of the whole population N. Here, $\Delta_a Y_t$ is the effect of the intervention on those directly involved, identified in the relevant trial data; Z_t is a matrix of relevant aggregate characteristics, including the business-as-usual scenario outcomes, but also macro-economic circumstances and aggregate measures of social outcomes such as average education and social trust. $f(Z_t, \Delta_a Y_t)$ is then a short-hand for a simple macro-economic model that captures the overspill and general equilibrium effects of the changes in the behaviour of the patient group on the rest of society. An initial choice for

$f(Z_t, \Delta_a Y_t)$ in the early stages of the project is to take $f(Z_t, \Delta_a Y_t) = \rho \Delta_a Y_t$ where ρ can be interpreted as a multiplier that either increases or decreases the effect of the initial change on patients.

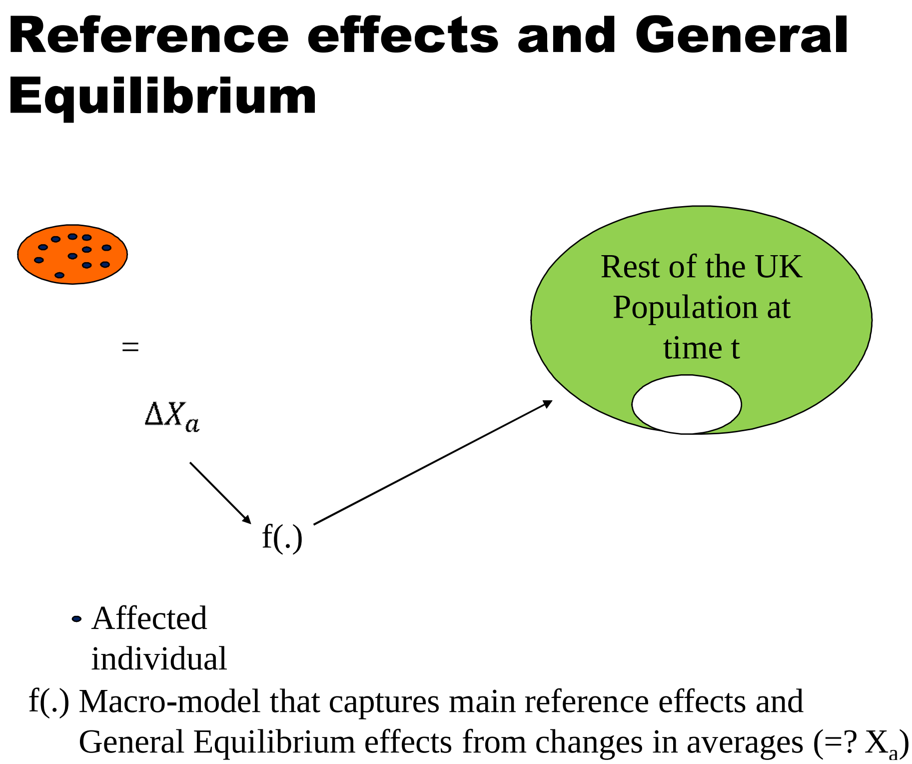
From the literature, we for instance already know that the multiplier on changes to patient's health and wellbeing is positive such that improvements get amplified: for example, Mervin and Frijters (2014) find a multiplier of around 0.15 on changes in mental health of partners. A similar number is found by others, so that is one of the multipliers we will include.

From basic economics, we can also suspect that the multiplier on labour market behavioural changes is negative, such that increased labour supply of patients would lead to reduced labour supply of complementary others as wages adjust. Indeed, Nickel and Saleheen (2015) find for the UK that a 10% increase in labour supply amongst the low-skilled and medium skilled (from an influx of migrants) leads to a 2% drop in wages for those occupations, whilst Blundell et al. (2011) find that a 1% drop in hourly wages reduces labour supply by around 0.4 on average. These two estimates of the labour demand and labour supply function can be combined to generate changes in overall wages and employment for the UK population due to health interventions that increase the number of potential workers in the UK. There is also a lot of evidence to suggest that mental health improvements lead to substantial shifts in physical health services demands (see the survey of Layard and Clark, 2014), which again requires an equilibrium model of physical health services to evaluate.

Initially, we will thus populate the model with multipliers and general equilibrium-feedback estimates from the literature, but later on we plan to model the function $f(Z_t, \Delta_a Y_t)$ more extensively by sub-group.

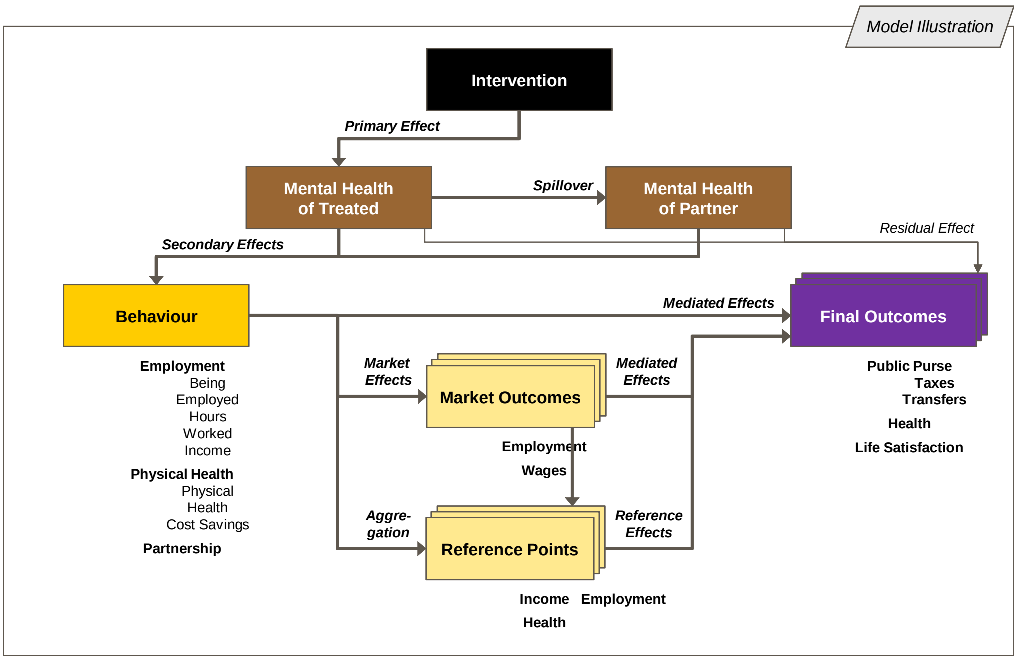
The separation between who is immediately affected and who is not greatly simplifies the problem, as it means that we do not (yet) have to worry about exactly who else is affected by, for example, an increased relationship stability of someone treated for a mental health problem. In a complete model of behaviour one would indeed want to work through what would have happened to, for example, a husband and his future relationship if he no longer got divorced in 2012 from a wife suffering from depression. Working through such effects adds a whole level of complexity though, as it requires a full model of relationship formation. To keep the problem tractable, a simplified approach is to model second-round effects via aggregate variables on the whole of the not-directly affected population. Those aggregate variables are then allowed to have effects on each other, for instance via the effects of changed labour market supply on the incomes of everybody and the taxes of everybody. This is a key innovation in the mental health and wellbeing literature which has not been seen before: it allows us to overcome the otherwise almost impossible hurdle that one cannot completely mimic all aspects of behaviour unless one has a 'model of everything'. Figure 3 illustrates this approach.

Figure 3: Intervention effects on the General Population



The full ineraction model of the UKWBS is then best decribed via a diagram:

Figure 4: The pathways in which an intervention works



Here, the top part of the diagram describes how the intervention has a primary effect on a target group's primary outcome, such as patients' mental health. This has a spillover effect on the primary outcome of their close ones, such as the mental health of their partner. For both of these changes, the lower part of the diagram describes the chain of effects that this set of primary effects leads to.

The effects of main interest are the secondary effects of the intervention on behaviour, such as employment, physical health care costs, and relationships. Sometimes such information is in an original trial, but often not so that these effects have to be imported from related studies. The changes in these behavioural variables then themselves lead to mediated effects on the outcomes of final interest (health, life satisfaction, net expenditure). Apart from these 'known' pathways, there is also a residual effect from the primary outcome of the intervention, essentially effects for which we do not know the pathway but that we can observe in the intervention study or that is known from the literature. We for instance know that the effects of mental health on life satisfaction are quite direct and thus not mediated much by changes in the realms of behaviour we have literature for: the main effect from changes in mental health on life satisfaction is residual. Yet, the main effect from changes in mental health on the public purse is mediated via an observed channel, which is the physical health costs and changes due to employment.

The very lowest part of the diagram captures the macro-effects within the model, as well as the importance of reference levels. The input into this part comes from the changes in aggregate behaviour for the primary target group and their partners. That change then in turn has market effects in the sense of changes in aggregate prices, like wage levels, till market forces equilibrate market demand and supply. The change in aggregates (both from the primary target group and via markets) then in turn change reference levels, such as reference incomes and reference levels of health. The changes in market outcomes then has aggregate mediated effects on the final outcomes of interest, which changes in the reference levels has reference effects.

Each of the arrows in this diagram above is thus a whole field of investigation, relating to at least one literature and sometimes multiple literatures (such as marekt effects which in principle relates to many different markets). Filling in these relations as best we can with knowledge from the literature is then our basic task.

Having described the basic elements of the methodology, we turn to the application.

Part II

Application to the IAPT: mental health in the UK

A 2009 survey of psychiatric disorders in the UK concluded that about 25% of respondents suffer from a mental health condition each year (Health & Social Care Information Centre, 2009), and some 50% of the US population has been estimated to suffer from a mental health condition at least once in their life (Kessler et al., 2015). The estimated costs of mental ill health in the UK range between £70 and £100 billion annually, accounting for about 4.5% of GDP. It is the leading cause of sickness absence, resulting in up to 70 million days lost from work every year (Davies, 2014). The World Health Organisation concluded in 2011 that mental health issues, in particular depression and anxiety, are amongst the most widespread and costly diseases chronically straining national health systems. Preventing them early is a recognised priority for governments (Park et al., 2016), as is the need for a life-course perspective on mental health and its treatment.

Mental health problems are usually not confined to the life of a patient alone: anxiety and depression, the two most prevalent mental health problems, disrupt many aspects of life, both of the sufferer and of others. Research has found that depression is associated with physical health problems (Moussavi et al., 2007; Naylor et al., 2012; Smith et al., 2014); lower productivity, lower wages, and higher risk of unemployment (Lerner et al., 2004; Adler et al., 2006; The Sainsbury Centre for Mental Health, 2007; Goodman et al., 2011), disruptions to education (Fletcher, 2007, 2010), divorce (Goodman et al., 2011), and the mental health of children and dependents (Gianfrancesco et al., 2005; Ramchandani et al., 2008; Marryat and Martin, 2010; Frijters et al. 2014; Claessens et al., 2015). Similar effects are known for anxiety and several other mental health conditions.

While there have been major intervention studies that evaluate the effectiveness of various types of treatment of different forms of mental health problems, these studies typically limit themselves to (mental) health outcomes for the patients, and are usually short-term in terms of follow-up.[2] This is partially because of the cost of keeping track of individuals and, more importantly, because of high attrition to repeated surveys, rendering the data

[2]See, for example, the systematic reviews by Barry et al. (2013), Das et al. (2016), and Clarke et al. (2015) on adolescent mental health interventions.

less representative over time. Particularly in medical trials, where individuals are at higher risk of dropping out when they respond less positively to treatment, this may lead to biased estimates (Dumville et al., 2006).

From a policy perspective, however, it is essential to get a picture of how interventions change several outcomes, not merely the immediate mental health outcomes. First, there are costs and benefits to the public purse, via usage of the health system, changes in tax receipts, welfare take-up, educational expenses, and so on. Second, changes in the mental health outcomes of patients have spillover effects on others in the community, for example, in terms of family and peer relations, as well as relationships at work. Finally, and perhaps most importantly, changes in mental health and changes in the circumstances of others need to be evaluated in terms of their impacts on key outcomes of interest, i.e. the health and wellbeing of the whole UK population. Needless to say, tracking both the short-run and the longer-run impacts of interventions is crucial for accurate cost-benefit analyses.

What is thus needed for wellbeing policy and mental health policy is similar to what was once needed in the areas of national income accounts and labour markets: a model that combines key lessons from many different studies into an overall model which simulates the impact of a change to one part of the system on its other parts. In the UK, early models of this kind led to the now widespread practice of simulation models at the micro and macro-level. These are used, for example, by the Bank of England, the Institute for Fiscal Studies, the Treasury, CEP, and Office for Budget Responsibility to simulate important policy changes and major shocks, such as changes in tax and welfare systems on the public purse and changes on the overall UK economy from large shocks (like Brexit). Simulation models to mimic aspects of the economy are now used widely around the world. A similar development also needs to happen for wellbeing and mental health, and we here start with a simple model as a 'proof of concept' and extending it with additional modules to make it more useful to academics and policy-makers alike.

2 Calibrating the Micro-Macro Simulation Model

In this section, we describe how to calibrate the micro-macro simulation model, and in particular, how to map clinical trial to population data. It is subdivided into three subsections: the first focuses on calibrating the primary effects of introducing a hypothetical mental health intervention on the mental health of the treated population; the second focuses on calibrating the secondary effects of these mental health benefits on their various life domains. For example, a rise in the mental health of a particular patient may lead to a higher likelihood of that patient to be employed or a rise in working hours. The third subsection then relates these effects – both primary and secondary – to life satisfaction, our ultimate outcome.

2.1 Calibrating the Primary Effects (Mental Health)

To measure the primary effects of introducing a hypothetical mental health intervention on the mental health of the treated population, one has to, first of all, have an idea of what kind of intervention one wishes to simulate. Ideally, the intervention is based on a rigorously impact-evaluated clinical trial which shows promising results that are of high interest to policy-makers and practitioners working in mental health care, and is thus worth simulating.

2.1.1 Selection Criteria for Clinical Trials

We applied the following selection criteria to select relevant clinical trials worth simulating from the mental health literature:

- High success rates

- Targeting the most common mental health problems (at least depression, ideally also anxiety disorders)
- Covering various degrees of severity (mild, moderate, major)
- Covering various forms of (combinations of) treatment (at least one being CBT)
- Data availability: types of outcomes (objective, self-assessed); width of outcomes (mental health and wellbeing, physical health, employment, relationships); breadth of outcomes (short-run, long-run); covering basic set of covariates, costs; covering different country contexts (at least UK, ideally also US)
- Potential to simulate mainstreaming and scaling-up
- Rigorously impact evaluated (ideally RCT with â€œreal-worldâ€İ randomisation design, i.e. randomized choice sets, in field)

In the context of the UK, the clinical trial that is most likely to satisfy these criteria is the *Improving Access to Psychological Therapies*, in short *IAPT*, scheme.

2.1.2 Selected Clinical Trials

IAPT targets mild to moderate depression (plus mental health problems such as anxiety), and offers a stepped care mode that provides low-intensity treatment first (either guided self-help or computerised CBT), and in case of failure, forwards patients to more intense forms (or combinations) of treatment such as, for example, one-on-one CBT. The intervention was impact evaluated at two demonstration sites in the UK – Doncaster and Newham – before having been mainstreamed and upscaled by the NHS, starting in 2008. It is now available through self-referral or referral by general practitioner, and is accessible both online and offline, to the general public. The impact evaluations were conducted by Clark et al. (2008, 2009) and Parry et al. (2011), and they follow participants up to 18 months after last treatment, reporting on their self-rated depression (PHQ); self-rated anxiety (GAD); self-rated wellbeing, problems/symptoms, life functioning (CORE-OM); and employment, sick days, and welfare benefits.

Simulating an increase in access and capacity of IAPT services for the general public is interesting to policy-makers and practitioners working in mental health care as the NHS aims at, amongst others, increasing throughput from currently 900,000 patients served annually to 1.5 million by 2020, or in other words, from 15% of the depressed population to 25%, as formulated in its Five Year Forward View on Mental Health.

2.1.3 Challenges of Mapping Clinical Trial to Population Data

When mapping clinical trial to population data, that is, when translating between variables that are typically available in clinical trial data and those that are typically available in population data such as the British Household Panel Study/Understanding Society, we face several challenges. More than often, measures in clinical trial do not match those in population data, so that assumptions have to be made in terms of equivalence, or measures have to be converted using either existing rules or simple rules of three. Moreover, most clinical trials do not include long-run follow-ups, rendering inference regarding longer time horizons often incurred in population data difficult: missing years have to be either predicted using previous years and rates of change, or additional information from other trials that offer long-run follow-ups has to be used. Similarly, clinical trials often provide only infrequent follow-ups, reporting, for example, on outcomes only every other year. In such cases, a common workaround is to predict missing years using the mean of observations in preceding and succeeding years. Finally, in terms of external validity, clinical trial data are often highly location and time specific, whereas population data are more representative of the overall population; in terms of internal validity, researchers are well advised to focus on rigorously impact-evaluated RCTs and to focus on compliers, that is, participants who remained in the intervention from start to finish (which renders reported estimates more conservative, as these are most likely lower-bounds of the true estimates.)

In short, mapping clinical trial to population data is inherently complex: a multitude of assumptions inevitably have to be made, and mappings should be interpreted with caution against this background.

2.1.4 Translating IAPT Measures to British Household Panel Survey/Understanding Society Measures

Since clinical trial data from the IAPT do not cover the same measures and time periods as population data from British Household Panel Survey/Understanding Society, these have to be derived and imputed, ideally under minimal assumptions.

SF12 We start by looking at the first time period in both clinical trial and population data, $t = 0$, and observe that the clinical trial data include only

PHQ9 and GAD7 as relevant mental health outcomes, whereas the population data include only GHQ12 and SF12. Thus, to map measures between both datasets, we have to establish equivalence between any of these measures. We do so by exploiting *Cognitive Behavioural Therapy as an Adjunct to Pharmacotherapy for Treatment Resistant Depression in Primary Care*, in short *CoBalT* – a randomised controlled trial conducted in 73 general practices in three UK centres (Bristol, Devon, and Glasgow) – as an auxiliary dataset: it targets the same mental health conditions as IAPT and reports similar pre-intervention values for PHQ9 and GAD7. Importantly, it also includes SF12, so that we can use a simple rule of three (to the best of our knowledge, there is no official conversion rule between these measures) to derive the pre-intervention value for SF12 in IAPT.

We first generate the same composite measure of mental health in IAPT and CoBalT by taking the mean between PHQ9 and GAD7 in each of these trials. The pre-intervention value for this composite measure in IAPT is 14.53*, whereas it is* 14.15 *in CoBalT; the value for SF12 in CoBalT is* 28.50 *at baseline. Thus, using a simple rule of three and assuming linearity, we can derive the pre-intervention value at* $t = 0$ *for SF12 in IAPT as* 29.27*.*

How would SF12 in IAPT evolve over time? To answer this question, we next look at how the composite measure of mental health evolves, and in particular, calculate rates of change from one time period to the next. Note that we can track the evolution of this composite measure in IAPT only up to one year: the first follow-up is at $t = 0.5$, the second at $t = 1$ (in fact, the impact evaluations include follow-ups after four and eight months only, which we round up to six and 12 months, respectively, for comparability with other clinical trials).

The rate of change from $t = 0$ *to* $t = 0.5$ *is* -0.52*, that from* $t = 0.5$ *to* $t = 1$ *is* 0.16*. Applying these rates to SF12 in IAPT, and keeping in mind that the composite measure and SF12 run in opposite directions, yields the first time series of values for SF12 in IAPT:* 44.49 *at* $t = 0.5$ *and* 37.37 *at* $t = 1$*.*

Now, to complete this time series over the entire observation period that is available in the population data, we can assume different scenarios.

The first scenario is called *Naive SF12*: here, we assume that there are no further changes and that the value for SF12 in all following time periods remains constant at 37.37. This is probably not the most realistic case, as interventions targeting depression suffer from relapse rates, implying that after five to six years only about 60 percent of the treated remain depression free (Fava et al., 2004). An alternative scenario, therefore, introduces a relapse rate: it is called *Relapse SF12*, and it assumes that the value for SF12 decreases to about 60% (implying a relapse rate of about 40%) of the initial mental health improvement (in other words, it decreases to 34.13) at the end of the observation period. For simplicity, we take *Naive SF12* as our baseline scenario, but will simulate the alternative scenario in addition in order to benchmark both scenarios against each other.

GHQ12, LS We now have our preferred time series for SF12 in IAPT: *Naive SF12*. The next step is to derive corresponding time series for GHQ12, the most frequent mental health measure in population data, and for life satisfaction.

The idea is very simple: since we now have an entire time series for SF12 in IAPT, we can calculate corresponding rates of change from one time period to the next. Once this is done, we can look into the population data and check which initial value for GHQ12 at baseline corresponds to a value equal to or greater than four: this threshold value is typically applied to define *caseness*, that is, the likely presence of a mental health condition. In our case, the mean GHQ12 value in the population for which GHQ12 is equal to or greater than four at baseline is 6.98. From this initial value, we can then compute, using the rates of change observed in our preferred time series for SF12, the subsequent values for GHQ12.

2.2 Calibrating Secondary Effects (Various Life Domains)

In this subsection, we describe how to measure the secondary effects of a rise in mental health on various life domains. To keep the problem traceable, we initially look at three life domains: employment, with a particular focus on employment status (extensive margin, i.e. being employed) and productivity (intensive margin, i.e. hours worked); physical health, including physical health care cost savings; and partnership.

2.2.1 Employment

To obtain credible estimates of how a rise in mental health translates into better employment opportunities, we carefully selected well-published causal-design studies from the relevant mental health literature. Two studies stand out, and form the backbone of our model in this particular domain.

Rollman et al. (2005) evaluate the impact of a telephone-based collaborative care management system for panic and generalised anxiety disorders that was introduced in four primary care practices in the greater Pittsburgh area. The intervention, which involved 191 adults aged 18 to 64, was implemented as a randomised controlled trial: after screening patients for panic and generalised anxiety disorders, patients were randomly allocated into either a treatment group in which non-mental health professionals provided psychoeducation, assessed preferences, and monitored progress, or a control group in which patients and practitioners were only given notice of the condition. At a 12 months follow-up, the intervention group showed significantly improved mental health (between 5.8 and 7.1 points on the SF12 mental health summary score, depending on the initial severity of the condition), and importantly, had a higher likelihood of being full-time employed by 15 percentage points, conditional on having been employed at baseline.

Simon et al. (2000) conducts a secondary analysis of a randomised controlled trial that tested three types of drugs against major depression in seven primary care clinics in the greater Seattle area. The trial randomly allocated 536 adults beginning antidepressant treatment into three treatment groups corresponding to these drugs, and provided both a 12 and a 24 months follow-up. When comparing patients in the remitted relative to the persistent group, i.e. individuals freed from depression with individuals still having symptoms, at the 24 months follow-up, patients in the remitted group showed a significantly higher likelihood of being full-time employed by 15.3 percentage points – similar to the impact reported by Rollman et al. (2005).

In light of the similarity of these results, we assume that a hypothetical mental health intervention that frees patients from depressive symptoms leads to a higher likelihood of being full-time employed by 15 percentage points. This is likely to be a conservative measure, as the mental health improvement reported by Rollman et al. (2005) is lower than what we assume in IAPT.

Besides evaluating the impact of the intervention on the extensive margin of employment, i.e. employment status, Rollman et al. (2005) also evaluate its impact on the intensive margin, i.e. hours worked: they report a rise in hours worked for patients in the treatment group relative to those in the control group by 6.6 percent.

To achieve consistency with our effect estimates for employment status, we thus assume that being freed from depressive symptoms raises hours worked by 6.6 percent.

2.2.2 Physical Health

It is well established in the mental health literature that the direct physical health benefits of interventions targeting major depressive symptoms are minor. Rather, physical health benefits manifest themselves indirectly, through reductions in medical service use, which can lead to large cost savings.

Cho et al. (2010) provide prima facie evidence that direct physical health benefits are relatively minor. The authors employ a prospective cohort study of 351 adults aged 60 and above in three urban communities in the US, and compare – in a difference-in-differences setting – adults (matched in terms of age and gender) with and without prior history of depression over time: whereas the treatment group had a history of depression but was in remission, the control group had none. At a 24 months follow-up, individuals in the treatment group showed lower physical health, measured in terms of the SF36 physical health summary score, than those in the control group, but the effect was small: -0.42. And even if individuals eventually fell back into depression during the observation period, the effect remained small, at -1.66. Since the target population was relatively old (adults aged 60 and above), it is conceivable that effect sizes for younger target groups are even smaller.

The indirect physical health benefits through reductions in medical service use, however, are substantial: in a meta-analysis of the impact of mental health interventions on medical service use, involving 91 studies published between 1967 and 1997 of which 28 include the costs of the intervention, Chiles et al. (1999) show that, on average, treatment reduced annual costs of medical service use by 20 percent. This was especially true for behavioural interventions such as cognitive behavioural therapy.

We can thus calculate the potential health care cost savings of a hypothetical mental health intervention in the UK as follows: we know that the annual costs of medical service use in the UK are about GBP 75 billion, and that there are about 18 million people with physical health conditions of which 4 million also have co-morbid mental ill health. Since the latter cost about 50 percent more in terms of medical service use than the former, we arrive at annual costs of medical service use for patients with physical health conditions and co-morbid mental ill health of about GBP 6,000. A 20 percent reduction in annual medical service use then leads to GBP 1,200 gross savings, and given that about 60% of the mentally ill also have co-morbid physical illness, GBP 720 net savings per treated person per year (Katon, 2003; Layard and Clark, 2014).

In light of these findings, we therefore assume that a hypothetical mental *health intervention that frees patients from depressive symptoms leads to annual medical service use net savings of GBP 720 per treated person per year – a conservative estimate. Finally, to nevertheless account for direct physical health benefits, we assume that being freed from depression (and remaining free) leads to an improvement in the SF36 physical health summary score by 1.66; for individuals eventually falling back, we assume this improvement to be only 0.42.*

2.2.3 Partnership

How does relief from depression affect relationship formation? Unfortunately, there is little evidence on this particular life domain: it is often not the focus of interventions, while being inherently difficult to estimate in quasi-experimental settings.

Reichman et al. (2015) nevertheless make a promising attempt: the authors employ cohort data from the Fragile Families and Child Wellbeing Study in the US, which focuses on families with children born in 20 major US cities between 1998 and 2000. The study involved a baseline interview of parents immediately after birth, and follow-up interviews one year and three years later. To estimate the causal effect of depression on relationship formation, Reichman et al. (2015) exploit the fact that post-partum depression – a major depressive symptomatology – is largely random, conditioning on prior mental health history. The authors show that having been diagnosed with post-partum depression within 12 months after delivery reduces the odds of remaining married by seven percentage points and of remaining cohabitating by 11 percentage points at the three-year follow-up.

To incorporate relationship formation into our model, we therefore assume that, inversely, being freed from depression leads to a higher likelihood to remain partnered by 7 percentage points. For simplicity, and given that the impacts are quite comparable, we assume, so far, equivalence between being married and cohabitating.

2.3 Calibrating Mediated Effects

Now that we have established how a rise in mental health translates into changes in behaviour in the life domains of employment, physical health, and partnership, we next ask how these changes in behaviour affect our ultimate outcome of interest: wellbeing, measured in terms of life satisfaction. This section elaborates on these so-called *mediated effects*. It is subdivided into two sub-sections: the first describes the *direct* effects of employment, physical health, and partnership on life satisfaction; the second describes the *indirect* effects through changes in references points. For example, a rise in income for a patient that has newly been freed from depression leads to a higher life satisfaction of that patient, but at the same time, may also change that individual's reference point: she may now compare herself to individuals in a higher reference category of income, and this relative comparison effect may dampen some of her initial rise in life satisfaction. So far, we focus on reference effects in three key areas: employment, income, and health.

2.3.1 Direct Mediated Effects

Employment It is well established that employment (for simplicity, we assume equivalence between being unemployed and not being employed, or in other words, between not being unemployed and being employed) leads to a rise in life satisfaction. For the purpose of calibrating our model, we resort to two studies in the life satisfaction literature that document this rise: Clark et al. (2008) and Kassenboehmer and Haisken-DeNew (2009), both of which use linear individual fixed effects models and panel data from the German Socio-Economic Panel (SOEP) to estimate the effect of unemployment (Clark et al., 2008; Kassenboehmer and Haisken-DeNew, 2009) and of log net household income (Kassenboehmer and Haisken-DeNew, 2009) on life satisfaction, measured on a zero to ten scale, in total and separately by gender (Clark et al., 2008; Kassenboehmer and Haisken-DeNew, 2009) and by region in Germany (Kassenboehmer and Haisken-DeNew, 2009). To arrive at more representative effects that are less dependent on sample composition and model specification, we take averages of these effects, separately for each gender, yielding effects of unemployment on life satisfaction of -0.73 for males and -0.43 for females as well as of +0.35 for log net household income (the effect size is exactly the same for each gender).

Physical Health Estimating the effect of physical health on life satisfaction is inherently difficult: more physically healthy people are more satisfied with their lives, while people who are more satisfied with their lives are more likely to engage in behaviours that lead to more physical health. In other words, it is difficult – at least in quasi-experimental settings – to disentangle the endogenous relationship between physical health and life satisfaction, simply because there are little credible exogenous variations in physical health that do not, at the same time, affect life satisfaction through various other channels. To nevertheless provide a credible estimate of the effect of physical health on life satisfaction, we resort to Layard et al. (forthcoming), who report an effect estimate of +0.12.

Partnership Various studies document the positive effect of being partnered on life satisfaction. To achieve consistency with our employment effects, we again resort to Clark et al. (2008), who uses linear individual fixed effects models with leads and lags in the variables of interest and panel data from the German Socio-Economic Panel (SOEP): the authors report an effect size for getting married of +0.31 for males and +0.39 for females. Similar to employment, for the time being, we assume equivalence between being married and being partnered.

2.3.2 Indirect Mediated Effects

Indirect mediated effects occur through changes in reference points that follow from changes in behaviour, and via these changes, affect life satisfaction. For example, re-entering the labour force and earning more income for a patient who has newly been freed from depression may lead to a change in that patient's reference group: she may now compare herself to other employed (rather than unemployed) individuals, who are in a different income group. This may dampen some of the initial rise in her life satisfaction. Similar effects, although not having received much attention in the literature so far, are conceivable for health. To account for these indirect mediated effects through changes in reference points, we resort to Ferrer-i-Carbonell (2005) and Luttmer (2005) for the case of income: the former author uses ordered probit individual random effects models and panel data from the German Socio-Economic Panel (SOEP), defining reference groups by age, education, year, and region. She finds that reference income, measured in terms of log average net household income in the respective reference group, reduces life satisfaction by -0.23. Luttmer (2005) finds similar effects in the US, using panel data from National Survey of Families and Households: in his individual fixed effects specification, he finds that reference income in public use microdata areas reduces life satisfaction by -0.23 and by -0.19 when adding, in addition, state and year fixed effects. To arrive at more representative effects that are less dependent on sample composition and model specification, we again take averages of these effects, yielding an effect of reference income on life satisfaction of -0.22.

Regarding the indirect mediated effect of unemployment (recall that we assume equivalence between unemployment and non-employment), we resort to Layard et al. (forthcoming), who finds that local unemployment reduces life satisfaction by -1.58 points. In other words, if the local unemployment rate increases by 100%, this rise in local unemployment would decrease residents' life satisfaction in that area by 1.58 points. For reference effects regarding health, which are less well documented, we assume an effect of -0.09 – three quarters of the original effect of physical health on life satisfaction, as implied by Mujcic and Frijters (2015).

2.4 Budgetary effects methodology

From the rest of the model, we will in effect get ΔX_{it} and ΔY_{it} for a sub-set of Y's and X's. This crucially needs to be translated into changes in the public purse.

What one ideally wants is whole simulators for the use that someone with particular characteristics has of all the major government programs that cost money. This is clearly too big a task.

Our current approach is to use datasets that already have estimated taxes and transfers in them. Call those Tax_{jt} and $Trans_{jt}$. This need not be the same dataset, but it turns out that Understanding Society does have such estimates.

What we then do is estimate a model of the form

$$\begin{aligned} Tax_{jt} &= a_j + X_{jt}\gamma + I_t\delta + u_{jt} \\ Trans_{jt} &= \tilde{a}_j + X_{jt}\widetilde{\gamma} + I_t\widetilde{\delta} + \widetilde{u}_{jt} \end{aligned}$$

note the use of individual fixed effects here, but the lack of information on prior levels (ie, no Arrelano-Bond term like λTax_{jt}) which means that for predictions of changes one does not need to know the previous levels of taxes and transfers:

$$\Delta Tax_{jt} = \Delta X_{jt}\widehat{\gamma}$$

which one can hence use in the target dataset to calculate expected changes in taxes and transfers for the entire population for which one has ΔX_{it}. For future work, it is important to have more fine-grained information on the types of public purse expenditures (ie, the specific programs used more or less) and sources of taxation. We will also at some point check whether our estimates of tax and benefit effects are similar to that what you get from more expansive models of the tax and benefit system.

3 Implementation: the UK WBS as an IAPT intervention

In this chapter we illustrate some of the possibilities of the Wellbeing Micro-Macro-Simulation model by simulating a major mental health intervention: the Improved Access to Psychiatric Therapies program (IAPT). At this stage, we focus on two final outcomes of the intervention, namely life satisfaction and the public purse. Regarding the latter, we can discuss how long it takes for the direct cost of the intervention to be paid back, through higher taxes, lower social benefits and savings on health care costs (if demand shifts are monetised), but also estimate the cost-effectiveness of intervention in terms of cost per wellbeing.

Three main advantages of the microsimulation approach are presented here. First, the possibility to discuss how the intervention impact is distributed within the population (or sub-groups of the population), or between UK regions. Second, we can emphasize the relative contribution of each channel, from secondary effects to the strength of reference effects[3] or market effects.

[3] Clark et al. (2008) discuss the large empirical literature documenting the effect that the consumption and incomes of neighbours and countrymen have on individuals, following on from the classic Easterlin Hypothesis argument that reference (status) effects nullify the effects of increased incomes on happiness in the long run.

Lastly, the primary effect on mental health corresponds to what we know of the IAPT target group. However, we can easily modify the target group, along with the type of mental health shock, from its initial level to the relapse rate, and test different scenarios. Because we sometimes lack evidence regarding the shape of the $Y(X_{it}, INT_{it})$ function, we should of course remain careful regarding the external validity of alternative scenarios.

In this section, we first provide relevant descriptive statistics from the Understanding Society data. We discuss in particular the representativeness of the target group. We then describe how the microsimulation assumptions programmed in LIAM2 fits with the general methodology discussed in section 3. Lastly, we present and discuss the results of the simulation.

3.1 Understanding Society (2010-2015)

The simulation uses the six waves of the Understanding Society (UKHLS) data from 2010 to 2015. This corresponds to a panel of about 20,000 individuals per period. We only keep individuals for which none of the main variables have missing values (life satisfaction and GHQ-12). When missing, we impute secondary variables affected by the intervention, such as working hours for self-employed[4]. We use longitudinal sample weights and all income variables are expressed in terms of 2010 prices using the national Consumer Price Index.

Table 1: descriptive statistics, Understanding Society (2010-2015)

	2010	2011	2012	2013	2014	2015
% depressed (GHQ 12 $\geq$ 4)	16.5	16.6	16.9	16.7	17.8	16.8
Average life satisfaction (0-10)	7.28	7.17	7.01	6.84	6.80	7.02
GHQ-12 (0-12)	1.59	1.59	1.63	1.61	1.72	1.60
SF-12 mental (0-78)	51.4	50.5	49.9	50.0	49.4	49.8
Age	46.5	47.5	48.2	48.9	49.6	50.2
% women	0.52	0.52	0.52	0.52	0.52	0.52
Average net monthly income (2015 GBP)	1240	1352	1426	1459	1506	1587
Average hours worked of workforce	21.2	21.1	20.4	20.3	20.4	19.6
Unemployment rate (%)	6.4	5.9	6.1	6.2	5.4	5.4
% single	18.8	18	18	18	18.1	18.1
% graduates	38.5	39.2	38.7	38.6	39.0	38.5

Table 1 shows the population averages for some of the selected variables. Overall, the sample means are close to their national ONS equivalent, except for the unemployment rate which is slightly lower in Understanding Society.

[4]We take the mean number of hours worked by the self-employed each year, which matches official ONS figures.

The average life satisfaction of UK individuals has declined from 7.3 in 2010 to 6.8 in 2014, with some recovery in 2015. The Office for National Statistics (ONS) does not collect information on clinically diagnosed cases of anxiety or depression. Estimation hence comes from self-reported measures from the GHQ-12 questionnaire. A GHQ-12 score of 4 or more indicates symptoms of mild to moderate illness such as anxiety or depression. According to this definition, between 16.5% and 18% of individuals are in a state of depression or anxiety each year.

Currently, about 15% of all people with anxiety and depression are seen by IAPT services each year. We will simulate the treatment of 25% of the depressed (i.e. 4.5 % of the UK population), which corresponds to the priority target set by the NHS regarding IAPT services development for 2020-2021. Table 2 compares the sample of depressed individuals from UKHLS to what we know of the characteristics of treated individuals in the IAPT impact studies.

Table 2: UKHLS individuals with GHQ-12 $\geq$ 4 vs. Clark et al. (2008, 2009)

	Clark et al. (2008, 2009)	Understanding Society (depressed, 2010)
GHQ-12 (0-12)	7.0	7.2
SF-12 mental (0-100)	33.2	38.1
Age	38	43.5
% women	60	57.5
Average life satisfaction (0-10)	?	5.3
Average net monthly income (2015 GBP)	?	1111
Average hours worked of workforce	?	19.4
Unemployment rate	?	11.6
% single	?	24
% graduates	?	36

On average, depressed individuals are less happy and have lower income levels than the rest of the population. They work less and have a twice higher unemployment rates (11.6% against 5.4%). They are also more likely to be single, but there is no significant difference in terms of education. Importantly, if we compare their average mental health scores (GHQ-12 and SF-12) to the average score of treated individuals in IAPT trials, the numbers are very similar between the two samples. The share of women is also very close. The only significant difference is that the target group in UKHLS is on average older[5]. We hence expect the average mental health improvements measured in the Doncaster and Newham trials to be a reliable estimate for the overall depressed population in the UK.

3.2 Description of simulation

To programme the simulation model, we use the modelling framework LIAM2. It is a free, open source framework designed for the development of discrete-time dynamic models. LIAM2 is developed primarily in Python and can be used to design almost any microsimulation model, from pension systems to taxes and benefits. It has been acknowledged in the literature as one of the few recent attempts to develop a tool that can be used by others, hence exploiting economies of scale in the construction of microsimulation models and making the process more transparent (De Menten et al. ,2014; Li, O'Donoghue & Dekkers, 2014). Another important functionality of LIAM2 is that it allows for retrospective modelling by recognising the existing values of a variable in a certain period. Thus, if a value for an endogenous variable is available for one or more periods of time, LIAM2 will not overwrite this

[5] Thou we can only recover the age profile of the IAPT trials from partial information on the age distribution across groups. Also, if we define the target population as the depressed individuals within the workforce, the age difference becomes not significant. Such alternative definition of the target group will also be tested in the analysis.

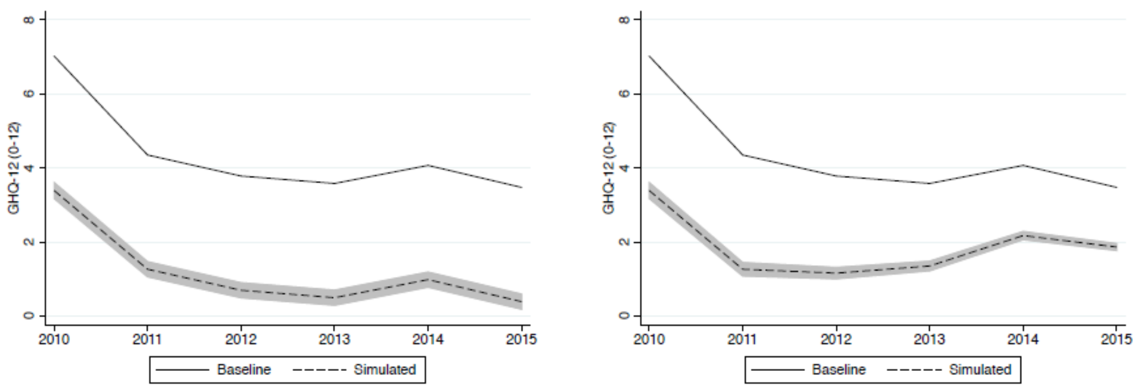
value but use it in the remainder of the model instead. This is particularly useful for us as we are interested in changes of X_{it} and Y_{it} based on their existing levels[6].

The model follows the general methodology described in part I. We define the treated population as a share of individuals within the target population of depressed individuals (GHQ-12 ≥ 4). We start with a share of 25%, which corresponds to about 4% of the population. The mental health intervention is partially transmitted to partners or children living in the same household as treated individuals, what we call spillovers. In line with the literature, we assume 15% of the primary effect gets transmitted within households (Layard et al. 2017, Mervin and Frijters 2014, Powdthavee and Vignoles 2008). Adding these individuals to the group of treated, the share of the population whose mental health improves after the intervention goes from 4.5% to 6%. Two scenarios are shown on figure 5 regarding the primary effect on the GHQ-12 score of the treated. In the optimistic ("naive") scenario, the primary effect partially relapses after one year at a 15% rate, and then remains the same in the following 4 years. This is our main scenario that we will develop in the rest of the paper. A more pessimist scenario ("relapse")

[6] In a more advance version of this project, we will also simulate artificial data forward, exploiting the alignment functionalities of LIAM2.

assumes a constant relapse rate over the entire period. We also provide cost-per-wellbeing estimates in this case to have a lower bound estimate on the overall effect. Lastly, as an attempt to provide confidence intervals for our results, all estimations account for the standard deviation of the primary effect that we recover from the trial studies.

Figure 5: GHQ-12, the primary effect on the treated population



(a) Optimistic (naive) scenario

(b) Pessimistic (relapse) scenario

The primary effect on mental health lead to a number of changes for the people whose mental health improves. We focus on four major indirect effects of better mental health: employment, income, partnership and physical health. We also add the residual effect of mental health on life satisfaction estimated by Layard et al. (2017). Each of these factors changes according to the mental health shock in period t, and in turn affects life satisfaction along with the public purse in the same period. We use the coefficients introduced in section 2 to calibrate the model. Individual hourly wages are assumed to be constant, so that an x% change in hours worked leads to an x% change in the individual's gross income. For the newly employed, we choose to impute the individual's net income, gross income and social benefits based on the average income of individuals by region, skill group, age group and gender[7]. We exploit the recursive possibilities of LIAM2 for some of the effects described later on. For instance, we know from Cho et al. (2010) that the impact of having left depression before has a long lasting positive effect (though smaller) on physical health for those who remain not depressed the subsequent periods.

The timing of the feedback effects (labour market and reference effects) follows the dynamic procedure described earlier: at the beginning of each period, new prices are determined based on the aggregate changes which happened last period. This is the case for the labour market, where we define four markets each period based on gender (male or female) and skill group (high skills or low skills). For the latter, we define high skilled individuals as those who have a graduate diploma. The macro feedbacks play on

[7] We could also take the average income of the individual in the previous years in which she was employed.

the extensive margins (employed or not) as well as intensive margins (hours worked) of the labour market. Regarding reference effects, individuals' reference group corresponds to the individuals in the same region and belonging to the same skill group, age group and gender cell. There are 144 reference groups each year with an average number of 100 individuals per group.

Lastly, in order to estimate the impact of the intervention on the public purse, we translate changes in gross income, employment status and family status into estimated changes in taxes and transfers. To do so, we run the following fixed effect regressions on the full UKHLS sample:

$$Tax_{jt} = a_j + y_{jt}\gamma_1 + h_{jt}\gamma_2 + u_{jt}\gamma_3 + P_{jt}\gamma_4 + h_{jt}\gamma_5 + I_t\delta_{tax} + u_{jt} \tag{1}$$

$$Transfer_{jt} = a_j + y_{jt}\gamma_1 + h_{jt}\gamma_2 + u_{jt}\gamma_3 + P_{jt}\gamma_4 + h_{jt}\gamma_5 + I_t\delta_{trans} + u_{jt} \tag{2}$$

Where γ_1 captures the effect of a change in gross income, γ_2 the effect of a change in the number of hours worked, γ_3 the effect of being unemployed, γ_4 the effect of being single and γ_5 the impact of the number of children. Both regressions include individual effects a_j and year effects I_t.

In Understanding Society, taxes include labour income taxes, capital income taxes and national insurance contributions. We recover the the total amount of taxes paid substracting the personal gross monthly income from the personal post-tax net-income. Transfers include a large list of social and work benefits, from child benefits to working tax credits or rent rebates[8]. Understanding Society imputes missing values on income, taxes and transfers using a combination of cross-sectional and longitudinal imputation methods. Results of the fixed effect regression are shown in Table 3.

[8] See documentation provided by Understanding Society for the full list.

Table 3: Taxes and transfers fixed effect regressions

	(1) Taxes paid	(2) Transfers
Total monthly personal gross income	0.214***	-0.0117***
	(0.00716)	(0.00122)
No. of hours normally worked per week	4.757***	-2.521***
	(0.273)	(0.129)
Single	-76.46***	77.44***
	(11.37)	(8.219)
Unemployed	-11.44	41.14***
	(9.814)	(9.059)
One child	-51.37***	64.15***
	(8.247)	(5.065)
Two children	-74.41***	96.85***
	(10.76)	(7.182)
Three children or more	-140.9***	155.2***
	(17.90)	(14.63)
Individual FE	Yes	Yes
Year FE	Yes	Yes
Observations	127308	127308
Adjusted R^2	0.772	0.685

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

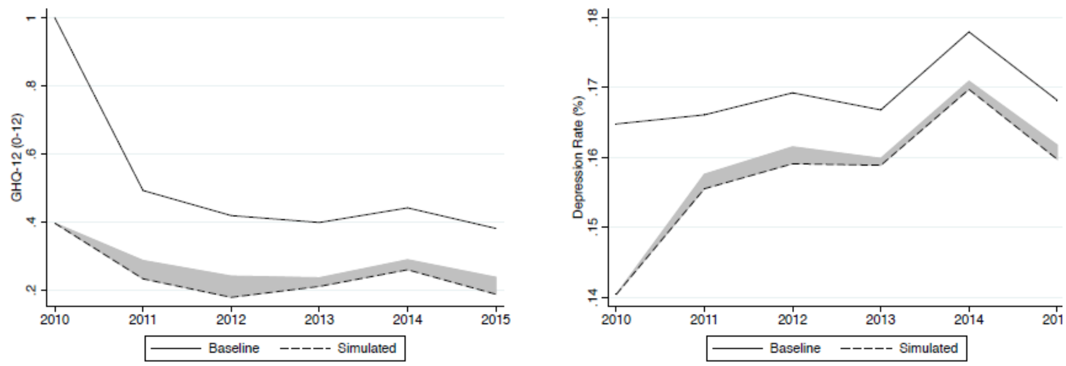
Overall, the sign and value of the coefficients are in line with what would be expected from a tax and transfer system. The level of transfers does not react much to gross income however, even if we do not include working hours as a control. The fact that it reacts strongly to the latter may be indicative of measurement errors or under-reporting of income compared to hours worked. Since we model changes in working hours as well as changes in income, we use all the information available from the γ's to estimate associated changes in taxes and transfers, and use them to compute the individuals' new net income.

Regarding health care costs, we use the literature estimates from Clark and Layard (2014) on the annual health care costs saved per individual who gets out of depression, i.e. about 720 pounds. Note that these have mainly been interpreted as actual cost savings to the public health sector, but this is not entirely appropriate: what happened was a shift in demand from those with depression for health services. Since the health system has long queues and works on a fixed-supply basis, the slack will be taken up by other patients, implying that the shift in demand will not be monetised into actual savings unless the mental health intervention is accompanied by a reduction in the availability of physical health services. It is thus yet to be worked out what wellbeing benefits are likely to accrue from the availability of more physical health services to others in the scenario that there is no change to service supply.

3.3 Preliminary results and discussion

We can now compare the actual population to the simulated population after treatment. We choose to treat 25% of the depressed in period 1 and look at their life satisfaction profile over the five subsequent years. The intervention has an obvious impact on the depression rate of the treated that can be seen in figure 6. About 60% of the treated leave depression in the first year. The size of the initial drop compared to latter periods can be explained by two factors. First, the drop itself is stronger in first period compared to the next periods due to the relapse rate of 15%. But more importantly, almost all of the treated individuals are in short-term (minor) depression, and tend to have GHQ-12 level close to the clinical depression threshold. This is in line with the mental health literature: Layard et al. (2009) mention a natural recovery rate of 30% after four months. The impact is smaller for longer term depressions but the depression rate of the treated remains significantly lower, from 40% without treatment to 22% after treatment. If we look at the entire UK population, the treatment corresponds to a 3 percentage point fall in depression rate initially, down to a 1 percentage point fall in later periods.

Figure 6: reduced rates of depression over time due to the intervention, primary effects



(a) Depression rate, Treated population

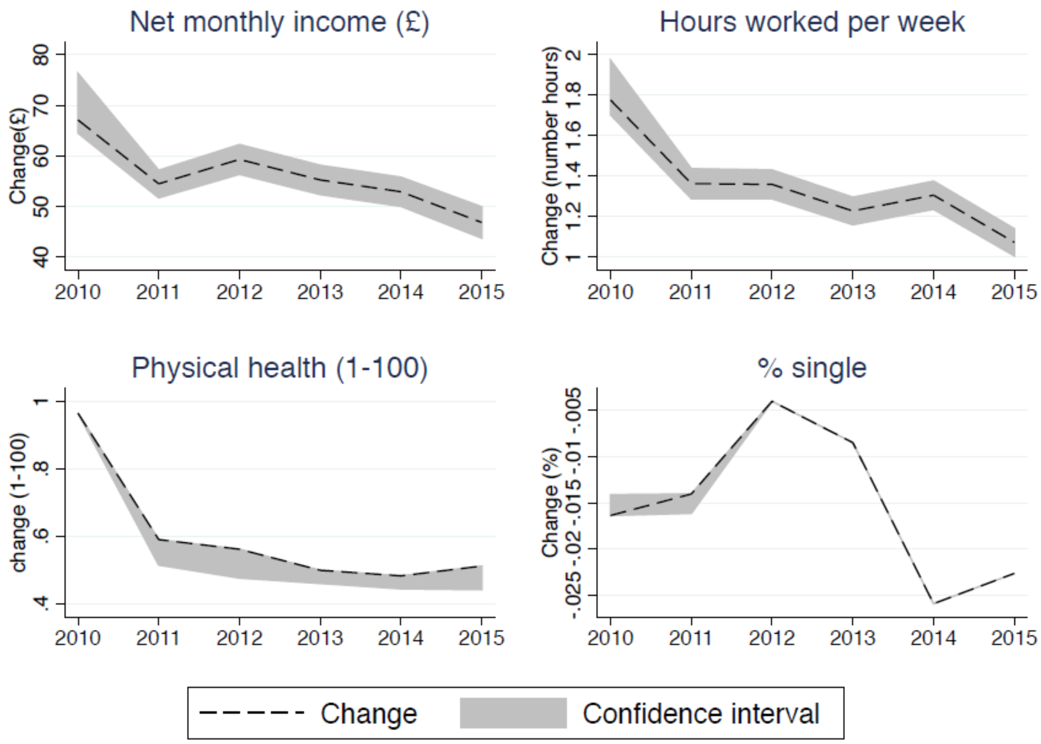
(b) Depression rate, UK population

We can also look at the spatial distribution of the drop in depression rate across the twelve UK regions, so that we have an idea of the regions in which people are most depressed. Figure 7 maps the average regional fall in depression rate over the entire period. The fall is twice bigger in London or North West compared to Northern Ireland or the North East region.

Figure 7: Mapping of regional fall in depression rates due to primary effects

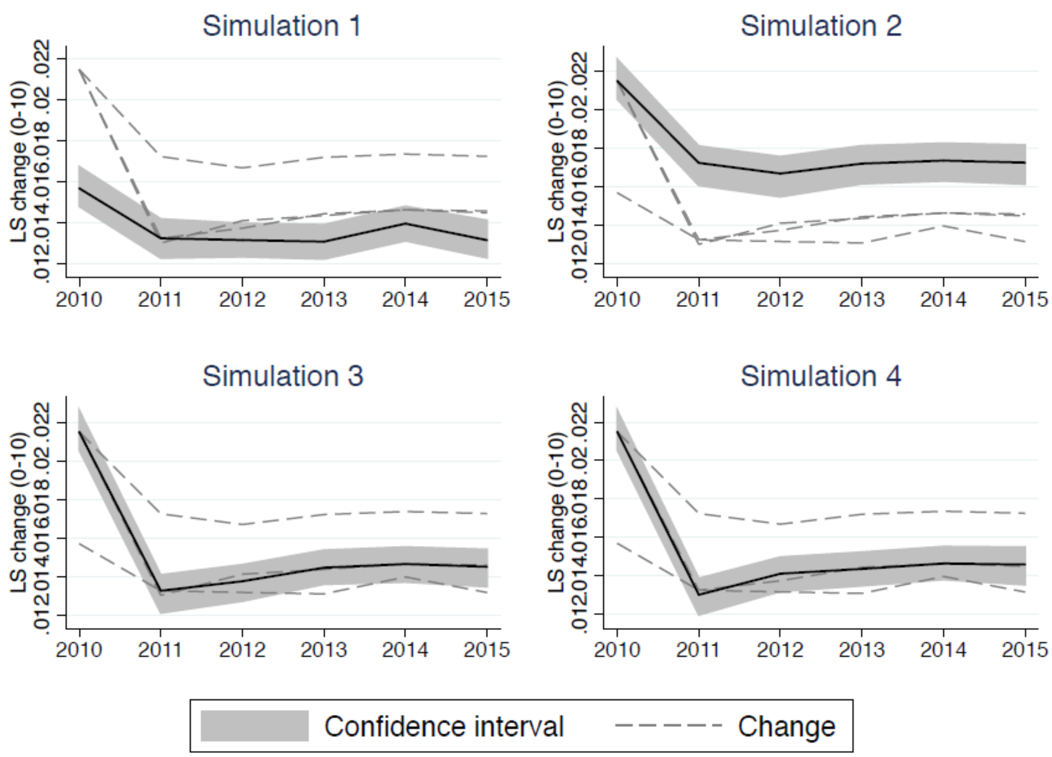
We now turn to the secondary effects of the intervention on the treated individuals. We focus on four main variables: net monthly income, hours worked per week, physical health captured by the SF-12 physical health measure, and partnership (percentage of single individuals) . Figure 8 plots the average yearly changes in the associated variables due to the intervention. The intervention leads to an increase in net monthly income which lies between 70£ and 40£, with the average treated individual working 1.5 hours more during the week. Physical health improves by 1 to 0.5 point, and the treated are 1.5% less likely to be single.

Figure 8: secondary effects on individual behaviour



These changes in turn leads to improvements in life satisfaction, but also implies a reduction in the life satisfaction of others through reference effects and market effects. The final effect hence combines four different channels and besides secondary effects, the three other channels (household spillovers, reference effects and market effects) modify the life satisfaction of the non-treated. We are therefore interested in the overall impact on the entire UK population. In Figure 7, we compute the life satisfaction change per capita (i.e. looking at the entire population) for a series of four simulations. Each simulation progressively adds a different channel. In simulation 1, we only account for the mediated effects of mental health on employment, income, physical health and partnership, along with the residual impact of mental health. In simulation 2, we add the within household spillovers. In simulation 3, we account for the reference effects and in the last simulation we add the market effects.

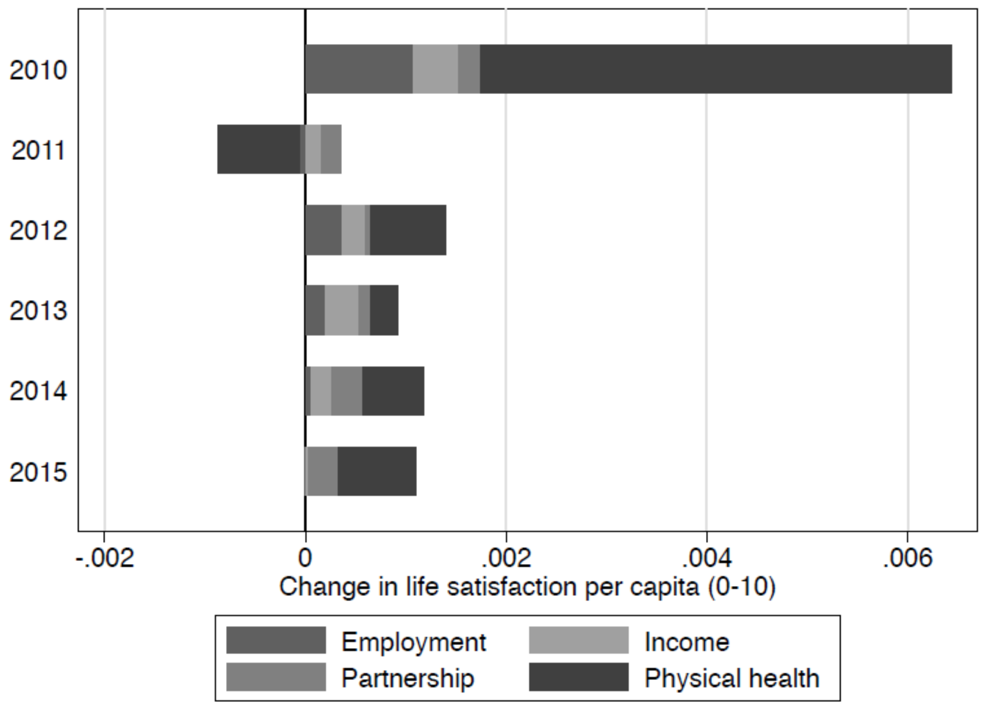
Figure 9: Life Satisfaction changes after the Intervention, All Individuals



As we can see, the well-being gains of the intervention range from 0.012 to 0.022 life satisfaction point per capita, depending on the period after intervention and whether we account for within-household spillovers, reference effects and market effects. Interestingly, the reference effects almost fully offset the spillover effects. On the contrary, market effects have no significant impact. This is due to three reasons. First, the population directly affected by the shock is small, and an even smaller fraction is unemployed, which means the extensive margin has a limited effect. Second, even if a higher fraction of the treated are affected via the intensive margin, we know income as a small impact on life satisfaction compared to other factors. Third, market effect lowers the negative impact of the reference effect as it reduces the value of the reference income and employment levels.

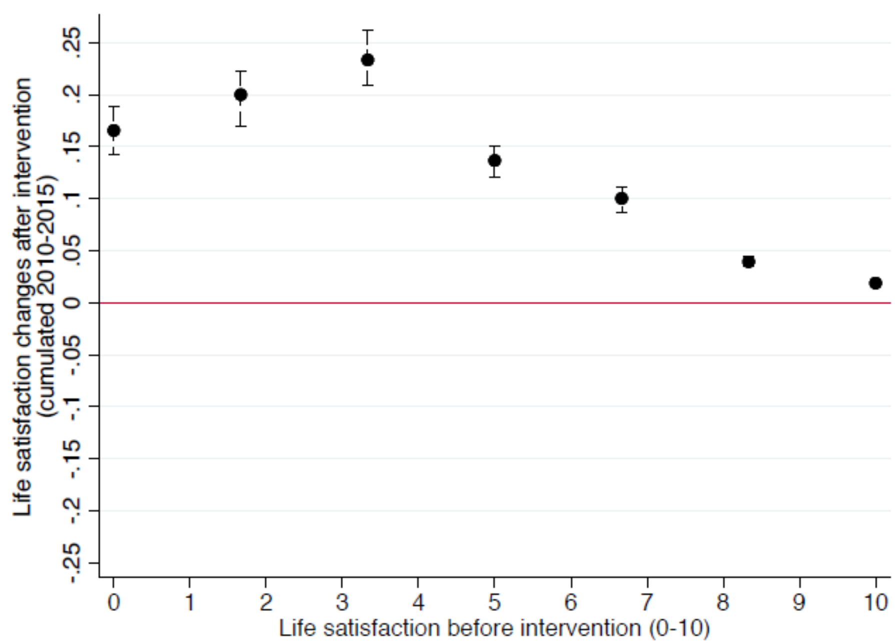
We can also decompose the secondary effect channel to see which of the four categories (employment, income, physical health and partnership) plays the biggest role in the overall change in life satisfaction. Since reduction in the unemployment rate of the treated must be associated to a change in reference employment and labour market effects, we maintain the other channels in the analysis and isolate the contribution of each secondary effect combined with its associated reference and market effects. This decomposition is shown in figure 10. Interestingly, the main contributor to the change in life satisfaction per capita due to the intervention is physical health. In 2010, i.e. the year of the intervention, reference and market effect play no role yet, which explains why secondary effects lead to higher improvements. We also saw there was a strong reduction in depression rates in the first year, and smaller reductions hereafter. Hence, in 2011, reference health strongly reduces the contribution of physical health, which even becomes negative, along with employment. In subsequent periods, all four effects play positively, but improvement in physical health keep playing a major role.

Figure 10: decomposition of secondary effects



We now turn to the distribution of the life satisfaction gains, across individuals and over space. In figure 11 we plot the average life satisfaction change (cumulated over the period 2010-2015) by the individuals' initial level of life satisfaction[9]. The bottom 20% individuals in terms of life satisfaction report a life satisfaction level of 5 or below. We can see that these are the individuals who benefit the most from the intervention, with a cumulated gain of 0.2 life satisfaction point per capita, compared to 0.05 for happier individuals.

Figure 11: distribution of LS increases by prior levels of LS.



The effect is also distributed differently across regions, as shown in figure

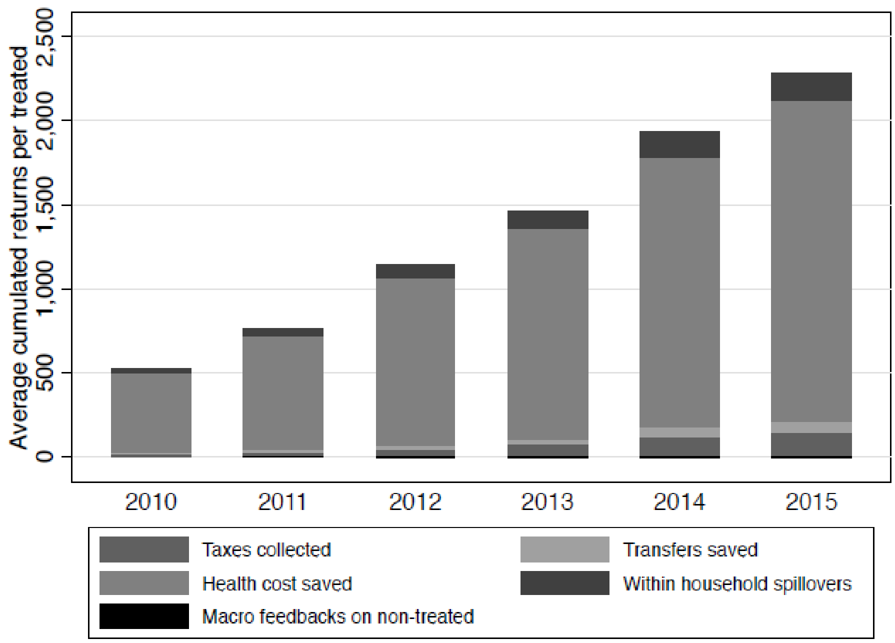
[9]In Understanding Society, life satisfaction is assessed on a scale from 1 to 7, which we normalize from 0 to 10 in line with the Cantril Ladder. This explains why figure **??** only shows seven points.

12, which plots the cumulated regional change in life satisfaction per capita over the 2010-2015 period. The life satisfaction improvements are concentrated in the western regions of the UK, with gains of 0.11 LS point per capita, compared to 0.06 LS point per capita in Northern part of the North East. The fact that regional life satisfaction improvements do not necessarily match the reduction in regional depression rates shows the relevance of microsimulation modelling. Indeed, the characteristics of the treated and non-treated individuals across regions are essential to predict the final life satisfaction impact of the intervention.

Figure 12: distribution of accumulated LS increases by region, 2010-2015

Lastly, we can compare these gains to the cost of the intervention per treated, and more importantly see how much of the cost is paid back through higher taxes, lower transfers and savings on health costs. The cost per session is evaluated to be about 650 pounds (Layard and Clark, 2015). This includes the cost per session (five on average), along with staff and facility costs. In Figure 13, we plot the cumulated returns per treated over the 2010-2015 period. Public spendings per treated are entirely recovered after the second year, mostly through lower health costs. Indeed, they account for about 80% of the total money saved after five years. The within household spillovers includes the savings on health costs of members of the household who may also get out of depression, and accounts for 7.5% of the total. However, labour market feedbacks reduces the average returns per treated by a very small fraction: about 0.5% of the cumulated returns per treated.

Figure 13: decomposition of Public Purse changes, calculated per patient



With these very preliminary numbers in mind, we can also do back-of-the-envelope calculations about the costs per wellbeing within this 5 year period. Per treated individual, the life satisfaction gain is around 0.41 per year, hence 2 points over 5 years. If we include the effects on the rest of the population, which are on average negative due to the effects of the labour supply expansion of the treated and the reference effects that their improved positions entail, then the next benefits per treated drop by 15% to around

1.7 points over 5 years. The cost of this are 650 pounds on average, of which about 150 pounds is recouped within 5 years in terms of more taxes and less benefits, meaning that the cost per 'wellbe' is 300 if we round upwards.

The costs per wellbe are radically lower if we assume that the shift in physical health service demands is monetised. Then, even under very conservative estimates of the costs saved (720 pounds per individual who gets out of depression), the program pays itself back within 2 years, and within 1 year under mainstream estimates. Put differently, the costs per wellbe then become -380 pounds within the 5 years we looked at. Table 4 shows the cost per wellbe estimated for different sub-groups of the population. Indeed, depending on the group of individuals we look at, the cost per wellbe will change, not only because some groups benefit more in terms of life satisfaction gains, but they also contribute more to the public purse.

Table 4: cost per wellbe by scenario and subgroup

	5-years (net) LS gains per treated	Net cost (£)	Cost per wellbeing (£)
All treated (Naive scenario)	1.7	500	300
Unemployed	2.3	90	40
Retired	1.6	650	410
Below 30	1.8	430	240
All treated (Relapse scenario)	1.4	530	380

As we can see, unemployed individuals have a much lower cost per wellbe than retired individuals. The table also shows the estimate we get when we simulate the more pessimistic scenario described in figure 5. In that case, the average cost per wellbe goes from 300 to 380 pounds. Obviously, all these amounts change if we apply discounting and assumptions on the longevity of all the effects, but that would require extrapolation well beyond the measured effects of any intervention.

4 Conclusions

In this little booklet we introduced the UK Wellbeing Simulator (UKWBS) model which looks at the effect of large-scale interventions on the distribution of wellbeing in the UK over time. It's first version is strictly limited to modelling changes in both individual and national life due to large interventions, starting with a hypothetical introduction in 2010.

We explored the early-diagnosis and treatment of depression, introduced in England in 2008 under the Improving Access to Psychological Therapies (IAPT) programme. Although we cannot identify in the Understanding Society dataset who was actually affected, we could evaluate within these data what the impact of an additional intervention of the same scale and targeting would have been in 2010-2015. We can in later work compare the outcomes of our simulation model with what the evaluation studies that looked just at the patients in isolation found (Clark et al., 2009; NHS Digital, 2015). This will be both a check on that evaluation and a demonstration of how important accounting for knock-on effects actually is. Future modifications include investigating how changes of a further improvement in access to or in efficiency and equity (Knapp et al., 2015) of mental health support services affect the key outcomes of interest of the treated, different dependents (spouses, children, or other dependents such as elderly in care in the household), and the public system (through effects on health, tax, and welfare systems).

Our hypothetical intervention thus mimicks the found patient profiles in Clark et al. (2008, 2009), recently updated by Wiles et al. (2016), in essence the information from the trial interventions in Doncaster and Newham.

Though results are highly preliminary and subject to ongoing refinements in the model and checks on our numbers, we can mention three main preliminary findings regarding the IAPT-style intervention:

1. A full IAPT in 2010 would have recouped no more than about 20% of the public investments in terms of increased taxation and reduced benefit take-up by 2015

2. The largest effect on the public system would come from a demand shift for physical health care, though not due to an improvement in the physical health of those out of depression but rather a strongly reduced tendency to demand NHS services. That reduced demand shift would pay back the intervention in about 2 years if it were monetised (ie if the size of the physical health part of the NHS was reduced), but would have an as yet uncalculated (positive) effect on the health and wellbeing

of others if unmonetised.

3. The costs per unit of wellbeing (a 1 point shift on a 0-10 scale for 1 year) is around +500 pounds if we do not monetise the shift in physical health demand but instead presume it has no benefits, and -300 pounds if we monetise the physical health demand shift.

Our model is easily applied to other large mental health, physical health, and social service expansions in general. It can be tailored to particular regions, cities, and countries, and can easily be used to look at effects for sub-groups and time-periods. It is useful at getting reasonable numbers for the effects of interventions, but because it extrapolates from many different studies at once, comes with many caveats and assumptions that one can object to. Nevertheless, it forces the users to think through effects of interventions on the system as a whole and as such combines the results of different parts of the whole literature, in particular the micro-literature on effects on individuals, and the macro-literature on the effects of whole shifts in markets, as well as of national reference points. In that sense, our model is the first such model to attempt an integration of micro and macro effects for wellbeing.

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Part III

Methodology

Here, we go over the methodology of the UKWBS, starting with the highest level of abstraction.

4.1 General methodology

At the highest level of abstraction, we think of wellbeing policy as an optimisation problem given limited resources. We realise that reality is not this simple, for instance because programs invariably work out differently from intended and depend as much on the mindset on the ground as the mindset of those giving the go-ahead, but we think it important to have a coherent overal intellectual framework to guide our thinking. Having a goal in mind helps with adjustments along the way.

What we look at in essense is a very simple excercise of based on how the overall wellbeing of society today (U_t) depends on societal interventions ($\mathbf{INT}^l$) and the expenditures of interventions ($E(\mathbf{INT}^l)$):

$$
\begin{aligned}
U_t &= \sum_i w_{it} LS_{it}(\mathbf{INT}^l) - \lambda_t E(\mathbf{INT}^l) \\
LS_{it} &= \text{Life Satisfaction of i at time t} \\
w_{it} &= \text{weight} \\
\mathbf{INT}^l &= \text{matrix of l'th set of interventions} \\
E(\mathbf{INT}^l) &= \text{balance of public expenditure as depending on interventions} \\
\lambda &= \text{LS multiplier of the public purse}
\end{aligned}
$$

Here we have hence set up the wellbeing of the UK population as consisting of a weighted average of the life satisfaction of its citizens ($\sum_i w_{it} LS_{it}$), with the individual life satisfactions depending on interventions. By summing over the citizens, we implicitly count the deceased as 0 and thus also allow for the possibility that interventions save lives and increase the wellbeing in the UK by allowing more citizens to survive. The net cost of interventions to the public purse appears as a negative to this wellbeing, since there is an opportunity cost of public funds.

We can see the general problem as finding whatever set of interventions $\mathbf{INT}^l$ that maximise

$$\sum_{t=0}^{T} U_t(\mathbf{INT}^l)$$

where $\sum_{t=0}^{T}$ denotes our interest in maximizing the wellbeing of the UK over time, allowing the weights w_{it} to include time-discounting or some other reason to weigh some more than others. It would for instance seem politically sensible to put a higher weight on current voters than on the citizens of the future that are yet to migrate to the UK under particular policies! To reiterate, we of course accept that this is a highly utopian notion of societal decision making.

If we fix the budget at $MaxE$ and thus take λ to become infinite at point $MaxE$, this problem becomes a knap-sack problem of including those interventions that maximise $\sum_{t=0}^{T} U_t(\mathbf{INT}^l)$ subject to $E(\mathbf{INT}^l) \leq MaxE$. The knap-sack problem is known to be NP-hard, meaning that the complexity is potentially going up non-polynomially in the number of possible interventions. This is subtly different from having a marginal payoff cutoff that all interventions must satisfy because there are possible interactions between interventions and interventions are taken to be discrete (and hence not of arbitrary size).

Still, from the point of view of the optimal package, it would have to be true that the last unit of intervention to be included would have to have a higher payoff per investment than all non-funded interventions and hence that

$$\frac{\Delta \sum_{t=0}^{T} U_t(\mathbf{INT}^l)}{\Delta E} > \widetilde{ME}$$

where $\widetilde{ME}$ is the cut-off marginal cost-effectiveness of interventions. In the UK, when deciding on medicines to reimburse, an implicit cutoff point of around 30,000 pounds per happy life year is used.

4.2 Methodological summary of the IAPT application

We made the following choices in the June 2017 version

1. We start with the Understanding Society data (the old BHPS), the individual-level panel. We take the individuals for whom we can construct reasonable life-histories (ie, after imputations of some of the lesser variables) for 2010-2015. We find weights to make them fit the national UK population. Name that population (including the youngest, partners, etc) $i = 1..N$ at t=1,..5. Hence we do not look beyond 5 years at this point.

2. For each individual we take a whole set of outcomes of interest. The primary outcomes of interest are Life Satisfaction, Expected Length of Life (at the moment this is empty), and the Public Purse (benefits minus taxes). Lesser outcomes are Employment, Relations (in a relationship or not), Education level, Physical Health, Mental Health (different types), Taxes, and specific Government Expenditure from all sources (welfare, education subsidies, etc.). Potentially, some of these are unknown. Name an individual outcome at time t of one of the metrics Y_{it}^k with $k = 1, .., K$

3. For each individual, we take a large set of X's that we think are the main drivers of the key outcomes of interest. Some of these X's can also be Y's. They would include education level, social class of parents, geographical area, criminal history and other history, personality, recent social shocks, extended physical and mental health information. Name a vector of this X_{it} and an individual one X_{it}^m with $m = 1, .., M$. It is important that these X' include the shocks that come in via others, such as divorce, the loss of a friend, an employee quitting, being victim of crime last year, etc.

4. For each intervention we want to look at, we divide the sample into those at risk of the intervention, and those not directly at risk. We order the sample such that $i = 1, .., N_{risk}$ denotes those at risk, with $i = N_{risk} + 1, .., N$ those not at risk. For shorthand, I will name the groups 1 and 2 sometimes. So $X1_t$ would denote the intermediate variables in the at-risk group.

5. We will generically look for an intervention for which we can say how it affects $X1_t$ for t=1,..,5, then ghow that affects $Y1_t$. We then look for an overspill function that allows us to say something about the changes in $Y2_t$. Name this generic function f(...). The simplest way to think of this is as the effect on the general population of the changes in the directly affected population: if there are 100,000 more divorced individuals in the directly affected population, there will be around 90,000 more in the rest of the population, and this will cost them a certain amount in terms of final outcomes of interest.

6. We will look to describe certain aspects of the outcomes. This includes $\sum_i w_i Y_{it}^k$, $\sum_i w_i e^{-rt} Y_{it}^k$, and derives ratios and variances. This includes changes in Wellbe's (= changes in $\sum_i w_i$[life expectancy*average Life

Sat]), changes in the public purse ($=\sum_i w_i[benefits-taxes]$), etc. Note that we will generically not be interested in accurate describing the level of taxes or benefits, nor even that of the wellbeing or life-expectancy of the population. What we are after is a reasonable estimate of the changes in these things as a result of an intervention.

4.3 Remark on the programming language

We needed a programming language that allows us to do the following:

1. Upload large datasets with years and individuals.

2. That allows for within-year calculations of overspill functions, such as simple macro-economic models (with a degree of solving maximisation problems, ie some parameter-search module based on an evaluation function).

3. That allows us to generate appropriate graphs, or at least exports results easily into packages that generate graphs.

4. That allows us to work with overlapping identifiers (individual, regions, households, etc.).

5. That we can in the future use to do complicated data-mergers based on things that are estimated (such as propensities, likelihoods, search algorithms, etc.).

We chose LIAMII, an ofshoot of Python to do this in as it is used a lot for micro-simulation studies and is relatively easy to learn and implement.

4.4 Overspill effects f(.)

4.4.1 Labour markets

What we have in mind here is labour markets differentiated by an X_i^m which would be a sector, a skill level, or an occupation. What an intervention in one of the determinants of labour supply gives us is, in the simple case, a shift in the labour-supply curve. In the more expanded case, the shift would be in some level of capital that would feed into labour-supply. Let us here think about the simple case.

$$\begin{aligned} \ln(LD_t^m) &= a_{LDt}^m - \gamma_{LD}^m \ln(w_t^m) \\ \ln(LS_t^m) &= a_{LSt}^m + \gamma_{LS}^m \ln(w_t^m) \end{aligned}$$

where LD_t^m is labour demand in the m^{th} separate labour market at time t, LS_t^m labour supply in the m^{th} separate labour market at time t, $\ln(w_t^m)$ average hourly log-wages in the m^{th} separate labour market at time t, with the rest market-specific parameters.

Within this specification, the main question of the literature is γ_{LD}^m and γ_{LS}^m. In a more expanded specification, γ_{LS}^m could depend further on an X, and one could also distinguish between the intensive and the extensive margin (ie, whether number of hours formal work is positive).

We can link this up to the micro-model by presuming that the intervention on the target-group gives us a shift in a_{LSt}^m, notably:

$$\widetilde{a}_{LSt}^m = a_{LSt}^m + \Delta EMP_{mt}$$

where ΔEMP_{mt} is now the estimated effect on labour supply of the the target-group in terms of the units of labour supply in the whole population (ie, percentage increase in additional hours per member of the potential workforce in the UK).

With ΔEMP_{mt} as the implied movement of the intercept of the labour supply curve (in percentages because we are now modelling in logs), the implied equilibrium is then:

$$
\begin{aligned}
\ln(\widetilde{w}_t^m) &= \frac{a_{LDt}^m - \widetilde{a}_{LSt}^m}{\gamma_{LS}^m + \gamma_{LD}^m} = \frac{a_{LDt}^m - a_{LSt}^m}{\gamma_{LS}^m + \gamma_{LD}^m} - \frac{\Delta EMP_{mt}}{\gamma_{LS}^m + \gamma_{LD}^m} = \ln(w_t^m) - \frac{\Delta EMP_{mt}}{\gamma_{LS}^m + \gamma_{LD}^m} \\
\ln(\widetilde{LS}_t^m) &= \widetilde{a}_{LSt}^m + \gamma_{LS}^m \ln(\widetilde{w}_t^m) = \ln(LS_t^m) + \Delta EMP_{mt} - \gamma_{LS}^m \frac{\Delta EMP_{mt}}{\gamma_{LS}^m + \gamma_{LD}^m} \\
&= \ln(LS_t^m) + \Delta EMP_{mt} \frac{\gamma_{LD}^m}{\gamma_{LS}^m + \gamma_{LD}^m}
\end{aligned}
$$

As an initial estimate for labour demand, we can use the estimates for the impact of additional migration levels to the UK on local wages. Nickel and Saleheen (2015) estimate that for low-skilled and semi-skilled, the impact of a 10% increase in the proportion of migrants in the working population has a wage-reducing effect of 2%. Now, a 10% increase in the proportion of migrants in the working population is almost the same as a 10% increase in the working population as a whole (because the proportion of migrants is on average below 0.2). So if we interpret this effect as a labour-demand effect, then $\gamma_{LD}^m = \frac{10}{2} = 5$. For higher-skilled, Nickel and Saleheen (2015) find much lower effects on wages of more migrants (ie, the effect on the wages of those already with a job is minimal), less than 0.5% wage change for a 10% increase in migrant proportions, implying that $\gamma_{LD}^m > 20$ for the higher skilled.

As to labour supply elasticities, these have been estimated quite often for the UK. Blundell et al. (2011) give as a mainstream estimate for all labour in the age range 30-44 a figure between 0.3 and 0.44. They suggest the figure is a bit higher for other age groups, so if we take 0.45 as a reasonable estimate of the labour supply elasticity, then we get $\gamma_{LS}^{m} \approx 0.45$ for all m. However, there are clear differences between genders as within occupational groups for labour supply estimates that could be used for a more extensive treatment later on. We may note that as a rule of thumb, the elasticity for women is abour 50% higher and that the bulk of the overal effect is generated by the extensive margin, ie changes in whether people work or not (rather than adjustments in hours).

For the simple model, this means we can take:

$$\begin{aligned}
\Delta^{Females} Number\widetilde{EMP}_{mt} &\approx \Delta^{Females} NumberEMP_{mt}(1 - \frac{0.5}{\gamma_{LD}^{m}}) \\
\Delta^{females} Hours\widetilde{EMP}_{mt} &\approx \Delta^{Females} HoursEMP_{mt}(1 - \frac{0.5}{\gamma_{LD}^{m}}) \\
\Delta^{Males} Number\widetilde{EMP}_{mt} &\approx \Delta^{Males} NumberEMP_{mt}(1 - \frac{0.3}{\gamma_{LD}^{m}}) \\
\Delta^{Males} Hours\widetilde{EMP}_{mt} &\approx \Delta^{Males} HoursEMP_{mt}(1 - \frac{0.3}{\gamma_{LD}^{m}})
\end{aligned}$$

where γ_{LD}^{m} now differs by skill group (as in Nickel and Saleheen, 2015).

Note that this over-spill effect will be an input into any final changes on well-being, mental health, and all the rest: to allow for this overspill effect, we need to include the effect of these changes on the average outcomes.

4.4.2 Reference effects

The simplest and most widely studies reference effect is that of income. Despite the long-running controversy on the Easterlin paradox, it remains uncontested that in the longer-run an increase in average income has no effect on average wellbeing, that the business cycle is related to wellbeing, and that higher relative income buys more happiness. We know from the aftermath of the GFC in the US that the effect of the large downturn last no longer than 14 months in terms of the average level of happiness. And we know that in the strongest causal-design studies, the coefficient on log-income is around 0.4 (Frijters et al. 2004; also http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0079358
For an individual country there is furthermore some benefit of getting ahead of other countries (national pride). So a reasonable first-pass average micro-macro function of happiness and income would read:

$$Hap_{it} = 0.4 \ln Y_{it} - 0.3 \ln \overline{Y_{it-1}} + \text{other stuff}$$

which would hence mean that 3/4 of any income increase in year t would be nullified in the subsequent year by increased aspirations captured by $\ln \overline{Y_{it-1}}$. We can simply add this feed-back to our time-profiles.

Other reference effects? We know that there are strong reference effects of education and probably also physical health. The multiplier here is less well-known though (see Layard 2017 book on education and Frijters and Mujcic 2015 on relative health). A current rough guess would be:

$$\begin{aligned} Hap_{it} &= 0.4 \ln Y_{it} + \alpha_2 PhyHealth_{it} - 0.3 \ln \overline{Y_{it-1}} - \alpha_1 * \overline{YearsEduc_{it}} \\ &\quad - \frac{3}{4}\alpha_2 \overline{PhyHealth_{it}} + \text{other stuff} \end{aligned}$$

but this would have to be populated with better numbers. It is unknown whether there are reference effects on relationships and mental health, two other major aspects of individual wellbeing.

4.5 Combining different estimates from different sources.

A generic problem is going to arise when using information from different sources and from causal studies generally about a whole system of interrelations: how to interpret them, add them up, combine them, and work out when to stop with calculating further effects from.

To set the scene, note that we will generally be looking at estimates for things like $\frac{\partial y}{\partial x}|^{z}$ which is more properly written as $s^{w} = \frac{\partial E[y_{it}|x_{it}, Z, z_{it}]}{\partial x_{it}}$. Here, y is some outcome, x is some input, Z is some background variable for all, and z is a specific set of 'control variables'. We will have lots of statistics s^{w} that all condition on different z and Z.

Ideally, what we would like is to have some global causal model for the entire system that gives rise to all things that vary over time, depending on deep policy parameters that are subject to discretionary choices. That system can be static, dynamic, whatever, but crucially it would be complete. The statistics s^{w} would then allow us to estimate the behavioural parameters of that whole global model, after which the effects of any effect on the deeper policy parameters can be shown. However, this is too hard for anyone at this moment. Down the line, when we get our heads round the issue of mimicking behaviour, we might revisit this.

Second-best would be to have continuous time-processes wherein it is modelled how things depend on each other once there is movement on some dimension. Like a duration model. This too is too much to hope for as very few studies report events in such a fashion and the data requirements are prohibitive (if everything can change incrementally at any moment in time, one needs continuous observations on everything - far too data intensive).

So we are going to have to rely on much simpler methods. The one that comes to mind is standard Simultaneous Equation Modelling (SEM). To illustrate, suppose we have 3 outcomes that are all inputs into something else later (think of income, relations, and mental health: all outcomes and all inputs into wellbeing).

$$
\begin{aligned}
Y_{1it} &= \alpha_1 X_{it} + \beta_1 [Y_{2it}, Y_{3it}] + e_{1it} \\
Y_{2it} &= \alpha_2 X_{it} + \beta_2 [Y_{1it}, Y_{3it}] + e_{2it} \\
Y_{3it} &= \alpha_3 X_{it} + \beta_3 [Y_{1it}, Y_{2it}] + e_{3it}
\end{aligned}
$$

$$
Y_{it} = [\alpha, \beta][X_{it}, Y_{it}]'
$$

where X_{it} is a whole vector of other factors, with a particular correlation matrix. The three outcomes have indendent errors, but hence directly affect each other.

The statistics s^w then for instance relate to $\frac{\partial E[Y_{1it}|Y_{2it},X_{it},Z,z_{it}]}{\partial Y_{2it}}$. Now, we can also write the reduced form of this system:

$$\begin{aligned}
Y_{1it} &= a_1 X_{it} + b_1[e_{1it}, e_{2it}, e_{3it}] \\
Y_{2it} &= a_2 X_{it} + b_2[e_{1it}, e_{2it}, e_{3it}] \\
Y_{3it} &= a_3 X_{it} + b_3[e_{1it}, e_{2it}, e_{3it}]
\end{aligned}$$

where $\{a_1, b_1\}$ are particular and known functions of $\{\alpha, \beta\}$. We can then even re-write this as

$$\begin{aligned}
Y_{1it} &= \widetilde{a}_1 V_{it} + \widetilde{\beta}_1[Y_{2it}, Y_{3it}] + \widetilde{e}_{1it} \\
& \quad etc.
\end{aligned}$$

where V_{it} is now a particular subset of X_{it}. These parameters would not be known perfectly from $\{\alpha, \beta\}$ unless we presume something about how the conditioning on X_{it} affects estimates (something to worry about next....).

The generic issue is that we will have from the literature and from interventions statistics that refer to $a, \alpha, b, \beta, \widetilde{a}$, and/or $\widetilde{\beta}$. These statistics are hard to combine.

The simplest way forward that we should take at the start is, for instance, to equate any $\frac{\partial E[Y_{1it}|Y_{2it}, X_{it}, Z, z_{it}]}{\partial Y_{2it}}$ with a b_1. What this means is that $\frac{\partial E[Y_{1it}|Y_{2it}, X_{it}, Z, z_{it}]}{\partial Y_{2it}}$ is interpreted as a final effect of an innovation in Y_{2it} via e_{2it} that hence has no knock-back effects on Y_{2it} via any other change. One might call it the partial effect. It ignores the possibility that the conditioning sets are different, but is easier to explain. So this is what we should do in the short run.

The more complicated way forward is to take any statistic s^w as an estimate of a particular parameter that has a known uncertainty around it (because people will public the standard deviations). This means that we can start with the non-reduced form system of equations and interpret the statistics from the literature as particular pieces of information. We can then use this to estimate the maximum likelihood of the correct parameters:

$$L[s^1, .., s^W|\alpha, \beta, \sigma_1, .., \sigma_{W+K}]$$

for which we will need particular assumptions to nail $\{\alpha, \beta\}$ down. The obvious ones are that the statistics s^w all have a known but independent error distribution (given in the papers they derive from in the form of σ_w) and that each statistic s^w has a known mapping to the actual $\{\alpha, \beta\}$. From the estimated $\{\alpha, \beta\}$ we could then derive the reduced form $\{a, b\}$ to plug into our program.

4.5.1 What we should practically do with different studies

We practically presume that individuals indeed have their outcomes given by

$$
\begin{aligned}
Y_{1it} &= \alpha_1 X_{it} + \beta_1 [Y_{2it}, Y_{3it}] + e_{1it} \\
Y_{2it} &= \alpha_2 X_{it} + \beta_2 [Y_{1it}, Y_{3it}] + e_{2it} \\
Y_{3it} &= \alpha_3 X_{it} + \beta_3 [Y_{1it}, Y_{2it}] + e_{3it}
\end{aligned}
$$

$$
Y_{it} = [\alpha, \beta][X_{it}, Y_{it}]'
$$

We pick outcome 1 as an ultimate outcome, implying it has no feed-back effects. We can then for a particular outcome 1 and outcome 2 (say, wellbeing and mental health) with a single intermediary outcome 3 (say, employment) thus write this as

$$
\begin{aligned}
Y_{1it} &= \alpha_1 X_{it} + \beta_{11} Y_{2it} + \beta_{12} Y_{3it} + e_{1it} \\
&= \frac{(\alpha_1 + \beta_{12}\alpha_3) X_{it} + (\beta_{11} + \beta_{12} * \beta_{32}) Y_{2it} + \beta_{12} e_{3it} Y_{3it} + e_{1it}}{1 + \beta_{31}} \\
&= (\alpha_1 + \beta_{12}\alpha_3) X_{it} + (\beta_{11} + \beta_{12} * \beta_{32}) Y_{2it} + \beta_{12} e_{3it} Y_{3it} + e_{1it}
\end{aligned}
$$

and where we are thus treating all the X_{it} as being independent of all the endogenous variables Y_{it} (they don't co-move). We then can fill in the parameters we need to get at

$$\Delta Y_{1it} = (\beta_{11} + \beta_{12} * \beta_{32})\Delta Y_{2it}$$

by either having direct information within a trial on the total parameter $(\beta_{11} + \beta_{12} * \beta_{32})$ or else to find it in the literature from a causal design study. Now, suppose we have a study that tells us about β_{11} and that hence comes from a study that conditions on the third outcome and hence does not have the term $\beta_{12} * \beta_{32}$. In that case, $\beta_{12} * \beta_{32}$ has to be found from other studies if that avenue is likely to be important. Conversely, we might know $\beta_{12} * \beta_{32}$ because we have studies on the effect of outcome 2 on outcome 3 and other studies on the effect of outcome 3 on outcome 1. We then do not know about β_{11}. In that case we should pragmatically presume that what we do not know is zero (ie, not counted) unless proven otherwise.

What do we do with conflicting literature information? We should preferably make an ordering about the most relevant study, which would be on the same country, the same, period, the same variables, and the cleanest identification strategy. We thus normally would take a single study as the best.

What do we do with things that are not the final outcome but that depend on various things that are all affected? Essentially, we do the same as above but now do not presume that $1 + \beta_{31} = 1$. Usually in causal effects trials or studies, we will have information on either $\frac{\beta_{11}}{1+\beta_{31}}$ or $\frac{\beta_{12}*\beta_{32}}{1+\beta_{31}}$. The fact that we might not be able to tease out β_{31} separately (the feedback loop) is irrelevant.

If we have a large number of variables all affecting each other, we thus need a large set of estimates.

4.6 The timing of causal effects and f(.)

We need a general framework of all the timing to nail down when what gets updated. That general framework needs to combine the micro with the macro. Let us start with the outcome as it depends on other factors: the vector of outcomes Y_{it} is now envisaged as

$$Y_{it} = g_0(c_i, p_t, Y_{t-1}, INT_{it}, INT_{jt})$$

where c_i now is a fixed trait, p_t is an economy-wide vector of prices (which can include regional prices: basically it is outside individual control), and Y_{t-1} is the average outcome of the previous period. Hence each individual is a mypoic agent this period, taking as given the prices of this period and Y_{t-1}, the behaviour of everyone else previous period; Y_{it} is here a vector of individual outcomes, now including all kinds of social capital stocks, with INT_t being an intervention into the outcomes of i, INT_{jt} being the interventions on close others (j). Now,

$$p_t = g_1(Y_{t-1}, M_t)$$

meaning that prices are given by aggregate capital stocks of last period (Y_{t-1}) and Macro-economic circumstances M_t.

Within this set-up, g_0 might well include anticipated future prices, but even then, behaviour is determined by the information available at the start of the period. An intervention is then understood as a change in the idiosyncratic element of one of the outcomes Y_{kit} which then feeds through into the rest of Y_{it} which then gets aggregated to change Y_t and thereby prices and aggregate behaviour next period.

As a first-order approximation, we can thus write the hypothetical outcomes Y_{it}^*, p_t^*, Y_{t-1}^* as linear functions of the actual outcomes and reaction-functions:

$$Y^*_{kit} = Y_{kit} + INT_{ikt}$$

for $i \in INT$ and hence those intervented directly. So if we then collect the k aspects into the vector Y^*_{it}, we can write

$$Y^*_{it} = Y_{it} + \beta \Delta e_{ikt}|_{\Delta e_{ikt}=INT_{ikt}} = Y_{it} + \Delta Y_{it}$$

for those directly affected. As an approximation, we can then write of the average other members of the population

$$Y^*_{jt} = Y_{jt} + \rho \frac{Ni}{N} \Delta Y_{it} = Y_{jt} + \Delta Y_{jt}$$

using the notation that ρ is the externality of each unit of intervention (hence a vector in itself). If we then add this together, we get

$$Y^*_t = Y_t + \frac{Ni}{N} \Delta Y_{it} + \frac{N - Ni}{N} \Delta Y_{jt} = Y_t + \Delta Y_t$$

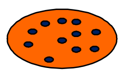
where INT_t is now a matrix of changes in error terms of the k domains in the average of the population (which thus has averaged the errors over N). Note here that Y^*_t is a vector of averages, meaning that we do not model the various interactions between members other than through this average.

With this in mind, the changes each period become an interactive procedure:

$$
\begin{aligned}
p^*_{t+1} &= p_{t+1} + \frac{\partial g_1'}{\partial Y_{t-1}} \Delta Y_t \\
Y^*_{it+1} &= Y_{it+1} + \beta \Delta e_{ikt}|_{\Delta e_{ikt} = INT_{ikt}} \frac{\partial e_{ikt+1}}{\partial e_{ikt}} + \\
& \quad \beta \Delta e_{ikt+1}|_{\Delta e_{ikt+1} = INT_{ikt+1}} + (p^*_{t+1} - p_{t+1}) \frac{\partial g_0(c_i, p_t, Y_{t-1}, INT_{it})}{\partial p_t} \\
Y^*_{jt+1} &= Y_{jt+1} + \rho \frac{Ni}{N}(Y^*_{it+1} - Y_{it+1}) + (p^*_{t+1} - p_{t+1}) \frac{\partial g_0(c_j, p_{t+1}, Y_t, INT_{jt+1})}{\partial p_{t+1}} \\
&= Y_{jt+1} + \rho \frac{Ni}{N} \Delta Y_{it+1} + \delta \Delta p_{t+1} \\
Y^*_{t+1} &= Y_{t+1} + \frac{Ni}{N} \Delta Y_{it+1} + \frac{N - Ni}{N} \Delta Y_{jt+1} = Y_{t+1} + \Delta Y_{t+1}
\end{aligned}
$$

$$
\begin{aligned}
p^*_{t+2} &= p_{t+2} + \frac{\partial g_1'}{\partial Y_{t-1}} \Delta Y_{t+1} \\
& \quad etc.
\end{aligned}
$$

General and precise sequence



By applying causal input-output model
Preliminary Outcomes to patients

$$\Delta U(INT) = \sum_i \sum_{t=0}^{T} w_{it} Y(X_{it}, INT_{it}) - \sum_i \sum_{t=0}^{T} w_{it} Y(X_{it}, 0)$$

Spillover and feedback

- Affected individual

f(.) Macro-model that captures main over-spills

Final Outcomes to patients
Final Outcomes to the rest

Causal input-output in IAPT

Mental Health Intervention

Indirect effect of Mental health

Direct

Input Behaviours:
Employment
Habits
Relationships
Physical health

Intermediary outcomes:
Wages, hours worked

Prelim outcomes:
Tax
Transfers
Wellbeing

Spillovers and feedback

$\Delta_a Y \longrightarrow \Delta_a Y + \rho \Delta_a Y \longrightarrow$ General Equilibrium feedback treating combined patient and spillover as exogenous shock.

Vector of changes to patients

Additional spillover to near ones (partners, kids, etc.). In averages.

General equilibrium feedback

Labour-market feedback → Changed effects on the average (including the patients!) → Calculation of changes in patients and whole population. Construction of relative variables.

Final Outcomes patients
Final outcomes rest