Regional Dynamics Under Adverse Physical and Behavioral Shocks: The Economic Consequences of a Chlorine Terrorist Attack in the Los Angeles Financial District

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Abstract

Emergency management decision makers must make contingency plans for a wide range of threat scenarios. In undertaking ex-ante cost/benefit evaluations of contingency plans, they must understand the economic benefits of threat deterrence and reduction. Appropriate emergency response and recovery activities ex-post can attenuate business interruption (BI) impacts. Regional economic modeling can provide quantitative input to these evaluations. In this paper, we

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use a large-scale dynamic regional computable general equilibrium (CGE) model of the Los Angeles economy to perform an economic consequence analysis of a terrorist attack with chlorine gas. We divide the event's direct effects into resource losses (injuries, BI) and behavioral reactions stemming from fear. We provide a decomposition of aggregate economic effects in terms of these various loss components, allowing us to elucidate the relative sizes of potential loss channels. We also discuss the effect of geographic shifts of economic activity within the affected region and in neighboring regions in estimating the losses. Our analysis can assist risk managers in developing plans for pre-event mitigation and post-event resilience.

16.1 Introduction

By elucidating the benefits of threat reduction and post-event response, economic consequence analysis can be an important input to the contingency planning of emergency management decision makers. In this paper we show how dynamic regional CGE modeling can elucidate behavioral and dynamic elements relevant to such planning. We considered several modeling approaches to perform our analysis. Methodologies for analysing the regional economic consequences of specific threats have developed from the use of regional input-output models to investigate the direct and indirect effects of physical destruction, transport disruption and BI (Gordon et al. 1998) to applications of regional CGE models to also analyse the consequences of behavioral responses (Rose et al. 2009).

Input-output models are practical tools but lack behavioral content, the crux of the issue at hand. They also lack the ability to effectively model the workings of markets through factor and product price changes. Econometric models are a valuable approach, especially for forecasting but less so for simulation. They are highly dependent on time series or cross-sectional data, and less conducive to the incorporation of simulation results. Moreover, econometric models typically are based on aggregate relationships, as opposed to micro behavioral responses of consumers, firms, and providers of factor services. Agent-based modeling on the other hand is especially adept at analyzing individual decision-makers and their interactions. However, they are not yet able to scale up to the macro level and to analyze the full effects of the workings of markets. As we expand upon below, CGE models have behavioral content, are able to mimic the role of markets and prices, and can readily be recalibrated with simulation data. Moreover, they have been successfully applied to topics such as the focus of this chapter [see, e.g., Giesecke et al. 2012)].

Regional CGE models embody much detail describing economic structure (e.g. production technologies, and regional resource constraints); the behavior of economic agents (e.g. household preferences, and investor return requirements); and policy variables (e.g. the instruments of government taxing and spending). This detail has allowed these models to be applied to a wide range of issues relating to the structural, behavioral and policy drivers of regional growth and decline and the consequences of policy interventions. While regional CGE modeling has a three decade history of providing input to evidence-based policy making, research exploiting the exogenous structural, behavioral and policy detail in these models to carry shocks describing the direct effects of catastrophic events is more recent.[1] Early applications examined natural disasters. Rose and Liao (2005) examined the effects of water utility disruption following an earthquake, noting the role of pre-event mitigation and post-event resilience in influencing potential impacts. More recently, the CGE method has been turned to terrorism threats. Rose et al. (2009) examined the consequences of the 2001 World Trade Center attacks, investigating BI costs, and behavioral impacts via reduced air travel. The importance of behavioral responses within the overall economic consequences of a terrorist event was examined more generally in Giesecke et al. (2012). Investigating the consequences of a radiological dispersion device (RDD) attack in the financial district of downtown Los Angeles (LA), they compare economic costs arising from behavioral responses with the direct resource costs arising from casualties, property damage and BI.

In this paper we use a dynamic regional CGE model to perform a consequence analysis of a terrorist chlorine attack with a focus on behavioral impacts and dynamic outcomes. We perform a decomposition of the event's various loss components to explain and compare behavioral impacts with more standard resource loss effects over time. Given the potential for multiple economic loss channels, risk managers would be well advised to distinguish the many types of consequences of a terrorist attack or natural disaster. Unfortunately, most consequence analyses have not offered such decomposition analyses of the broad range of components. Furthermore, whereas previous studies have used comparative static models, our model is dynamic. A dynamic model offers a number of benefits relative to its comparative static counterpart: first, by providing a more plausible time-path for key regional stock variables (like population and capital) by allowing for gradual adjustment in regional wages, migration, and investment; and second, by facilitating a better matching of time-specific inputs to the CGE model with the projected time-path of peak and decay in behavioral responses to a particular hazard or disaster.

To provide a comparison with the scenario in Giesecke et al. (2012), we choose the same downtown LA area as the attack site: the heart of the financial district. The attack involves detonation of a chlorine storage tank, leading to the formation of a large chlorine plume. Consistent with the approach outlined in Giesecke et al., we divide the event's direct effects into two broad sets of inputs to the CGE model: (1) reduction in effective resource supply (the resource loss effect) and (2) shifts in the perceptions of economic agents (the behavioral effect). The resource loss effect describes the event's physical destructiveness, subsuming such direct impacts as deaths and injuries, BI during evacuation, clean-up and repair, and medical

[1] Recent reviews of regional CGE model applications to the analysis of public policy and regional development are provided by Partridge and Rickman (2010) and Giesecke and Madden (2013).

expenses. These shocks represent either a reduction in effective resource supply to the regional economy, directly reducing regional GDP, or in the case of medical expenses, a diversion of regional income to cover otherwise avoidable costs. The behavioral effect relates to economic adjustments stemming from fear and risk perception on the part of firms, households and government. Behavioral effects generate regional economic loss additional to the resource loss effects. Employees may require compensating higher wages to work, businesses may require compensating higher returns to invest, and consumers may switch their preferences away from goods produced in the affected region. Such responses will increase production costs in the affected region, while simultaneously reducing demand for the region's output.

Scientists, public officials and laypeople have long recognized society's vulnerability to large-scale disasters. This has been especially evident with respect to disasters involving potentially toxic substances such as radiological and chemical materials. Hazards that are poorly understood and that are potentially catastrophic carry for the public a high risk signal value (Slovic 1987). In fact, such hazards tend to inspire fear and heightened perceived risk well beyond what risk experts would expect based on their assessed likelihood of occurrence. Public reaction to radiological risks has been well documented since the accident at Three Mile Island, but these same concerns extend to chemical hazards as well. Kraus et al. (1992) studied public judgments of chemical risks and found that laypeople: (1) largely view chemicals negatively and see little benefit to them; (2) believe harmful exposure to potentially toxic chemicals is all or nothing rather than dose specific and (3) feel any contact with toxic chemicals is contaminating. These findings are important for understanding the consequences of a chlorine attack. Chlorine is a highly toxic chemical capable of killing large numbers of people. It also dissipates quickly if released in an outdoor area; hence, hours later it poses little risk. However, as noted above, toxic chemicals are thought by the public to contaminate objects and areas they touch and so people may be reluctant to resume normal activities in an area impacted by such an attack regardless of what officials and experts believe. This contrast between expert and public assessment poses a challenge for local authorities wishing to communicate about public safety following such events. Public reaction to different hazards also poses a challenge to risk managers who need to gauge the economic impact of a potential mishap.

16.2 Attack Description

16.2.1 Attack Scenario and Direct Loss Estimation

Our scenario is based on a combination of DHS' National Planning Scenario 8, "Chemical Attack—Chlorine Tank Explosion" (HSC 2004) and the chlorine tank truck attack scenarios of Barrett and Adams (2011). In our scenario, the attacker drives a tank truck of pressurized chlorine into the financial district of downtown LA (zip code 90071). Detonation of the tank releases tons of chlorine, creating a cloud that is poisonous by inhalation. The attack causes 182 fatalities, 104 serious injuries, and 1,040 minor injuries. Significant chlorine contamination covers approximately 36 city blocks, as in the RDD attack scenario of Giesecke et al. (2012). The number of deaths is selected to be similar to the 180 fatalities of the RDD scenario, and the numbers of serious and minor injuries are scaled proportionally to the number of fatalities in the HSC (2004) chlorine scenario. Chemical vapor settling on outdoor and indoor surfaces causes authorities to close the area until they can complete enough decontamination and remediation.

Official decisions on when to reopen an area after chemical contamination may not be simply dictated by existing safety standards. Decisions on clean-up options may involve tradeoffs between public safety levels and the costs and economic impacts of decontamination. With BI a cost of chlorine attack, we discussed our scenario with City of Los Angeles public officials, to understand their assessment of the range of clean-up options. Less decontamination would typically be required after a chlorine attack than after an RDD attack. Surfaces affected by chlorine potentially could be re-opened after dilution with water and neutralization with sodium bicarbonate. More extensive technical decontamination could take longer, as could law enforcement investigation. Our discussions with LA officials indicated that the decision to reopen would take into account both the desires of local businesses (who might press for rapid reopening, to minimize business impacts) and the concerns of the public (who desire not only access but also safety in the face of an unusual hazard). To reflect a medium-cost chlorine clean-up effort, in Sect. 16.4 we model a 3-day shutdown of zip code 90071 (one-tenth of the 30 day shutdown for the RDD event modeled in Giesecke et al. 2012).

16.2.2 Medical Expenses and Lost Labor Inputs Via Fatalities and Injuries

We assume that the incident generates medical expenses of \$4.0 million. We develop this from assumptions for case-specific expenditures for the HSC (2004) categories of fatalities, serious injuries and minor injuries.[2] We assume that "serious injury" means hospitalized and "minor injury" means emergency room or clinic outpatient visit (as in Van Sickle et al. 2009). Our estimates of per person treatment costs for these categories are based on the influenza treatment costs for the 18–49 age group in Molinari et al. (2007), who distinguish treatment costs by risk of serious complications, with 25 % of the population assumed to be at high risk of serious complications, and 75 % assumed to be non-high-risk. We noted that the definitions and proportions given by Molinari et al. are consistent with the chlorine exposure "vulnerable population" definitions and proportions given by Withers and Lees (1985), i.e., with 25 % of the chlorine scenario population in the vulnerable/ high risk category. As such, we used the Molinari et al. complication risk

[2] Calculations are available from the authors on request.

weightings in calculating per person treatment costs for our case categories. We assumed that one in nine fatalities will first be hospitalized, based on the pattern of the Graniteville chlorine incident (Van Sickle et al. 2009). Patients who die are assumed to have incurred "high risk" hospitalization costs in line with Molinari et al.

Based on 182 fatalities and 1,144 injuries, we estimate the resource loss associated with the dead and the injured using the method outlined in Giesecke et al. (2012). This generates $9.5 million (m.) of lost labor inputs, comprising $1.9 m. from injuries and $7.6 m. from fatalities.

16.3 LA-DYN: A Dynamic CGE Model of the LA-County Economy

16.3.1 Overview of the Structure of LA-DYN

LA-DYN is a dynamic CGE model of the LA-County economy.[3] The model's theoretical structure begins with the comparative-static CGE model ORANI-LA, an LA-County implementation of the single U.S. region model ORANI-R, documented in Giesecke (2011) and used in Giesecke et al. (2012) to examine the short-run and long-run consequences of an RDD event. ORANI-LA is a single-region sub-national variant of the well-known single country models ORANI-G (Horridge 2003) and ORANI (Dixon et al. 1982). The model is implemented using IMPLAN data for LA-County (Minnesota IMPLAN Group 1997) and relevant parameter values from the large-scale CGE model of the U.S., USAGE.[4]

Production and capital formation is modeled for 72 sectors, along with commodity- and agent-specific demands for 15 "margin" commodities.[5] Consistent with Isard et al. (1998), who argue for the importance of modeling transport margins (the cost of transportations, exclusive of the goods transported) in regional CGE models, 3 of the 15 margins relate to transport services differentiated by mode.[6] Decision-making by firms and households is governed by optimizing behavior. Each representative industry is assumed to minimize costs subject to

[3] The model is solved using GEMPACK (Harrison and Pearson 1996).

[4] IMPLAN is a widely-used and accepted resource for small region U.S. input-output tables. A balanced input-output table is required as an initial solution to the LA-DYN system of equations. USAGE is a detailed, dynamic CGE model of the U.S. It has been developed at the Centre of Policy Studies in collaboration with the U.S. International Trade Commission. Prominent applications of USAGE by the U.S. International Trade Commission include USITC (2004 and 2007).

[5] The starting point for the LA-DYN model is a comparative static LA County model, implemented with IMPLAN data at the finest level of disaggregation—440 sectors. While computationally uncomplicated for comparative statics, 440 sectors is not practical for dynamic modeling. At 72 sectors, our aggregation is based on the standard IMPLAN 64 sector aggregation scheme, but with expanded detail for trade margins, consistent with a model with a business district focus.

[6] Namely, truck transport, air transport and other transport.

nested constant returns to scale production technologies and given input prices. Household commodity demands are modeled via a representative utility-maximizing household. Units of new industry-specific capital are assumed to be cost minimizing combinations of commodities sourced from the local region, the rest of the U.S. and overseas. Imperfect substitutability between local, rest-of-U.S. and foreign varieties of each commodity are modeled via CRESH functions.[7] Inter-regional and foreign export demands for local commodities are modeled via commodity- and destination-specific constant elasticity export demand schedules. The model includes the consumption of commodities by state and federal government, funded by direct and indirect taxation instruments. Commodity markets are assumed to clear and to be competitive. Purchasers' prices differ from basic prices by the value of indirect taxes and margin services.

Three dynamic processes distinguish LA-DYN from ORANI-LA: two describing stock/flow relationships between capital and investment, and between population and migration; and one describing a process of lagged adjustment in regional wages to changes in regional labor market conditions. Broadly, these mechanisms draw together the investment theory of Dixon and Rimmer (2002), and the regional labor market and migration theory of Giesecke and Madden (2013). Before describing these mechanisms, we first distinguish two types of dynamic simulation: baseline and counterfactual (Dixon and Rimmer 2002; 15). The baseline simulation is a business-as-usual forecast of the LA County economy. The counterfactual simulation is identical to the baseline simulation in all respects other than the addition of shocks describing the issues under analysis (in this case, chlorine release). The distinction between baseline and counterfactual is important for two reasons. First, the theory governing the regional employment rate relies on the distinction. Second, we present model results as percentage deviations in the values of variables in the counterfactual simulation away from their corresponding values in the baseline.[8]

16.3.2 Investment and Capital Accumulation

LA-DYN carries the assumption that investment undertaken in industry i in year t becomes operational at the beginning of year $t + 1$. That is:

[7] This specification allows us to use a broad range of substitution possibilities among inputs (Hanoch 1971).

[8] In this paper we are concerned with reporting the impact of a chlorine gas attack, not with the baseline forecast for the LA economy. As such, we report all results in terms of deviations in the values of variables in the attack scenario away from their baseline (no attack) forecast values. While details of the baseline are unimportant for the present application, this need not be the case for all simulations. Dixon and Rimmer (2013) note that baseline details can be important when: (1) the aim is to supply CGE forecasts to business or government; (2) the counterfactual shocks are heavily weighted towards very fast- or slow-growing sectors; (3) the focus is an evaluation of the adjustment costs of policy change. These are not relevant considerations in the present application.

$$K_{i,t+1} = K_{i,t}(1 - D_i) + I_{i,t} \tag{16.1}$$

where

$K_{i,t}$ is industry i's capital stock in year t;

D_i is industry i's depreciation rate; and,

$I_{i,t}$ is the quantity of new capital created for industry i during year t.

Investment is a function of the expected rate of return on capital, via:

$$K_{i,t+1}/K_{i,t} - 1 = F_{i,t}[EROR_{i,t}] \tag{16.2}$$

where

$EROR_{i,t}$ is the expected rate of return on investment in industry i in year t; and

$F_{i,t}$ [·] is an increasing function of the expected rate of return.

In implementing (Eq. 16.2), we assume that $F_{i,t}$ takes the inverse-logistic form described in Dixon and Rimmer (2002, pp. 190–195). This is the functional form used in the USAGE model, whose investment specification is discussed in Dixon and Rimmer (2005).

16.3.3 Regional Wage Adjustment

LA-DYN allows for limited deviations in the short-run regional wage away from its baseline forecast values. With short-run regional populations also sticky (see below), short-run labor market pressures are mainly manifested as short-run deviations in the regional employment rate. More explicitly, the path of the regional wage in the chlorine attack simulation is governed by:

$$\left(W_t^{(C)}/W_t^{(B)} - 1\right) = \left(W_{t-1}^{(C)}/W_{t-1}^{(B)} - 1\right) + \alpha\left(ER_t^{(C)}/ER_t^{(B)} - 1\right) \tag{16.3}$$

where

$W_t^{(B)}$ and $W_t^{(C)}$ are year t values for regional nominal wages in the baseline and counterfactual (chlorine) simulation respectively

$ER_t^{(B)}$ and $ER_t^{(C)}$ are regional employment rates (1—the unemployment rate) in the baseline and counterfactual simulations respectively; and

α is a positive parameter.

With (Eq. 16.3) activated in the chlorine simulation, the deviation in the regional wage grows (declines) as long as the regional employment rate remains above (below) its baseline level. Equation 16.3 represents an implementation at the regional level of the national sticky wage mechanism described in Dixon and Rimmer (2002, p. 205) and implemented in the USAGE model of the U.S. We choose a value for α consistent with that in USAGE.[9] In practice, this ensures that

[9] We set $\alpha = 0.6$.

the bulk of the regional employment rate effects of a shock in year t are eliminated by year $t+5$.

16.3.4 Interregional Migration

While (Eq. 16.3) gradually returns the regional employment rate to baseline, this is not the same as assuming that regional employment returns to baseline. We allow for endogenous movements in the size of the regional workforce via interregional migration, using a single-region variant of the migration theory described in Giesecke and Madden (2013). This models interregional migration as a function of per-capita regional income. Hereafter, we call the measure of income relevant to the migration decision "migration income", defined as:

$$Y_t^{(M)} = W_t \cdot ER_t \tag{16.4}$$

where
$Y_t^{(M)}$ is migration income
W_t is the LA-County real consumer wage; and
ER_t is the LA-County employment rate.

We define disequilibrium in the regional migration income measure away from a level consistent with a trend rate of net interregional migration via:

$$Y_t^{(M)} = Y_t^{(Diseq)} \cdot F_t^{(M)} \tag{16.5}$$

where
$Y_t^{(Diseq)}$ is a measure of disequilibrium in migration income
$F_t^{(M)}$ is a shift-variable for calibrating (Eq. 16.5).

A plausible initial parameterisation of (Eq. 16.5) is $Y_t^{(Diseq)}=1$ and $F_t^{(M)}=Y_0^{(M)}$, where $Y_0^{(M)}$ is the initial (base period) value for $Y_t^{(M)}$. As we shall see, with such a parameterisation of (Eq. 16.5), we have assumed that the base period migration income measure is consistent with the trend level of net interregional immigration.

In (Eq. 16.5), $F_t^{(M)}$ will normally be exogenous, while $Y_t^{(M)}$ is determined by (Eq. 16.4) on the basis of regional labor market conditions (that is, outcomes for W_t and ER_t). Hence, (Eq. 16.5) determines $Y_t^{(Diseq)}$. We assume that a rise in $Y_t^{(Diseq)}$ will generate a rise in the net rate of inter-regional immigration of persons of working age (IMR_t) via:

$$IMR_t/IMR^{(Trend)} = G_t\left[Y_t^{(Diseq)}\right] \tag{16.6}$$

We use an inverse logistic function to describe G (Fig. 16.1). For modeling a region's net immigration rate, this function has three useful properties. First, it allows us to limit the minimum and maximum values for IMR_t within historically-

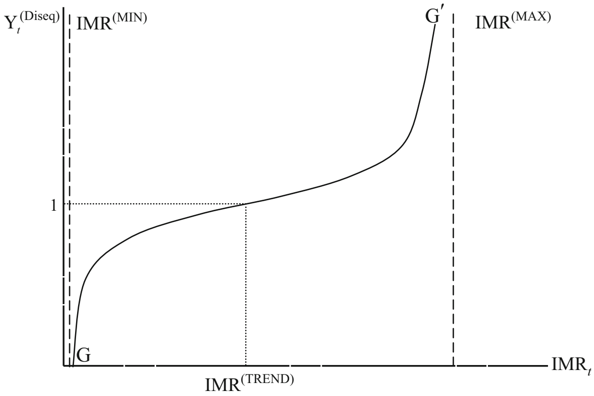

Fig. 16.1 The regional net immigration rate

observed bounds ($IMR^{(MIN)}$ and $IMR^{(MAX)}$ respectively). Second, by establishing a positive relationship between IMR_t and $Y_t^{(Diseq)}$, the function reflects the insight of Whalley and Trella (1986) that, because individuals differ in their preferences for residing within given regions, greater movements in relative regional wage rates are required to bring forth higher levels of interregional migration. Third, it allows us to model the autonomous component of net interregional immigration by establishing a trend value for IMR_t ($IMR^{(TREND)}$) consistent with a value for $Y_t^{(Diseq)}$ of 1.

To translate movements in IMR_t to movements in net interregional immigrant numbers, we multiply IMR_t by the year t regional working age population. The resulting population flow affects the start-of-year working age population in year $t+1$.

16.3.5 Economic Closure for the LA-DYN Model Under a Chlorine Attack Scenario

We outline here the main elements of the model's closure as they relate to factor markets and the expenditure side components of regional GDP.[10]

Within any given year of the simulation, we assume that the regional working age population is given. However, the regional working age population adjusts through time to changes in the migration income measure, in accordance with the migration theory described in Sect. 16.3.1.

Regional employment is the product of the working age population and the regional employment rate. In the short-run, the employment rate is endogenous, and

[10] This follows closely the closure described in Giesecke and Madden (2013, pp. 443–445), establishing an environment in which short-run capital stocks, population and the real wage are sticky (and rates of return, regional income relativities, and the employment rate are flexible), transitioning to a long-run environment in which rates of return, regional income relativities and employment rates are sticky.

the regional wage is sticky. As such, short-run labor market pressures are mainly reflected in changes in the employment rate. In the medium- to long-run, regional wage adjustment drives the employment rate towards its baseline level. As such, deviations in long-run employment are largely determined by deviations in the long-run working age population.

Within any given year, industry-specific capital stocks are given. Hence, in the short-run, demand-side pressures on capital stocks are largely reflected in changes in rates of return. Over time, movements in rates of return induce changes in investment, and eventually capital supply, that gradually return rates of return towards normal levels.

We assume that household consumption spending is a fixed proportion of household income. That is, the household savings rate is exogenous and unshocked. A potential behavioral effect that we have not modeled is a short-run rise in precautionary savings. Regional and federal government real public consumption spending is exogenous.

16.4 Simulation Design

16.4.1 Direct Resource Loss Effects

We summarize the direct resource loss effects of the scenario at:

1. 182 deaths, leading to lost labor input in the event year of $7.6 m., measured in wage bill terms.
2. Lost labor input due to injuries in the event year valued at $1.9 m., measured in wage bill terms.
3. BI, arising from evacuation and clean-up of 90071, valued at $140 m. of lost output in the event year.[11]
4. Medical expenses of $4.0 m. in the event year.

We model the direct impact of deaths as a reduction in regional population sufficient to withdraw $7.6 m. of labor from the LA County economy. We model lost labor input from injury as a decrease in regional labor productivity, calibrated to reduce effective labor input during the event year by $1.9 m. for a given level of employment. In translating this to industry-specific changes in labor productivity, we use Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages data together with sectoral ratios for LA County as a whole from the LA-DYN database, to estimate sector-specific values for output and payments to

[11] Giesecke et al. (2012) estimate the value of gross output in 90071 at $16.8 billion. We assume the event causes a three day shutdown of activity in 90071. This corresponds to $140 m. of lost output.

labor and capital for 90071.[12] We use the 90071 sectoral wage bill estimates to translate the $1.9 m. labor productivity loss into sector-specific shocks.

We model BI as deterioration in industry-specific, all-input-using technical efficiency. As discussed in the preceding paragraph, we use BLS and LA-DYN data to estimate output by sector for zip code 90071. BI results in 3 days of lost output in 90071. We translate this to sector-specific productivity losses for LA County as a whole based on industry-specific 90071 shares in LA County output by industry.

We model the $4.0 m in direct medical expenditure as an expansion in final demand for medical services. The medical resources used to treat the victims of the chlorine attack form part of the attack's economic costs. To make this explicit, we require that the medical spending be financed via a decrease in general government consumption spending.

16.4.2 Behavioral Effects

Our estimates of the behavioral inputs to the economic model are based on results from a nationwide survey in which 624 people participated. Our approach to hazard scenario construction and survey design was consistent with well-documented methods of querying people about perceived risk and risk-related behaviors (Fischhoff et al. 1978; Slovic 1987; Burns and Slovic 2010; Giesecke et al. 2012). Respondents were drawn from a panel developed by Decision Research in 2008 based on funding from the National Science Foundation.[13] Panelists were recruited online by a number of means (e.g., Google ads) to gather a diverse assortment of Americans. We statistically reweighted our sample using U.S. Census data to better reflect the U.S. population. In this paper we focus on the sub-group of panelists who reviewed a scenario with 182 chlorine deaths to invite comparisons of the economic impacts with the RDD attack, which had a similar number of deaths. The sample size for this group was 286.

Respondents were invited to participate and were given 1 week to review our chlorine scenario and answer our online survey.[14] Prior to reading the scenario respondents were asked their perceptions regarding the likelihood and severity of such an attack during the next 12 months. They then read a 500 word news article with headline "**Chlorine Bomb Rocks Financial District of Los Angeles! 182 Dead and Hundreds Potentially Exposed to Poison Gas as Mayor Requests Downtown to Seek Shelter for Hours".** The article included a statement by the Mayor describing the details of the attack, the fact that the contaminated area had

[12] Notes 12 and 13 of Giesecke et al. (2012) estimate sector-specific values for output and payments to labor and capital for 90071.

[13] The format for describing the survey results here conforms very closely with Giesecke et al. (2012) to facilitate behavioral comparison between the chlorine and RDD attacks.

[14] Available at http://www.decisionresearch.org/pdf/ChorineAttackAug2012.pdf

been blocked off and safety officials were assessing the risk (see online appendix for details). Respondents were then asked a number of questions pertaining to their initial reaction to the attack. Following this, respondents read a follow-up report describing the findings and actions of safety officials and the mayor over the previous 3 days with headline "**Chlorine Gas Levels Throughout Los Angeles Pose Little Threat says Panel of Health Officials! Today the Mayor Received a Reassuring Report from a Team of Chemical Experts Regarding Long-term Health Risks. The Downtown to Re-Open".** The report emphasized that the mayor received reassuring news about the area's safety and that the downtown area is cleared to resume normal activities.

Initial questions involved perceived risk (very low risk to very high risk), fear (not fearful to very fearful), attention to media coverage (none to more than 8 h/day during the first week), worry (not worried to very worried) and trust in first responders (no trust to very high trust). These were followed by questions pertaining to respondents' willingness to buy products or work near the financial district. Respondents were asked to indicate how long they would delay buying products, using services or working in this area ranging from no intention to delay to indefinite delay. Specifically, we focused on professional services, food products unique to LA, electronic products and taking a vacation near the downtown area. We also asked what incentives might be needed (e.g. product discounts, higher wages) to immediately resume buying products or working near the downtown area, Table 16.1 reports survey results for respondents who evaluated the chlorine attack.

Notice that willingness to use services, purchase goods, or work in downtown LA immediately following the Mayor's "all clear" is greatest for professional services and electronic products and least for food and vacation (first percentage in each cell). Using these responses we calculated the percentage of people who remain unwilling to use services, buy products or work near the financial district at different points in time (percentage in parentheses). For example, after 6 months, at least 18 % of respondents indicated they still would not consider economic transactions in the financial district. The greatest reticence involved food products and vacations with 11 and 14 % respectively saying they would never buy food or vacation near the financial district in the future. In comparison, Giesecke et al. (2012) investigated an RDD attack on the same area with similar casualties. The authors found that after 6 months, at least 41 % of respondents indicated they still would not do business in the financial district. The greatest reservation again involved food products and vacations with 17 and 12 %, respectively, saying they would never buy food or vacation near the financial district in the future. As we describe below, we use the percentages within each column to approximate the decay in perceived risk over time for each product type or job.

We also asked respondents what percentage price reduction or wage increase they would require to consider consuming or working in downtown LA immediately following the Mayor's "all clear" (see Table 16.2). Notice that almost half of the respondents said they would not buy food near the financial district right away

Table 16.1 Survey results depicting percentage wait times before doing business in the financial district

Wait time (at least)	Professional services	Vacation	Food	Electronic products	Job
Right after "All Clear"	45 %[a] (55 %)[b]	20 % (80 %)	22 % (78 %)	45 % (55 %)	38 % (62 %)
One month	26 % (29 %)	24 % (56 %)	18 % (61 %)	20 % (36 %)	25 % (37 %)
Six months	11 % (18 %)	18 % (38 %)	19 % (42 %)	14 % (22 %)	9 % (28 %)
Twelve months	8 % (9 %)	15 % (23 %)	19 % (23 %)	8 % (13 %)	7 % (21 %)
Thirty six months	4 % (5 %)	7 % (16 %)	8 % (15 %)	7 % (6 %)	8 % (13 %)
Sixty months	2 % (4 %)	2 % (14 %)	4 % (11 %)	1 % (6 %)	1 % (11 %)
Never in future	4 %	14 %	11 %	6 %	11 %
Sample size (N)	286	286	287	285	287

[a]Percentage indicating they would not wait to do business in the financial district
[b]Percentage who are still waiting

Table 16.2 Levels of required incentives to consume or work in the financial district right away

Required incentive	Professional services	Vacation	Food	Electronic products	Job
0 %	35 %	18 %	18 %	35 %	25 %
2 %	4 %	3 %	3 %	3 %	3 %
4 %	10 %	2 %	4 %	4 %	5 %
8 %	0 %	8 %	5 %	7 %	7 %
15 %	10 %	10 %	7 %	9 %	11 %
25 %	8 %	15 %	8 %	13 %	15 %
50 %	17 %	17 %	8 %	9 %	8 %
100 %	NA	NA	NA	NA	5 %
No amount is enough	18 %	28 %	48 %	21 %	20 %
Mean %[a]	15	20	14	13	20

[a]Average required % incentive for those who would consider interacting with the financial district right away

for any level of incentive. Whereas less than one fifth indicated they would not accept any incentive to use professional services right away. For those willing to accept some level of incentive the average percentage required is given in the bottom row of Table 16.2 and range from 13 % for electronic products to 20 % for vacations. Incentive for jobs may have been a little higher because respondents had an opportunity to select a 100 % wage increase. In the RDD study, again almost half of the respondents indicated they would not buy food near the financial district right away for any level of incentive. By comparison, less than one-fourth indicated they would not accept any incentive to use professional services right away. For those willing to accept some level of incentive the average percentage required range from 15 % for food and electronic products to 19 % for vacations.

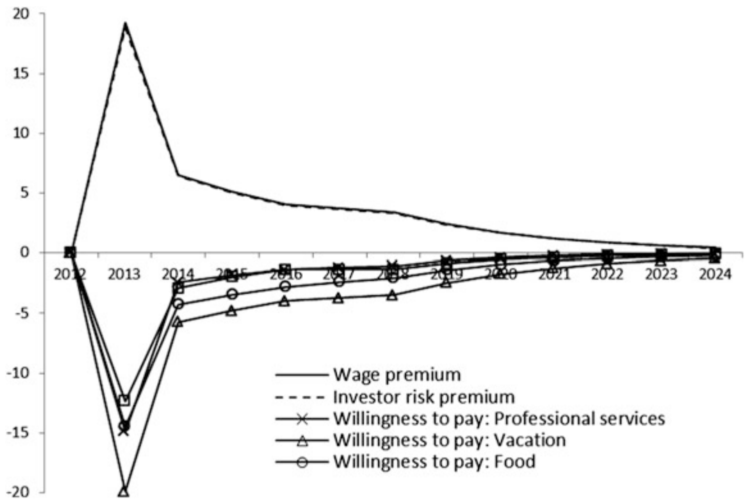

Fig. 16.2 Time paths for behavioral shocks in zip code 90071 (% deviation from baseline)

Figure 16.2 reports our translation of the Tables 16.1 and 16.2 results into shocks to behavioral variables related to activity in zip code 90071. For the event year (year 1) our behavioral shocks are based on the survey results for the mean incentives required to immediately resume business in the financial district (final row of Table 16.2). We interpret the results for incentives required to purchase professional services, vacation, food, and electronic products as elucidating vertical shifts in willingness to pay for these products, scaled to reflect 90071's share in LA County output of these commodities.[15] We interpret the job incentive as the wage premium required to maintain a given labor supply to the affected region. We implement this in LA-DYN as time-specific shocks to $F^{(M)}$, scaled to reflect 90071's share of the LA-County wage bill.

In calculating the time paths for our model shocks, we begin by noting that the Table 16.2 results for mean required incentives relate to the event year only. Our simulation runs over 12 years. To infer behavioral shocks for the remaining years, we use the decay rates for the "percentage who are still waiting" reported in Table 16.1. In calculating the decay rate between 2013 and 2014, we use Table 16.1

[15] LA-DYN models demand for LA County commodities by agents in three regions: LA County, the rest of the U.S., and the rest of the world. Demands by agents located outside LA County are modeled via constant elasticity demand schedules. Following Giesecke et al. (2012), we model declines in willingness to pay by these agents as vertical shifts in these schedules. For agents located within LA County, we follow Giesecke et al. (2012) in modeling the product incentive shifts described in Fig. 16.2 as fear-induced wedges driven between willingness to pay for LA County goods and willingness to pay for the competing product sourced from the rest of the U.S. or the rest of the world.

results for “Right after ‘all clear’” and “Twelve months”.[16] In calculating the decay rate between years 2014 and 2016, we use results for “Twelve months” and “Thirty six months”.[17] Similarly, in calculating the decay rate between 2016 and 2018, we use results for “Thirty six months” and “Sixty months”. After 2018, we assume a smooth decay rate for the behavioral shocks based on the annual average percentage change in Table 16.1 results for “percentage who are still waiting” between the “all clear” and “sixty months” marks.

The Fig. 16.2 pattern of response decay has been seen across several studies. Burns and Slovic (2007), using findings from the risk perception literature and expert elicitation, constructed a system dynamics simulation model to investigate public response to a terrorist attack. The results indicated that following news of an attack perceived risk and fear escalate rapidly, reaching a peak, and then decline quickly before levelling off slightly above pre-attack levels. Burns et al. (2011b) corroborated these simulation results by tracking public response to the attempted attack on Northwest Flight 253. Consistent with the simulation results, fear of flying and the intent to postpone air travel declined quickly before levelling off. Burns et al. (2011a) also surveyed Americans in March and April of 2011 in response to the triple disaster in Japan. They found fear of earthquakes, tsunamis and nuclear accidents declined markedly even within a month of the disaster. Most recently, Burns (2013) investigated public fear and perceptions of risk in reaction to the Boston attack. They conducted three surveys from April to July 2013 and found that public concern in July was a third of what it was in April.

The survey results do not directly elucidate the potential size of the investor risk premium, which would require an investor survey. Giesecke et al. (2012) addressed this by examining the literature on the asset price impacts of stigma related to various contamination risks. They noted an average implied risk premium in the vicinity of 20 %. This was in line with their RDD survey results for compensating wage premium. Based on this, they assumed that the two suppliers of primary factors (labor and capital) seek identical percentage movements in compensation. Like the RDD survey results in Giesecke et al., the Table 16.2 chlorine results also signal a 20 % increase in required wage compensation. Hence, we assume that firms require the same premium to invest in 90071 in the event year, and that thereafter the investor risk premium decays at the same rate as the wage premium (Fig. 16.2). We implement the increase in the risk premium in LA-DYN as increases in industry-specific required rates of return, scaled to reflect the share of each industry’s capital payments explained by activity in 90071.

[16] For example, the 2013 deviation in willingness to pay for professional services is -15 %. Hence the 2014 deviation is assumed to be -2.4 % ($= -15\ \% \times 9/55$).

[17] For example, the 2015 deviation in willingness to pay for professional services is assumed to be -1.8 % ($= -2.4\ \% \times (5/9)$^0.5).

16.5 Simulation Results

Our explanation of the economic modeling results is based around a series of decomposition figures explaining outcomes for regional macroeconomic variables in terms of the individual contributions made by the eight sets of shocks. The decomposition figures are created by running the CGE model nine times: one full simulation in which all eight sets of shocks are implemented simultaneously, and a further eight simulations in which each of the eight sets of shocks is implemented individually. This allows us to explain total impacts in terms of the individual contributions made by each of the behavioral and resource shocks.[18] We explain the figures in a logical sequence, relying on references to economic mechanisms within the LA-DYN model to support our narrative.[19] We begin our discussion with the event year (2013). There are two main points of entry to understanding the 2013 results: negative deviations in the regional terms of trade (Fig. 16.3), and investment (Fig. 16.4). In Fig. 16.3 we see that the dominant contributor to the 2013 terms of trade deviation is the decline in willingness to pay for LA County goods. This exerts a direct effect on the regional terms of trade, depressing prices of LA County goods relative to competing imports. In Fig. 16.4 we see three shocks exert a strong negative influence on 2013 investment: investor risk premium, willingness to pay and BI.

The rise in required rates of return on LA County capital directly affects regional investment, depressing capital formation relative to baseline for any given rate of return (e.g. by about 0.2 % in the event year).

[18] The sum, for any variable, of results from the eight individual simulations is close to, but not exactly equal to, the results from the full simulation. This is because the model is non-linear, and interactions between the individual shocks that are captured by the full simulation are missed when the shocks are implemented individually. The difference between the sum of the eight individual simulations and the full simulation is reported as "Residual". The value for this is small for all variables in all years.

[19] Dixon and Rimmer (2013) describe eight ways in which CGE model results can be benchmarked or validated. Not all the methods they outline are required for every application. Rather, they advocate tailoring the validation procedure to the purpose at hand. In our discussion of results, we use the third of Dixon and Rimmer's procedures: qualitative validation via a narrative relying on economic mechanisms within the model (pp. 1297–1298). At the same time, while not reported in this paper, we have also relied on the first two of their validation methods (test simulations for which the results are known a-priori, and within-simulation cross-checks of national accounts identities). Their remaining methods (particularly vi–viii, p. 1272) are well beyond the scope of the present paper, representing independent CGE validation modeling exercises in their own right. For example, Dixon and Rimmer discuss validation of CGE results through out-of-sample forecasting. Examining the question with a 500 sector model of the U.S. economy, they find their CGE model forecasts over a seven year period are more accurate than trend extrapolation. They go on to argue that CGE forecasts can be improved further with better forecasts for macro and trade variables, and greater use of publicly available information on plausible future paths for commodity-specific and industry-specific variables relating to tastes, technologies and policy (Dixon and Rimmer 2013, pp. 1314–1324).

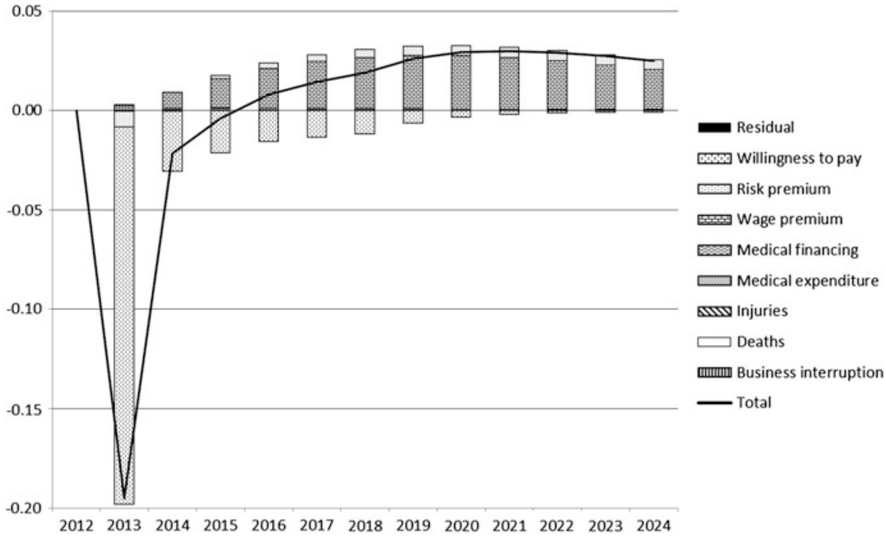

Fig. 16.3 Decomposition of the deviation in the LA County terms of trade (% point contributions to total deviation)

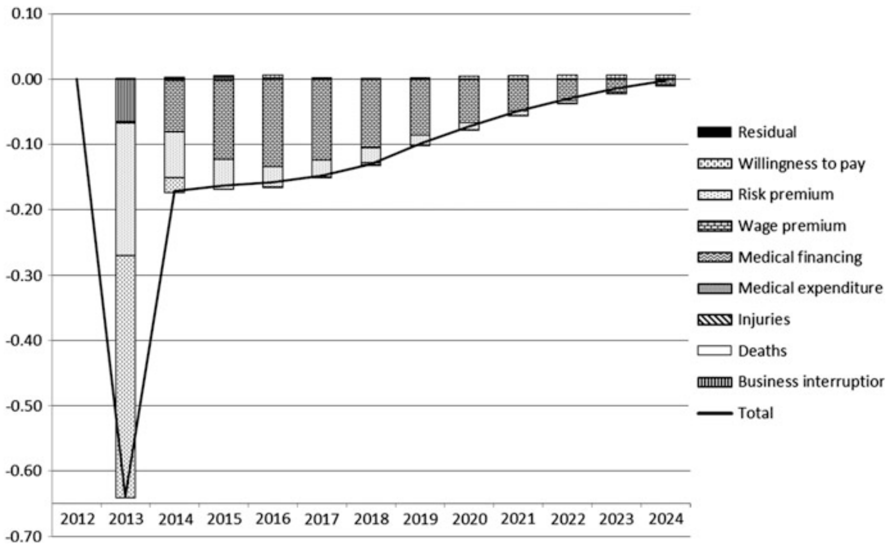

Fig. 16.4 Decomposition of the deviation in LA County real investment (% point contributions to total deviation)

The decline in willingness to pay exerts an indirect influence on regional investment, via its effect on the terms of trade (Fig. 16.3). In 2013, for a given level of the capital stock, the negative deviation in the terms of trade causes the value of the marginal product of capital to decline relative to baseline. This in turn

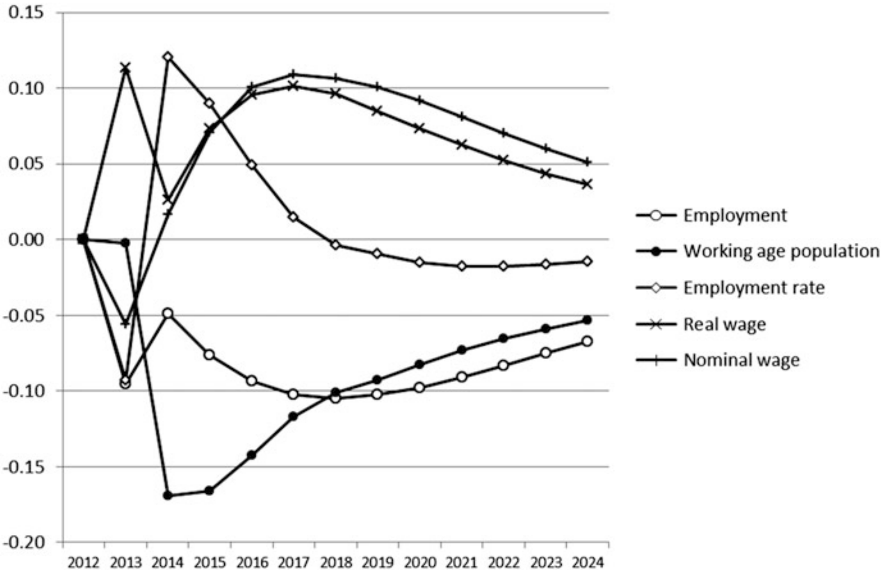

Fig. 16.5 LA County employment, working age population, employment rate and nominal and real wages (% deviation from baseline)

depresses the capital rental price, and with it, the rate of return. As is clear from Fig. 16.4, it is the decline in willingness to pay, via its effects on the terms of trade and ultimately the rate of return on capital, which has the largest impact on 2013 investment, reducing it by approximately 0.37 % relative to baseline.

BI is the third-largest contributor to the 2013 investment deviation (Fig. 16.4). As discussed in Sect. 16.4.1, BI is modeled as deterioration in input-using efficiency in industries in 90071. This causes the marginal physical product of capital to fall relative to baseline. Hence, for a given level of capital, the rate of return also falls relative to baseline. This accounts for BI's −0.06 % contribution to the 2013 investment deviation (Fig. 16.4).

Figure 16.5 reports five labor market variables. Outcomes for these variables are presented jointly to facilitate our explanation of the dynamic relationships between each. We begin with the 2013 outcome for the real wage and employment. Recall from Sect. 16.3.1 that nominal wages are modeled as sticky in the short-run. This causes the initial negative deviation in the terms of trade (Fig. 16.3) to generate a positive deviation in the real wage (Fig. 16.5). It is this initial rise in the real wage that accounts for much of the initial negative deviation in employment. This is confirmed by Fig. 16.6 which shows that the reduction in willingness to pay (via the terms of trade and real wage paths) makes the largest contribution to the 2013 employment deviation.

There is a small negative deviation in population in 2013 (Fig. 16.5). In the first year, the only influence on the size of the working age population is event-related fatalities. This is clear in our population decomposition (Fig. 16.7), in which deaths

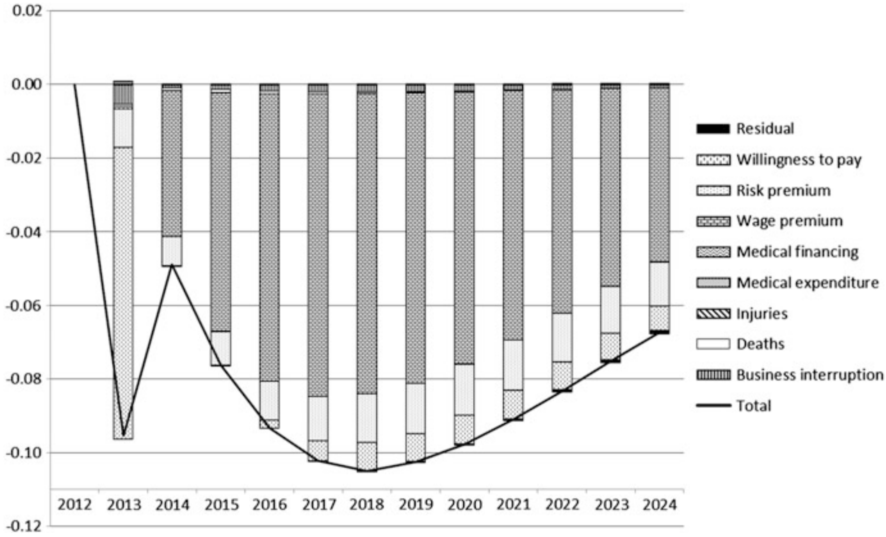

Fig. 16.6 Decomposition of the deviation in LA County employment (% point contributions to total deviation)

explain all of the 2013 deviation. Returning to Fig. 16.5, with employment sharply below baseline in 2013, and only a small negative deviation in the population, the regional employment rate must fall relative to baseline. As discussed in Sect. 16.3.1, the wage mechanism imposes sticky, but not fixed, nominal wages. With the 2013 employment rate below baseline, the sticky wage mechanism generates a negative deviation in the 2013 nominal wage (Fig. 16.5).

Figure 16.8 presents our GDP decomposition. In 2013, GDP is projected to be 0.08 % below baseline. Much of this decline is due to the negative deviation in 2013 employment, which, as discussed above, is largely due to the willingness-to-pay-induced reduction in the terms of trade. However, productivity loss, particularly via BI, also makes a substantial negative contribution to the 2013 GDP deviation (−0.03 %).

Turning to the post-event phase, we begin with Figs. 16.4 and 16.9. The negative deviation in 2013 investment (Fig. 16.4) is expressed in 2014 as a negative capital deviation (Fig. 16.9). From 2014 onwards, the magnitude of the negative investment deviation attenuates, eventually returning to baseline by the simulation's end. This reflects the gradual return of the investor risk premium to baseline (recall Fig. 16.2). However, the investment deviation lies below the capital deviation up to 2020, and, as a result, the negative capital deviation continues to grow to that year. Thereafter, as investment steadily returns to baseline, the negative capital deviation gradually attenuates.

In 2013, population falls slightly due to event-related fatalities (Fig. 16.5). In 2014, the regional population deviation reaches its lowest point (−0.17 %),

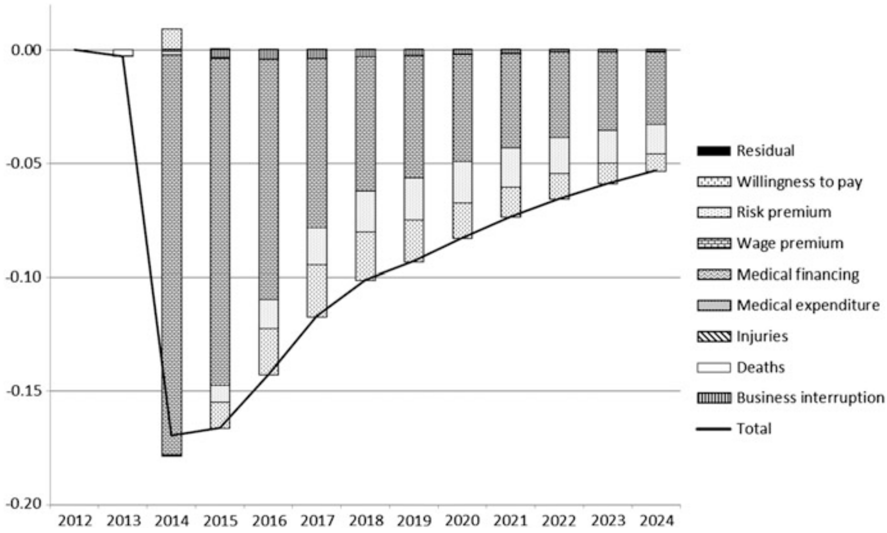

Fig. 16.7 Decomposition of the deviation in LA County working age population (% point contributions to total deviation)

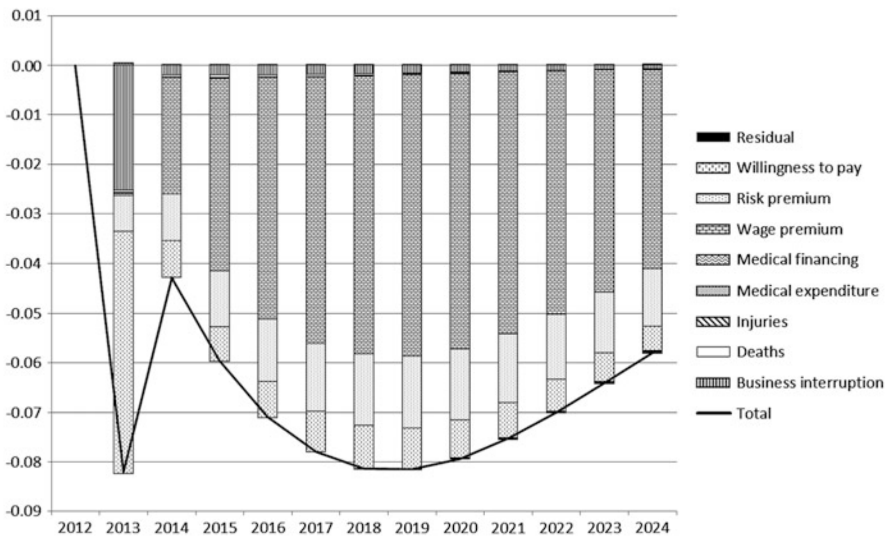

Fig. 16.8 Decomposition of the deviation in LA County real GDP (% point contributions to total deviation)

gradually returning to baseline thereafter. As shown in Fig. 16.7, for the years immediately following the event, the wage premium shock makes the largest contribution to the negative deviation in population. The wage premium operates directly on net inter-regional immigration via $F^{(M)}$ in equation (Eq. 16.5). In our

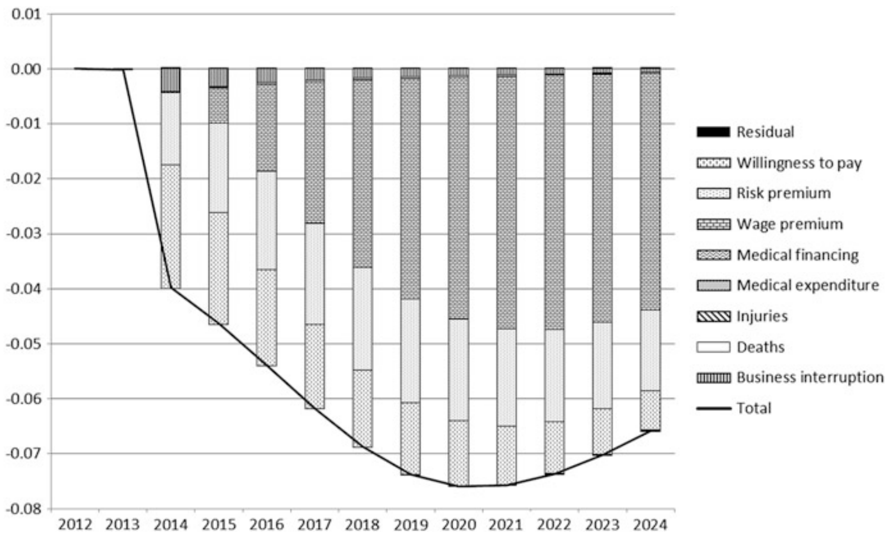

Fig. 16.9 Decomposition of the deviation in LA County capital stock (% point contributions to total deviation)

simulation, the deviation path for $F^{(M)}$ follows the path for the wage premium behavioral effect reported in Fig. 16.2.[20] With $Y^{(M)}$ determined in the regional labor market via (Eq. 16.4), the positive deviation in $F^{(M)}$ causes a negative deviation in $Y^{(Diseq)}$. Via (Eq. 16.6) this causes the net inter-regional immigration rate to fall, and with it, the regional population. After 2016, as $F^{(M)}$ gradually returns to baseline, the negative contribution of the wage premium shock to the regional population deviation gradually attenuates (Fig. 16.7). By the end of the simulation period, $F^{(M)}$ has almost returned to baseline (Fig. 16.2). Nevertheless, in Fig. 16.7, we see the wage premium continues to make a sizeable contribution to the negative population deviation. This reflects two legacies of the positive deviations in the wage premium in earlier periods. First, the working age population is a stock variable. At any given point in time, deviations in its value from baseline reflect accumulated past flows of deviations in net inter-regional migration. Second, over time, deviations in population and capital interact. By reducing the size of the regional population, and with it, regional employment, the wage premium reduces the marginal physical product of capital by lowering the labor/capital ratio. This explains the sizeable contribution made by the wage premium to the capital deviation in Fig. 16.9. However, causation also runs in the other direction. A lower capital stock, for any given level of the working age population and the employment rate, lowers the marginal physical product of labor, and with it the wage. This damping effect on the regional wage via

[20] With the size of the shock scaled to reflect the share of the wage bill in zip code 90071 in the total LA County wage bill.

the negative capital deviation feeds back into to the persistent negative deviation in the working age population in Fig. 16.7.

Returning to Fig. 16.5, the negative deviation in the working age population exerts a damping effect on regional employment in the post-event phase. In 2014, the deviation in the working age population is −0.17 %. If wages were fully flexible, the 2014 employment deviation would also be −0.17 % because the deviation in the employment rate would be zero. Recall however that we model short-run nominal wages as sticky. As such, the 2014 wage does not fully adjust to its new market clearing level, which accounts for the positive deviation in the 2014 employment rate. The model's wage mechanism requires the deviation in the nominal wage to grow so long as the deviation in the employment rate is positive. This accounts for why, in Fig. 16.5, we see the nominal wage deviation growing up to 2017, gradually driving the employment rate back towards baseline. Thus, we see the deviations in employment and the working age population tracking closely together from 2018 onwards (Fig. 16.5).

As discussed in Sect. 16.4.2, by the end of the simulation period, the deviations in willingness to pay, risk premium and wage premium have returned to close to their baseline values (Fig. 16.2). Despite this, in Figs. 16.7 and 16.9, we see that these behavioral shocks continue to make negative (although tapering) contributions to the deviations in two key stock variables: population and capital. The explanation lies in the short—to medium-run impact of these shocks on the regional capital stock, and the interaction between the capital stock deviation and the regional population and employment deviations. For example, consider the investment decomposition (Fig. 16.4). Here we see the contribution to the investment deviation made by the risk premium shock falling to zero by the end of the simulation period. This reflects the gradual return of the risk premium back to baseline, as the behavioral effect dissipates. In 2013, the risk premium shock makes a sizeable contribution to the investment deviation. In 2014, this is manifested as a negative contribution by the risk premium to the stock of capital (Fig. 16.9). In 2014, the risk premium makes a much smaller contribution to the negative investment deviation (Fig. 16.4). Nevertheless, in Fig. 16.9, the negative contribution of the risk premium to the capital deviation persists. This is so for two reasons.

First, investment and capital accumulation is modeled as a gradual process: it takes some years of steady investment to recover from the negative capital deviation generated by the 2013 risk premium shock. Second, the capital deviation and the employment deviation interact. In 2014 the risk premium shock makes a negative contribution to the real wage deviation because it lowers the 2014 capital stock relative to baseline (Fig. 16.9), lowering the marginal physical product of labor.[21] The inter-regional immigration function links year t net immigration to the year t expected wage, and links year $t+1$ population to year t net immigration. Via these mechanisms, with the risk premium making a negative contribution to the real

[21] This accounts for the temporary dip in the real wage deviation in 2014 (See Fig. 16.5). A decomposition diagram of the real wage deviation is available from the authors on request.

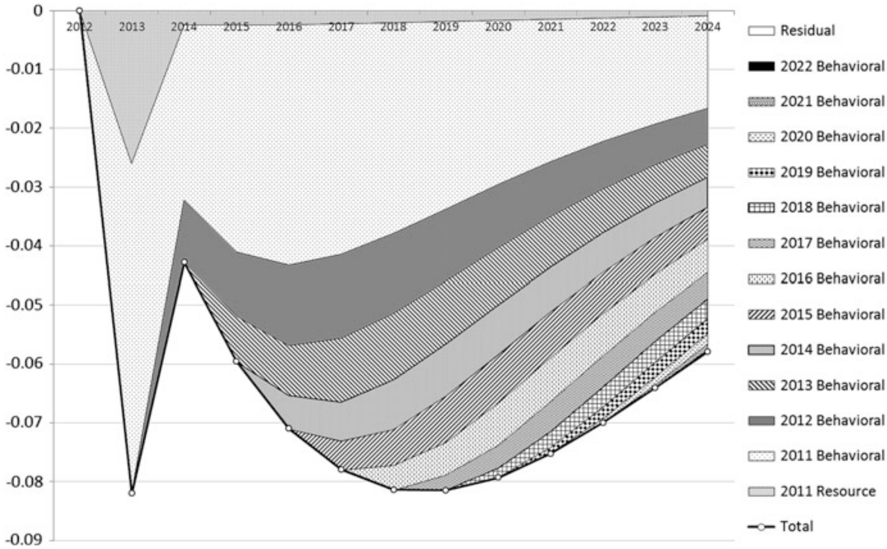

Fig. 16.10 Real GDP decomposition by year (% deviation from baseline)

wage in 2014, it also makes a negative contribution to the 2015 working age population (Fig. 16.7). For a given employment rate, this generates a negative contribution to 2015 employment (Fig. 16.6). By lowering the marginal product of capital relative to baseline in 2015, this attenuates what would otherwise be a positive investment response to the fact that the deviation from baseline in the risk premium in 2015 is significantly smaller than in 2014 (Fig. 16.2).

Examining Fig. 16.2, we see that the values of our key behavioral variables have returned close to baseline by the simulation's final year. However in Fig. 16.8, we see a persistent (but tapering) GDP deviation. The enduring GDP deviation at the end of the simulation period reflects the legacy of shocks in earlier periods, particularly those relating to behavioral variables. To make this clearer, Fig. 16.10 presents a new decomposition of the GDP deviation, distinguishing the contributions of the shocks within any given year to the GDP deviations of current and future years.[22]

For the event year, Fig. 16.10 distinguishes the effects of behavioral and resource shocks, while latter years identify only behavioral consequences (there

[22] Figure 16.10 is constructed from 14 simulations: (1) a 2013 resource loss simulation, in which all resource loss shocks are applied in 2013, and the simulation is run out to 2024; (2) 12 behavioral simulations, in which the values for shocked behavioral variables in year t are moved to their year t deviation values, returned to their baseline values in year $t+1$, and the remainder of the simulation run to 2024; and (3) the full simulation. The sum of the results of simulations (1)–(2) are very close to, but not exactly equal to, the results of simulation (3). This is due to interactions between the shocks, captured by simulation (3), but missed when the shocks are modeled as a sequence of unconnected simulations. We report the difference as “residual”.

are no direct resource loss shocks after 2013). Examining the legacy of the event year shocks, it is clear that while the enduring effects of the resource loss shocks have largely dissipated by 2024, this is not the case for the behavioral shocks. In the event year, the resource loss shocks depress GDP by -0.026 % relative to baseline. By 2024 this contribution has fallen to -0.0009 % (1/28th of the 2013 resource result). The event year behavioral shocks lower GDP in 2013 by -0.056 % relative to baseline. Examining Fig. 16.10, we see a tapering contribution by the 2013 behavioral shocks to the GDP deviations of future years. Nevertheless, by 2024, the 2013 behavioral shocks are contributing -0.016 % to the GDP deviation: just over 1/4th of the 2013 behavioral impact. Examining the time paths of the decomposition results for each of the post-event years, Fig. 16.10 shows a similar pattern of gradual tapering of the enduring effects of the deviations from baseline in the year $1 + n$ values for our risk premium, wage premium and willingness to pay variables. The persistence of the behavioral contributions to the GDP deviations of future years can be traced to our previous explanation of the dynamic interaction between the deviations in capital and population. That is, the interaction between these two variables, via their respective impacts on the marginal product of labor (and thus wages and inter-regional immigration) and the marginal product of capital (and thus rates of return and investment) damps the speed with which these variables return to baseline.

The advantages of a dynamic model in elucidating the long-run consequences of the behavioral responses arising from a terrorism event are demonstrated by a comparison of Fig. 16.10 with the estimated long-run real GDP consequences of an RDD attack as reported in Giesecke et al. (2012). As discussed in Sect. 16.3.1, the latter paper used a comparative static version of the dynamic model used in this paper. Because their model was not dynamic, Giesecke et al. inferred annual results between years $t + 1$ and $t + 10$ by assuming a linear transition of GDP impacts from short-run (event-year) results, through to long-run results for the year $t + 5$, and then to an assumption of a return to baseline (i.e. zero GDP impacts) by year $t + 10$.[23] However, their assumption of no enduring impacts by year $t + 10$ appears, in the light of Fig. 16.10, to under-estimate the potential for long-run adverse regional GDP consequences via behavioral effects.

Table 16.3 provides a comparison of event year and long-run real regional GDP outcomes in terms of contributions by BI, other resource losses, and behavioral effects. Consistent with Giesecke et al., Table 16.3 highlights the importance of behavioral effects in both the event year and the long-run. The total real regional GDP loss in the event year is \$447 m., of which \$311 m. arises from behavioral effects alone. Much of the remainder is due to the direct and indirect flow-on consequences of BI (\$81 m. and \$50 m., respectively). These BI losses are significantly lower than those calculated for an RDD event in Giesecke et al., in large part

[23] See Fig. 3 in Giesecke et al. (2012).

Table 16.3 Summary comparison of real regional GDP outcomes

Impact	Category	
(1) Event year	Direct business interruption (BI). (Output loss, \$m.)	−\$140
(2) Event year	Direct business interruption (BI). (GDP loss, \$m.)[a]	−\$81
(3) Event year	Indirect business interruption (BI). (GDP loss, \$m.)	−\$50
(4) Event year	Other resource loss. (GDP loss, \$m.)[b]	−\$3
(5) Event year	Medical expenditure & financing. (GDP loss, \$m.)	−\$1
(6) Event year	Behavioral effects. (GDP loss, \$m.)	−\$311
(7) Event year	Total short-run. (GDP loss, \$m.)	−\$447
(8) Long-run	Average annual long-run behavioral. (GDP loss, \$m.)[c]	−\$478
(9) Long-run	Total ten-year behavioral. (GDP loss, \$m.)	−\$4,780
(10) NPV	NPV (at 5 %) of total ten-year behavioral. (GDP loss, \$m.)	−\$3,622
(11) Ratio: [(2) + (3)]/(2)	S-R total BI/S-R direct BI	1.62
(12) Ratio: [(2) + (3) + (4) + (5)]/(2)	S-R ordinary loss/S-R direct BI	1.67
(13) Ratio: (8)/(2)	L-R one-year/S-R direct BI	5.89
(14) Ratio: (8)/(6)	L-R average behavioral/S-R behavioral	1.54
(15) Ratio: (9)/(2)	Total ten-year behavioral/S-R direct BI	58.9
(16) Ratio: (9)/[(2) + (3) + (4) + (5)]	Total ten-year behavioral/ordinary loss	35.3

[a]Based on a value-added/output ratio for zip code 90071 of 0.58. With BI generating lost output of \$140 m., this is equivalent to a direct GDP loss of \$81.2 m (=\$34 m × 0.58)
[b]Via deaths and injuries
[c]Annual average of the behavioral impacts in the ten years following the event

because the chlorine clean-up period is much shorter (3 days compared with 30 days). In the post-event phase, average annual real GDP losses from the behavioral effects are \$478 m., approximately 1.5 times the event year behavioral loss (row 14). This ratio is approximately half that found in the RDD study.[24] This highlights another advantage of dynamics over comparative statics. Under the long-run comparative static closure used in Giesecke et al., regional population and capital are assumed to fully adjust to the long-run behavioral shocks, at going regional wage rates and rates of return. However, in the present dynamic modeling, both regional population and capital respond slowly, not fully adjusting to the peak behavioral effects before these shocks begin returning to baseline.

[24] Giesecke et al. (2012) report an annual long-run behavioral loss of \$2,628 m. and an event year loss of \$889 m., a 3:1 ratio.

16.6 Spatial Analysis

16.6.1 General Considerations

In this section we discuss the spatial aspects of external shocks to an economy in general and with special reference to insidious terrorist attacks. The analysis thus far has been performed in a relatively aspatial manner. We have identified the contaminated area as the site of the impacts and translated the impacts into changes in factor availability and prices for firms located there. This affects firm competitiveness and hence imports and exports of the LA economy as a whole by averaging the direct impacts across all firms in the County. But several other spatial aspects have been omitted. Some of these relate to economic resilience, or how BI losses can be muted by ordinary and adaptive responses to a disaster (Rose 2009a, b). The prime example is the response to the 2001 attacks on the World Trade Center, in which 95 % of businesses and government agencies in the affected area relocated within several weeks, primarily to mid-town Manhattan or Northern New Jersey, thus avoiding 72 % of potential BI losses (Rose et al. 2009). That study indicates how the omission of resilience can lead to an overestimate of economic losses.

Walter Isard, perhaps more than any other American social scientist, injected a spatial dimension into the economy (see, e.g., Isard 1951, 1956; Isard et al. 1969). In the presentation below, we provide an overview of a systematic framework for the spatial analysis of the impacts of a terrorist attack, primarily with the objective of improving the accuracy of the estimates of economic consequences. We also indicate how the inclusion of a broader set of spatial dimensions would affect our results.

We begin by noting two special features of a chlorine attack that distinguish it from other types of disasters. The first relates to fear and stigma effects already analyzed in prior sections. Additionally, because of the uncertainty regarding the spread of chlorine gas or other insidious weapons whose dispersion is related to weather conditions and are difficult to detect, we should also consider that the fear/stigma will not halt abruptly at the financial district boundary. It is reasonable to consider a fringe zone where these behavioral considerations may spill over and have impacts, though likely less intensive than in the core area.

A behavioral consideration not addressed thus far relates to the likelihood and pace of business relocation. The 9/11 example indicates that the response is likely to be rapid and not far from the original site. Both of these responses were conditioned somewhat upon broader aspects of resilience, in the form of demonstrating to terrorists that they cannot defeat their intended targets (Flynn 2008). There is every reason to believe that this “we will show them” attitude would prevail in LA as well.

The spatial dimension is rarely if ever addressed in full in estimating the regional economic consequences of terrorism, as well as many other perturbations. Most analyses are undertaken with single region models, and relocation within them or across regions is rarely analyzed explicitly. When inter-regional or multi-regional models are used, some consideration of relocation is made but primarily with respect to overall economic activity levels, rather than the explicit movement of individual businesses. For example, Gordon et al. (2005) use a multi-regional input-output modeling approach with inter-regional trade flows. They divide the greater LA area into sub-regions, such that impacts do have spatial delineation. However, there is no explicit attention to the relocation of firms.

16.6.2 Spatial Analysis Framework

Various adjustments in economic models have been offered in relation to the relocation of businesses. For example, Isard and Kuenne (1953) provided various ad hoc adjustments to reflect an agglomeration effect associated with the entrance of a new steel mill into a region. Adjustments referred to the likelihood that support industries would develop in the area, thereby increasing the basic multiplier effects. Our analysis deals with the opposite situation, i.e., business exit. Hence, further adjustment of general equilibrium supply-chain linkages might be in order, particularly to the extent that the model's endogenous capital supply responses understate the magnitude of these effects.

Another complication is that relocation may not be entirely out of the region for which the impact analysis was performed but may also take place within the region, as in the case of World Trade Center area firms moving to Midtown Manhattan. Also, business activity in cyberspace and tele-commuting have increased significantly in recent years, further blurring boundaries. Finally, we have the longstanding issue of the ready ability to shift economic activity among branch plants of the same company. Given all these considerations, a quarantine plus geographic averting behavior may not result in losses as great as initially predicted.

Below we discuss in detail various aspects of the potential spatial realignment of economic activity in relation to the chlorine attack scenario:

Business Relocation Alternatives First we must consider relocation out of the financial district. This would potentially include: (1) actual physical relocation; (2) a shift of activity to other branches of the firm; and/or (3) work primarily in cyberspace.

Physical relocation is likely to approach zero in a case where quarantine/decontamination lasts only a few days. Shift of activity to branch offices is a possibility, especially for firms involved in banking, finance and insurance. However, we lack data on the extent of this opportunity and the extent to which businesses will exploit it. Work in cyber space, including tele-commuting, deserves special attention here because it is becoming more prevalent, especially in the banking and finance sectors that are predominant in the area affected by the chlorine attack. This activity may not be affected in any significant way by the attack. Increasingly, businesses are backing-up their systems such that even if main computers are located in the financial district, relevant files can be accessed from elsewhere. Similarly, data are being increasingly stored on various types of "cloud."

The prevalence of these cyber options warrants adjustment of direct impact estimates when data become available.

We must also distinguish shifts of locations *within* LA County from those going elsewhere. As in the NYC shift to Mid-town, there are several advantages to relocating in close proximity to the original site. Doing so would not lead to any reduction in economic activity within LA County, all other things being equal. If we were to apply 9/11 findings, we would estimate that 95 % of the businesses would in fact relocate, with most of them within the County. However, the 9/11 physical moves averaged 6–8 weeks, and thus are not pertinent to this case. If for some reason the decontamination were to take much longer, a good deal of equipment and material could readily be moved, since chlorine gas, unlike radiation, is not a lingering contaminant.

Of course, business relocation does have its costs. If this significantly increases the cost of doing business at the new location, this would have to be factored into the analysis, and would lower the level of economic activity in LA County by affecting its competitiveness.

Economic Activity Shift Out of the Region This aspect does not pertain to the actual physical movement of firms, but rather to their activity levels in place. It relates to an increase in their cost of doing business due to increased wage demands and increased investor rates of return to compensate for increased risk. It also relates to their likely reduced profits as they have to provide customer discounts. These have been addressed in our modeling approach above and also in Giesecke et al. (2012). However, both of these analyses implicitly assume no business relocation, but simply a decrease in economic activity. The modeling can be made more accurate if an adjustment is made for those firms actually relocating elsewhere in LA County and relocating outside the County. In the case of the later, the base for the activity shifts decreases (fewer firms to which to apply what are essentially declines in competiveness or product demand that lead to reduced sectoral output).

Temporal Dimension of Spatial Shifts It is important to distinguish between business relocation at various points in time. The implications of these decisions differ significantly for the consequence estimates between the initial contamination, clean-up, risk amplification, and stigma phases. While firms may not have time to physically relocate during the short-run response (decontamination), opportunities to do so increase over time, though the incentives to do so decline as well (see the discussion above of the decay rate for fear). Thus, some relocations decisions (including branch offices and cyber space activity) affect ordinary losses, and others affect behavioral losses estimated in this study. All will typically reduce the basic loss estimates, though the extent to which they affect the ratio of behavioral to ordinary BI losses is not known a priori.

One also needs to consider the potential for a reverse movement of businesses. Abadie and Dermisi (2011) are investigating the movement of WTC area firms who left Lower Manhattan right after 9/11 but are returning. The same phenomenon could take place for the type of terrorist attack that we have analyzed, though it is less likely because of (misplaced) fear of lingering contamination. One would also need to consider the extent to which the attack site is seen as a prime target for future attacks, contributing to persistent stigma.

Conclusions

We have developed a regional CGE model to analyze the time-path of the economic impacts of a terrorist attack. The model was applied to estimating the standard resource loss and behavioral impacts of a chlorine gas attack on the LA financial district. The results indicate that behavioral effects, stemming from the social amplification of risk and stigma affects, dominate. The ratio of Total Ten-Year Behavioral to Ordinary Losses is greater than 35. Moreover, the ratio of Total Ten-Year Behavioral/to Short-Run Direct Business Interruption is nearly 60. The model was designed to capture critical economic relationships pertaining to severe shocks, including migration, capital stock damage, and investment. The extent to which the relocation of business activity could affect the results was also explored. Behavioral responses were incorporated into the model by estimating the impacts of worker wage premiums, investment premiums, and shopper discounts required to induce economic agents to return to the impacted area. The empirical basis for the behavioral analysis was a survey of respondents reacting to a simulated chlorine gas attack. Adverse behavioral impacts are large but may be less costly to mitigate than are the various types of interdiction of terrorism and hardening of targets. Improved risk communication regarding the severity of the chlorine gas threat and its remediation has the potential to significantly quell fears that would otherwise translate into sizable negative economic impacts.

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