VOLUNTARY VERSUS MANDATORY STANDARDS:

PROTECTING WORKERS FROM ADVERSE CHEMICAL EXPOSURE

Stephen Finger

and

Shanti Gamper-Rabindran

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Authors are listed alphabetically. Stephen R. Finger, Assistant Professor, Moore School of Business, University of South Carolina, and Shanti Gamper-Rabindran, Assistant Professor, Graduate School of Public and International Affairs, University of Pittsburgh. We acknowledge funding from the National Science Foundation (SES 1127223), University of Pittsburgh's Center for Industry Studies, Central Research Development Fund, the Center for Social and Urban Research, and Global Studies and European Union Center for Excellence. The authors declare that we have no relevant or material financial interests that relate to the research described in this paper. Errors are our own.

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Abstract

Do voluntary standards, which provide safety information when mandatory standards are outdated, reduce exposure to contaminants? Our study is the first to (i) compare voluntary and mandatory standards defined as specific numerical limits and (ii) analyze measured exposure. We examine worker exposure to 75 chemicals whose standards vary substantially across chemicals and over time at 1,103 chemical plants in 1984-2009. A 1% increase in the stringency of voluntary standards that are initially stricter than mandatory standards leads to a 0.372% to 0.714% decline in exposure. These results are one-third to one-half of the exposure reduction achieved by stricter mandatory standards.

Keywords: private voluntary standards, public mandatory standards, private standard setting, environmental health, occupational health and safety, chemical industry, worker exposure

JEL codes: K32 J81 Q58 Q53 I18 L51

1. The role of private voluntary standards in protecting health

Voluntary programs, in which firms aim to achieve health or environmental protection beyond that required by regulations, have grown worldwide in response to the costs of traditional regulations (Lyon and Maxwell, 2008; Gray and Shimshack, 2011; Kitzmueller and Shimshack, 2012). In the context of food, product and workplace safety, voluntary standards, set by non-profit organizations, private standard-setting bodies, and trade associations play an important role in providing safety information to protect consumers and workers (Cheit, 1990, Coglianese et al., 2009). Mandatory standards, set by government agencies, are often out-of-date or non-existent because of onerous public rule-making procedures and court challenges (Adler, 1989; Cheit, 1990; Weimer, 2006). In contrast, voluntary standards can be updated quickly in response to new information on health risks and new technologies (Weimer, 2006; Meidinger, 2009). Moreover, standards designed by trade associations can tap into producers' information, expertise, and resources, which regulators lack (National Research Council, 2010).

Despite growing reliance on voluntary standards, a priori it is unclear whether firms face sufficient incentives to adhere to stricter voluntary standards that are not directly enforced. Moreover, empirical evidence is scarce on whether voluntary standards improve safety to the extent commensurate with mandatory standards. We study voluntary and mandatory workplace exposure standards to toxic chemicals which provide information on the levels of exposure that are harmful to workers (American Industrial Hygiene Association, 2002). Our study of 1,103 chemical manufacturing plants between 1984 and 2009 is the first to provide a sharp identification of the impact of voluntary standards on exposure to contaminants. First, we provide a head-to-head comparison of voluntary and mandatory standards that are defined analogously as specific numerical limits. Second, we examine worker exposure to 75 different chemicals, most sampled in the chemical industry, that vary substantially in their voluntary and mandatory standards both across chemicals and over time.[1] This variation allows us to identify the differential effects of each type of standard, controlling for other confounding effects. Third, we assess their relative effectiveness using measured levels of workers' personal exposure to air contaminants. The newly released Chemical Exposure and Health Data (CEHD), which archives

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[1] In our dataset, there were 62 updates to voluntary standards covering 46 different chemicals and 10 updates to mandatory standards covering 7 different chemicals.

data collected by Federal Occupational Safety and Health Administration (OSHA) in 29 states, is the largest and most detailed database on occupational health worldwide (Gray and Jones, 1991; Yassin et al., 2005). In contrast to our reasonably sharp identification strategy, previous studies on voluntary programs face difficulties in disentangling program effects from contemporaneous effects, or in estimating the effects of varying the strictness of programs. Those studies examine programs with single performance targets or programs without well-defined measurable goals and they often rely on self-reported pollution to measure outcomes.[2]

Workplace chemical exposure is one of the highest risk areas for human health (EPA, 1987; EPA-SAB, 1990), inflicting costs of $58 billion per year in the US alone (Leigh, 2011). The chemical manufacturing sector is among the top industries in violations of air contaminants standards (OSHA, 2012b). The American Conference of Industrial Hygienists (ACGIH), a non-profit scientific association of occupational health professionals from academia, industry, and government agencies, has published voluntary exposure standards since 1941. These Threshold Limits Values (TLVs) are regularly updated based on a review of the scientific literature (Culver, 2005; Ettinger, 2005). OSHA sets the mandatory standards for exposure limits, known as the Permissible Exposure Limits (PELs). In 1973, OSHA adopted the 1968 TLVs as the mandatory standards (Paustenbach et al., 2011). Stricter exposure standards are specified as lower numerical limits. Most chemicals have stricter TLVs than PELs because OSHA has only been able to update mandatory standards for 16 out of about 300 chemicals due to onerous rulemaking requirements (Mirer, 2007). For example, 19 of the 75 chemicals we analyze have TLVs that are more than 75% stricter than PELs. Public health experts, including the Assistant Secretary of Labor for OSHA, view PELs as “out-of-date and not sufficiently protective” (Presidential Commission, 1997; US House of Representatives, 2011). Therefore, industrial hygienists rely on

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[2] These studies examine the Environmental Protection Agency’s 33/50 which aimed to reduce pollution or the chemical industry’s self-regulation program, Responsible Care, which specify broad codes of conduct or voluntary programs to reduce greenhouse gas emissions (Khanna and Damon, 1999; King and Lenox, 2000; Gamper-Rabindran, 2006; Morgenstern and Pizer, 2007; Prakash and Potoski, 2009; Lyon and Kim, 2011; Finger and Gamper-Rabindran, 2012a; Gamper-Rabindran and Finger, 2013; Pizer et al., 2011).

the TLVs for safety information (McCluskey, 2003) and even OSHA requires employers to publicize the TLVs to workers (Weil et al., 2006).

Voluntary standards that are stricter than corresponding mandatory standards provide information, based on current scientific knowledge, to plant managers and employees that: (i) exposure at or above the outdated mandatory levels leads to significant health risks and (ii) appropriate worker protection requires plants to meet the more stringent updated voluntary standards. First, we test if stricter TLVs that are more stringent than PELs reduce exposure. Second, we compare the exposure reduction from these stricter TLVs to the reduction from stricter PELs. We examine how the levels of exposure vary with the gap in the strictness between (i) the contemporaneous TLVs and PELs, and (ii) the contemporaneous PELs and the 1984 PELs. We find that (i) voluntary standards (that are stricter than mandatory standards) significantly reduce exposure, but (ii) these voluntary standards lead to smaller magnitudes of exposure reduction than do mandatory standards.

First, we report results for the average plant. The Heckman selection model directly controls for the selected nature of our data. It allows us to extrapolate our results on the relative effectiveness of PELs and TLVs, which are based on the tested chemicals in individual inspections, to all 75 chemicals that are most frequently tested in the CEHD. The inspection fixed effect model allows us to focus on the marginal effects of PELs and TLVs, controlling for differences across plants. When TLVs are equally or more stringent than PELs, a 1% reduction in the TLVs leads to a 0.714% and 0.372% decline in exposure in the Heckman and fixed effect models, respectively. These results are about (i) one-half of the magnitude of exposure declines from a 1% reduction in PELs when TLVs are stricter than PELs and (ii) about one-third of that magnitude when TLVs are less strict than PELs. Three of these estimates are statistically significant at the 1% level, while the PEL estimate from the fixed effect model is significant at the 10% level. Stricter TLVs when TLVs are less stringent than PELs also reduce exposure, but by an order of magnitude less.

Second, the quantile regressions find comparable results at high exposure levels that are of most concern for health policy. When TLVs are more stringent than PELs, a 1% decrease in TLVs reduces the 95th percentile of exposure by 0.304%, while a comparable decline in PELs reduces the 95th percentile by 0.837%. These estimates, as well as the estimate that TLVs lead to smaller exposure reductions than do PELs, are significant at the 1% level. Our results are robust to alternative assumptions of inspectors' private information in the inspection process. We acknowledge that our results may overstate the effects of mandating mandatory limits if the subset of chemicals with updated mandatory limits has been perceived by industry to be more hazardous or cheaper to abate than the average chemical. Nevertheless, we argue that this overstatement is likely to be limited. The chemical industry supported updating the mandatory limits in 1989 using the 1987 voluntary limits (Ziem and Castleman, 1989) and continues to support stricter mandatory limits (US House of Representatives, 2002, 2011). This support suggests that a subset of plants, which influence the industry's collective position, believe that there is a net benefit from the entire industry meeting stricter limits for a broad range of chemicals.[3]

Our findings reveal two lessons on voluntary standards. First, plants do respond to the information provided by the voluntary standards on exposure levels that are potentially hazardous to worker health. Therefore, in many situations, voluntary standards can help fill part of the informational gap created by the difficulty in regularly updating mandatory standards. Second, voluntary standards have achieved smaller magnitudes of exposure reduction compared with mandatory standards. Plants face OSHA penalties for failing to meet mandatory standards, but face some, but limited, incentives to meet voluntary standards (see Section 2.3). These results suggest that updating voluntary standards to reflect current scientific knowledge is not a perfect substitute to ensuring that mandatory standards are regularly updated. For instance, we find that 18.1% of inspected plants between 2003 and 2009 have at least one measured exposure between the less strict mandatory standards and the stricter voluntary standards. This finding is consistent with the arguments of public health experts that some workers are placed at risk by the failure to update mandatory standards (OSHA, 1993; Presidential Commission, 1997; US House of Representatives, 2011; GAO, 2012). Finally, our conclusions on the ability of voluntary standards to prompt some exposure reduction may well be specific to the chemical manufacturing sector (see Section 6).

2 Mandatory and voluntary standards and plants' incentives

2.1 OSHA and mandatory exposure standards

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[3] See Section 3.1 and Footnote 9.

Industrial hygienists rely on occupational exposure standards to provide guidelines to help reduce the risks of occupational disease from workplace exposure. These standards provide the information that exposure above these standards are potentially harmful to worker health (AIHA, 2002).[4] In 1973, OSHA adopted essentially the ACGIH's 1968 list of voluntary private standards as the mandatory limits (Froines et al., 1995). Thereafter, to establish new or revised standards, OSHA must follow detailed rulemaking procedures (Froines et al., 1995). Since 1973, it has updated only 16 out of about 300 chemicals (Mirer, 2007). The obstacles in updating PELs are; (i) the courts requiring unrealistic evidentiary standards (Mendeloff, 1988), (ii) the onerous rulemaking procedure for federal agencies (Weimer, 2006; Howard, 2010), and (iii) OSHA's limited resources (Howard, 2010). In 1989, OSHA published a final rule revising 212 existing exposure limits and establishing 164 new exposure limits. However, the 1992 court decision to vacate these rules forced OSHA to revert to enforcing the pre-1989 mandatory limits (AFL-CIO vs. OSHA, 1992; DOL Federal Register, 1993). As a result, most chemicals have stricter TLVs than PELs, and twice as many chemicals have TLVs than have PELs (McCluskey, 2003).

2.2 ACGIH and voluntary exposure standards

The mandatory nature of PELs forces OSHA to comply with federal rulemaking procedures and high evidentiary standards, leading to rare updates. In contrast, the ACGIH regularly updates the TLVs using a less onerous process which is still scientifically robust and structured (Culver, 2005, AIHA, 2002; Paustenbach et al., 2011). The ACGIH's TLV Chemical Substances committee, made up of experts in industrial hygiene, occupational medicine, occupational epidemiology or toxicology, proposes the TLVs based on a technical review of existing scientific literature on the health effects of exposure (Culver, 2005). The Threshold Limit Values (TLVs) indicate "the level of exposure that the *typical* worker can experience without adverse health effects, but they are not fine lines between safe and dangerous exposures" (ACGIH, 2002). More recent TLV revisions do not evaluate economic and technical feasibility (ACGIH, 2002), while earlier revisions did (Mendeloff, 1988). The proposed TLVs are posted in various ACGIH publications and on its website, and public comments are accepted for six months (ACGIH, 2008). The Board of the ACGIH makes the final decision on adopting the

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[4] For ease of exposition, we describe exposure levels that are below and above these occupational exposure limits as more and less protective, respectively.

revised TLV (Culver, 2005). The full list of chemicals with TLVs is published annually in the TLV booklets, which can be easily purchased for $90 per booklet.[5]

2.3 Plants' incentives for adhering to the voluntary standards

A priori, it is unclear whether plants face sufficient incentives to adhere to stricter voluntary standards, thus necessitating an empirical analysis. First, plants face a trade-off between incurring abatement costs to reduce exposure and averting the costs of compensatory wages, higher insurance premiums and tort liability. While in theory, plants may face wage premiums for exposing workers to higher risks, in reality, many workers do not know about their adverse exposure, particularly, to chemicals with long latency periods. Furthermore, many workers lack the bargaining power to demand wage premiums or a safer workplace (Gray and Jones, 1991).

Second, plants that self-insure and large plants that pay experience rate premiums for worker compensation insurance, face incentives to reduce potential claims (Ruser, 1985). Similarly, insurance companies, to avert claims, have recommended stricter standards in developing exposure controls at insured plants. Insurance companies compare plants' exposure to both TLVs and PELs (Pressman, 2005), treating PELs as the minimum standards. However, this insurance channel creates only limited incentives because most plants pay a standardized premium regardless of their claim history (Ruser, 1985).

Third, plants, out of concern for tort liability to workers, may maintain exposure below the TLVs in order to assist in their defense (Karmel, 2008). However, in many states, employees cannot sue employers for workplace injury, as by law, worker compensation is the exclusive remedy (Gabel, 2000). While several states permit tort claims against employers who cause intentional harm or whose grossly negligent or reckless action causes harm (Fitzpatrick, 1982; Lynch, 1983; Cheney, 1991; Gabel, 2000), workers face significant obstacles in proving these elements (Gorton, 2000).

Fourth, chemical manufacturers, out of concern for product liability (Cheney, 1991), pressure plants that use their products to adopt stricter exposure standards, even choosing not to sell to plants with poor industrial hygiene (Allport et al., 2003). The 1973 Borel decision (Borel

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[5] We describe the procedures for setting the TLVs including the selection of the TLV Chemical Substances Committee in Finger and Gamper-Rabindran (2012c)

vs. Fibreboard, 1973) allowed employees to sue the manufacturers of asbestos, avoiding the exclusive remedy provisions of worker compensation schemes (Carroll et al., 2005). Workers have argued that a product which leads to exposure exceeding the TLV is a defective product (Karmel, 2008). However, chemical manufacturers can discharge their duty of care by providing adequate warning information to plants using their products (Laughery, 2005) and by arguing that these plants are ‘sophisticated’ users (Faulk, 1985).

Fifth, plants are mandated by the 1983 OSHA Hazard Communication Standard (HCS) to provide information to workers on the hazards posed by chemicals, including information on the TLVs and PELs. While the HCS does not mandate the adoption of TLVs, knowledge among plant managers, industrial hygienists, and workers about stricter voluntary standards, may prompt actions to reduce exposure. Large and medium-sized plants, staffed by professional industrial hygienists, often establish control programs that target exposure at or below the TLVs (Hoerger et al., 1983). However, the information is often not presented in ways comprehensible to workers (Fagotto and Fung, 2002) to enable their advocacy of safer workplaces or compensatory wages.

3. Method

3.1 Research questions and identification strategy

We ask two questions: (1) Do voluntary standards reduce exposure? (2) How do exposure reductions from voluntary standards compare to those from mandatory standards? We examine data on workers’ personal exposure to air contaminants collected during OSHA’s plant-level inspections (Gray and Jones, 1991; Finger and Gamper-Rabindran, 2012b). OSHA’s inspectors collect test samples of chemicals for which PELs have been enacted in order to establish violations of the mandatory exposure limits (Lofgren, 1996). One or more test samples for a given chemical are collected using personal monitoring devices worn by workers and are analyzed at the Salt Lake Technical Center (SLTC). Using information on the chemical concentrations and sampling durations for test samples of a given chemical collected during each inspection, and OSHA’s guidelines (Online Appendix 2), we calculate chemical-specific test results for that inspection. A given chemical has at least one of three limits (ceiling, short-term or time weighted average limits). Therefore, there may be more test results in an inspection than test samples collected. Our analysis has 19,474 test results, corresponding to 6,001 test samples collected during 1,353 inspections at 1,103 unique plants.[6]

Our dependent variable, exposure, is measured as the ratio of test results to the PELs in 1984, the first year of our study. As chemicals vary in their severity of health effects for the same level of exposure, measuring test results in reference to the PELs set in 1984 (PEL_{1984}) allows us to pool observations across chemicals (Gray and Jones, 1991; Finger and Gamper-Rabindran, 2012b). Lower numerical limits indicate stricter exposure standards. We estimate how exposures vary with (i) the gaps in strictness between the TLVs and PELs ($Relative\ TLV_t$) and (ii) the gaps in strictness between the contemporaneous PELs and PEL_{1984} ($Relative\ PEL_t$). We identify the effects of TLVs and PELs by exploiting the variation in $Relative\ TLV_t$ and $Relative\ PEL_t$, respectively, across different chemicals and variation within individual chemicals over time. During our study period, stricter PELs were enacted for 7 out of the 75 chemicals and stricter TLVs were established for 36 of these chemicals. No PELs or TLVs were made less strict.

If plants change their exposure in response to stricter TLVs, we expect the increase in the strictness of TLVs relative to PELs to correspond to a decline in exposure. The baseline for comparison is the exposure to chemicals with equally strict TLVs and PELs. The gap in the strictness of TLVs and PELs ($Relative\ TLV_t$) is measured as the difference between the contemporaneous TLVs and PELs, normalized by the 1984 PELs, i.e., $(TLV_t - PEL_t)/PEL_{1984}$. We are primarily interested in whether TLVs that are stricter than PELs reduce exposure. If they do, TLVs which are regularly updated can potentially serve as a policy tool to reduce exposure, given the difficulty in keeping the PELs updated. We separately estimate the effects of TLVs that are stricter than PELs and those that are less strict than PELs. Plants are likely to respond differently to the information from the TLVs in these two cases. A TLV that is stricter than its corresponding PEL indicates that, according to current scientific information, exposure at the outdated PEL level is hazardous and appropriate worker protection requires plants to meet the more stringent TLV. When the TLV is made even stricter, the updated scientific information indicates that worker protection requires the exposure to meet even more stringent limits. In

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[6] We also estimate an alternative model that examines any inspection between 1984 and 2009 that collects any test sample. This model examines 1,544 inspections at 1,252 unique plants, yielding 23,105 tests of 222 chemicals and 19,845 tests for the 75 chemicals. Results are qualitatively similar.

contrast, a TLV that is less strict than the corresponding PEL provides less information for plants to act on. Plants are already mandated to meet the stricter PEL and therefore, a marginal increase in the strictness of TLV may lead to only modest, if any, reductions in exposure.

If plants adjust their exposure in response to stricter PELs, we expect that an increase in the strictness of PELs relative to the 1984 PELs would correspond to a decline in exposure. The gap in the strictness of PELs relative to the 1984 PELs (*Relative* PEL_t) is measured as the percent difference between the contemporaneous PELs and the 1984 PELs, i.e., $(PEL_t - PEL_{1984})/PEL_{1984}$. When estimating the effects of stricter PELs, we account for the fact that TLVs provide less information to plants when the gap of strictness is reduced between the TLVs and PELs, as captured in the change in the *Relative* TLV_t measure. In estimating the effects of stricter PELs, the baseline for comparison is the exposure to chemicals for which contemporaneous PELs are equal to the 1984 PELs.

Our study attributes exposure reduction to the PELs from two possible channels. First, plants may reduce their exposure directly in response to PELs. Second, expectations of regulations may spur technological innovations by plants or their suppliers of equipment and inputs to reduce exposure. Innovations may occur during the lengthy period between OSHA's initial proposal and its final enactment of stricter PELs. To some extent, we can rule out the estimation concern that causality flows from innovations to OSHA's issuance of stricter PELs. The history of OSHA's enactment of PELs indicates that health concerns, not technological innovations, prompt OSHA's initiatives (Mendeloff, 1988). We may overstate the effects of PELs in reducing exposure if new knowledge of chemical hazards prompts both OSHA to enact stricter PELs and plants to reduce exposure independent of PELs. This concern is reduced as our identification is based on the year when OSHA enacts the final PEL rules. Plants that are leaders in industrial hygiene are likely to respond quickly to new information while OSHA's final enactment of PELs occurs after a fairly lengthy process (GAO, 2012).[7]

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[7] The time frame for the initiation to the enactment of the final rule is 1.6 and 2.4 years for ethylene oxide, which was updated twice, and 2.6 and 5.9 years for asbestos, which was also updated twice (GAO, 2012). The time frame for is 4 years for benzene, 5.2 years for cadmium and 12.8 years for butadiene (GAO, 2012)

Our analysis can potentially overstate the impact of a mandatory standard relative to a voluntary standard, if the chemical industry views the few chemicals for which OSHA implemented stricter PELs to be more hazardous or cheaper to abate than the average chemical. In that case, our estimate of the effect of PELs would capture both the mandatory nature of the limit as well as industry's perception that reducing exposure to these specific chemicals is cost effective. This concern is abated by the chemical industry's support for OSHA's 1989 proposal to adopt stricter mandatory limits, based on the 1987 voluntary standards, for a wide range of chemicals (Ziem and Castleman, 1989) and its continued support for stricter mandatory limits[8] (US House of Representatives, 2002, 2011). This support suggests that a subset of plants, which influence the industry's collective position, believe that there is a net benefit from the entire industry meeting the stricter limits for a broad range of chemicals.[9]

It is plausible that for some chemicals, it is more difficult to reduce exposure from high to moderate levels than from moderate to low levels. The effectiveness of PELs relative to TLVs may be overstated if the comparison had been between (i) PELs whose limits are moved from high to moderate levels and (ii) TLVs whose limits are moved from moderate to low levels. However, this is not the case in our study. In reality, for the chemicals for which stricter PELs

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[8] OSHA's mandatory standards apply to all industries. Only some industries, such as the chemical industry, support stricter mandatory standards.

[9] These plants can derive net benefits when the entire chemical industry meets stricter standards. First, leading firms in the chemical industry are concerned that poor safety performance by a few plants can lead regulators and the public to view the entire industry negatively (Barnett and King, 2008). Second, firms with deep pockets are concerned about product liability if their products contribute to high exposure when used at plants belonging to other firms (Cheney, 1991). Third, smaller plants, which pay standardized worker compensation insurance premiums regardless of their claims history (Ruser, 1985), can potentially benefit from lower premiums if workers at all other smaller plants were to file fewer claims. However, there are also firms that oppose stricter mandatory limits for specific chemicals (Markowitz and Rosner, 2002) and the chemical industry has fought OSHA's effort to update the crystalline silica exposure standard (American Chemistry Council, 2012).

are enacted, the mandatory limits have been moved to and beyond the TLV limits (See Appendix 1, Table A1).

3.2 Sample and selection issues

We focus on plant-level exposure to chemicals that have both TLVs and PELs, and specifically those 75 chemicals that make up most of the test samples (70%-95%), or test results (68%-94%), annually in the chemical sector. We restrict our dataset to inspections at chemical plants between 1984 and 2009 that collect at least one test sample of the 75 chemicals. Our inferences directly apply to this set of chemical plants. In generalizing our results to the population of chemical plants, we are cognizant the plants in our samples are likely to have above average exposure because OSHA targets industries and plants for which exposure is more likely to exceed the mandatory standards (OSHA, 2002).

We only observe the exposure level of a chemical (among the 75 chemicals) at a plant in a given year if a sample of that chemical is collected and tested. This pattern of observation gives rise to sample selection at two levels. First, the plant is selected among all plants in the chemical sector for an inspection in which samples are collected. Second, the inspector, who is responsible for enforcing compliance to all chemicals with PELs, collects samples for only a subset of these chemicals. We focus on the second level of selection as our study concentrates on the variation in exposure levels across chemicals as opposed to the variation across plants. If inspectors have private information, unobserved by researchers, which is correlated with both exposure levels and their selection of plants to inspect or chemicals to sample, estimation models which ignore selection would lead to biased estimates.

We address the potential selection bias in three ways. First, we estimate the Heckman selection model which addresses inspectors' sampling only a subset of the 75 chemicals within an inspection. For the intuition behind this model, consider an inspection which samples one of the 75 chemicals. While we do not know the actual exposure of the 74 other chemicals, we can infer, using information from the one sampled chemical, the relative exposure of the rest of the 74 chemicals. Because only inspections that sample at least one of the 75 chemicals provide information on the chemical-level variation of exposure, we exclude all other inspections. This model does not address the selection of inspected plants among the population of chemical plants. Other studies that document the exposure levels across plants and over time using the CEHD, examine only inspected plants (Gray and Jones, 1991) or plants inspected for selected chemicals (Froines et al., 1986; Froines et al., 1990), and do not model the selection of inspected plants.

Second, we estimate the inspection fixed effect model which addresses the potential bias from the selection of inspected plants among the population of plants. By restricting our comparison to exposure within an inspection, we are able to difference out the higher mean exposure in inspected plants relative to the average plant in the population. The model does not address the selection of a subset of chemicals among the 75 chemicals within an inspection. Finally, we check the robustness of our results to different assumptions on the private information available to the inspectors in the sampling process.

3.3 Estimation model

Our estimation model consists of two equations:

$$Exp_{s\,k\,p\,t} = \beta_1\,(Relative\ TLV_{s\,k\,t} \mid Relative\ TLV_{s\,k\,t} < 0) + \beta_2\,(Relative\ TLV_{s\,k\,t} \mid Relative\ TLV_{s\,k\,t} > 0) + \beta_3\,(Relative\ PEL_{s\,k\,t}) + \beta_4\,X_{s\,k\,p\,t} + \varepsilon_{s\,k\,p\,t} \qquad \text{- Outcome/Exposure Equation}$$

$$J_{s\,k\,p\,t} = 1\,[\gamma_1\,(Relative\ TLV_{s\,k\,t} \mid Relative\ TLV_{s\,k\,t} < 0) + \gamma_2\,(Relative\ TLV_{s\,k\,t} \mid Relative\ TLV_{s\,k\,t} > 0) + \gamma_3\,(Relative\ PEL_{s\,k\,t}) + \gamma_4\,X_{s\,k\,p\,t} + \gamma_5\,W_{s\,k\,p\,t} + v_{s\,k\,p\,t} > 0\,] \quad \text{- Selection/Inspection Equation}$$

where $\mu_{p\,t} + \xi_{s\,k\,p\,t} = \varepsilon_{s\,k\,p\,t}$ and $\alpha_{p\,t} + \psi_{s\,k\,p\,t} = v_{s\,k\,p\,t}$.

The first equation captures the level of worker exposure at a plant. The outcome variable, $Exp_{s\,k\,p\,t}$, is the level of exposure of workers at plant *p* to the chemical *k* at time *t*, as captured in the test result *s* relative to PEL_{1984}. The levels of exposure vary with observed plant characteristics, $X_{k\,p\,t}$, the voluntary exposure limits relative to mandatory limits measured as $Relative\ TLV_{s\,k\,t}$, the mandatory exposure limits measured as $Relative\ PEL_{s\,k\,t}$, and unobserved characteristics, $\varepsilon_{s\,k\,p\,t}$, which are composed of inspection specific, $\mu_{p\,t}$, and sample specific, $\xi_{s\,k\,p\,t}$, components. We allow the effects of TLVs to differ when the TLV_t is stricter than PEL_t, $(Relative\ TLV_{s\,k\,t} \mid Relative\ TLV_{s\,k\,t} < 0)$, and when the TLV_t is less strict than PEL_t, $(Relative\ TLV_{s\,k\,t} \mid Relative\ TLV_{s\,k\,t} > 0)$. The estimated marginal effect of a change in the TLV is β_1 if the TLV_t is stricter than the PEL_t and β_2 if the TLV_t is less strict than PEL_t. Because PELs are included in both the $Relative\ PEL_{s\,k\,t}$ and $Relative\ TLV_{s\,k\,t}$ measures, the estimated marginal effect of a change in the PEL is $(\beta_3 - \beta_1)$ if the TLV_t is stricter, and $(\beta_3 - \beta_2)$ if the TLV_t is less strict. Plants set target exposure levels in order to maximize profits, trading off between the costs of abating exposure and the costs from maintaining high exposure (e.g., expected OSHA penalties, wage premiums, tort liability and higher insurance premiums). Actual exposure levels vary from the target exposure levels due to failures in the abatement equipment, or human error (Shimshack and Ward, 2007).

The second equation describes the likelihood of observing a test result *s* collected during an inspection. The indicator variable $J_{s\,k\,p\,t}$ takes the value 1 if an inspection collects a sample *s* for chemical *k* in plant *p* at time *t*. For each inspection that collects only a subset of the 75 chemicals, we record that $J=0$ for each chemical that is not tested. Plants must adhere to the PELs for all 75 of these chemicals, leading inspectors to potentially sample any of these 75 chemicals multiple times in any plant in any year. The likelihood a sample is taken varies with observed plant characteristics, $X_{k\,p\,t}$, the mandatory exposure limits, $Relative\ PEL_{s\,k\,t}$, the voluntary exposure limits, $Relative\ TLV_{s\,k\,t}$, excluded variables, $W_{k\,p\,t}$, that affect the likelihood of a sample, but not the exposure level, and unobserved characteristics, $v_{s\,k\,p\,t}$, which are composed of inspection specific, $\alpha_{p\,t}$, and sample specific, $\psi_{s\,k\,p\,t}$, components.

3.4 Addressing selection in the sampling of a subset of chemicals

The sample selection problem arises because the outcome variable, $Exp_{s\,k\,p\,t}$, is observed only if an inspection of plant *p* in year *t* occurs and that inspection collects a sample *s* for chemical *k*, $(J_{s\,k\,p\,t}=1)$. The inspectors may observe factors, which are unobserved by the researcher, that are indicative of higher exposure and lead them to conduct a test. Selection leads to a positive correlation $(\sigma_{\upsilon\,\varepsilon} \neq 0)$ between $\varepsilon_{s\,k\,p\,t}$ and $v_{s\,k\,p\,t}$, leading to $E(\varepsilon_{s\,k\,p\,t} \mid J_{s\,k\,p\,t}=1) \neq 0$. For example, inspectors undertake pre-inspection reviews and may use detector tubes and direct-reading meters as screening devices to help determine whether or not to conduct formal sampling (OSHA, 1999). Results from a screening that are unobserved by the researcher may lead the inspector to conduct tests, and for test results to register high values.

We correct for potential selection bias using Heckman's two-step approach (Heckman, 1979). We include the predicted inverse Mills ratio from the selection equation as a right-hand side variable in the outcome equation to account for the correlation in the errors between the two equations, $\sigma_{\upsilon\,\varepsilon}$. Heckman's two-step method requires that $v_{s\,k\,p\,t}$ has a standard normal distribution and $\varepsilon_{s\,k\,p\,t}$ is mean zero. However, it does not require any assumptions on the functional form of ε_s

$_{k\,p\,t}$. We ensure that the model is not identified based purely on functional form by applying two excluded variables, $W_{s\,k\,p\,t}$, independent of $\varepsilon_{s\,k\,p\,t}$, which affect the likelihood of selection but not the underlying level of worker exposure.[10]

OSHA's inspectors face fixed costs in collecting the first sample, including the costs of visiting a plant, collecting a sample, and sending it for testing at SLTC. They also face the intangible costs of imposing an inspection at the plants, which intrudes on the plants' operations, for example, by requiring workers to wear personal monitoring devices for up to eight-hour shifts. However, once the inspector decides to collect a sample, she faces diminishing costs in collecting each subsequent sample. Therefore, additional chemicals can be collected using the personal monitoring device, and additional samples can be added to the package sent to SLTC. Diminishing marginal costs leads the inspector to be more discriminate in her initial decision to collect personal samples, i.e., she would need to have a strong enough belief that the exposure to a chemical exceeds the PEL to justify the costs associated with collecting the first sample. Having made the decision to collect the first sample, the inspector would be more willing to collect additional samples.

This diminishing cost for collecting additional test samples leads us to consider two excluded variables. The first excluded variable is the number of samples, other than samples for chemical *k*, which are collected during an inspection. We are more likely to see samples of a chemical when it is a part of an inspection that collects a larger number of other samples. Being part of an inspection that collects a larger number of samples lowers the cost of taking the additional sample, therefore raising the likelihood that a given sample is collected. However, it does not directly influence the underlying level of worker exposure to that chemical, independent of whether that chemical is sampled. Because inspectors' threshold for deciding to collect an additional sample is lower for subsequent samples, the number of samples is correlated with the level of a given test sample conditional on that sample being observed. In other words, the instrument $W_{k\,p\,t}$ may affect $E(\,Exp \mid X, PEL, TLV \text{ and } J=1)$. However, we argue that the exclusion requirement holds, i.e., $W_{k\,p\,t}$ does not affect $E(\,Exp \mid X, PEL, TLV)$.

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[10] The Heckman model when identified solely based on the nonlinear functional form of the inverse Mills ratio can lead to imprecise estimates in smaller samples (Little, 1985).

Our data is consistent with our description of the inspection process in which inspectors become less discriminating as they collect more samples. We find smaller means for test results/PELs$_{1984}$ from inspections with larger number of test results. We use as the cutoff the median number of other test results in an inspection for a given observation (35), or the median number of test results for an inspection in our sample (7). The mean test result/PELs$_{1984}$ is 0.209 in inspections with at least 35 test results (n=10,025) and 0.515 in inspections with fewer than 35 test results (n=9,788). The mean test results/PELs$_{1984}$ is 0.330 in inspections with at least 7 test results (n=17,546) and 0.593 in inspections with fewer than 7 test results (n=2,267). This variable would not be a valid instrument if the inspector were to conduct more tests when she believes the plant has higher exposure. If this scenario were true, the number of test results would be positively correlated with exposure levels. Instead, our data, as described above, indicate the opposite is true, consistent with our description that inspectors become less discriminating as they collect more samples.[11]

The second excluded variable is an indicator variable that chemical *k* is a non-target chemical collected during a chemical-specific emphasis inspections. OSHA conducts chemical-specific emphasis programs in which plants whose workers are exposed to specific chemicals would be selected for inspections.[12] Non-target chemicals are less likely to be sampled than target chemicals in chemical-specific emphasis inspections. Once the inspector is already at a plant collecting a sample of the target chemicals, she may test other chemicals as well. This decision process lowers the threshold for testing non-target chemicals due to diminishing

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[11] We use the total number of test results, other than for chemical k, in the inspection as the excluded variable. In contrast, we use the number of test results for chemical k in an inspection as a control variable. An inspector is likely to collect a large number of samples for the same chemical when she has private information that the exposure levels to that chemical are high. Indeed, we find that the mean test results/PEL$_{1984}$ is higher for chemicals tested at least 6 times within its inspection (mean=0.462; n=9,773) than those tested fewer than 6 times within its inspection (mean=0.268; n=10,040).

[12] Emphasis programs include national-level programs that have targeted asbestos, lead, chromium hexavalent, and silica, and local-level programs that have targeted benzene, formaldehyde, and ammonia (OSHA, 2012).

marginal costs of testing. Our data is consistent with the inspector being less discriminating in collecting tests for non-target chemicals than for target chemicals within chemical-specific inspections. We find smaller means for test results/PEL_{1984} for non-target chemicals than for target chemicals within chemical-specific inspections. The mean test results/$PELs_{1984}$ is 0.076 for non-target chemicals (n=1,078) and 1.148 for target chemicals (n=480) within chemical-specific inspections.

The sampling of non-target chemicals in chemical-specific emphasis inspections is also less likely than the sampling of the average chemical in non-chemical-specific emphasis inspections. In a chemical-specific emphasis inspection, conditional on the number of tests in the inspection, non-target chemicals are more likely to be among the marginal chemicals tested, as inspectors focus on the target chemicals. For comparison, in a non-chemical-specific emphasis inspection, conditional on the number of tests in the inspection, each chemical is equally as likely to be one of the first or one of the last chemicals tested. The larger mean test results/ $PELs_{1984}$ for the entire sample (0.360) than for target chemicals in chemical-specific inspections is consistent with our description of the inspection process. Finally, being part of a chemical-specific emphasis inspection simply reduces the likelihood that a non-target chemical is tested, but it does not directly influence the level of worker exposure.

We provide direct evidence in support of the first requirement of valid excluded variables. As reported in Section 5.4, these variables are strongly correlated with the probability that a sample is observed and these relationships are statistically significant at the 1% level. Nevertheless, it is difficult to demonstrate conclusively that the proposed instruments are not correlated with unconditional exposure. Therefore, our robustness checks explore the effect of selection on our estimates by examining other models that incorporate different assumptions on the inspection process (see Section 5.4).

3.5 Control variables

Exposure limits can be specified in three possible ways based on the time frame, i.e., time-weighted average (typically 8 hours), short-term exposure (typically 15 minutes), or ceiling limits (typically 5 minutes). The TLV and PEL for a given chemical can be compared only when these limits are defined using the same time-frame; thus, we include a dummy variable for test results for which TLVs and PELs are directly comparable. We also include a dummy variable for

PELs that have been revised during our study period. For the observation of test result *s* for chemical *k* in a given inspection, we include the log of the number of test results in the inspection for that specific chemical as a control variable because inspectors are more likely to collect multiple test samples for chemicals for which they expect high exposures.

Inspection-level control variables include indicators for samples collected during inspections that have occurred under the chemical-specific emphasis programs. Under these programs, OSHA targets inspections to industries where exposure levels for specific chemicals are potentially in excess of the PELs. Dummy variables control for the type of inspection, i.e., inspections undertaken in response to accidents, complaints or referrals from other agencies, follow-up inspections or other inspections, with programmed inspections as the omitted category.[13] We include a dummy to differentiate between health-focused inspections and safety-focused inspections and a dummy for inspections that cover only part of the plant. Plant-level control variables include a plant's union status and the regulatory pressure at the plant. For our study to be valid, we need to control for these factors, but we do not need to isolate the causal effect of these factors on exposure. Regulatory pressure is captured by the number of OSHA inspections, the log of the dollar penalties, and the log of the number of violations from inspections in the previous year and between two to five years. Time dummies and SIC-4 dummies account for changes in production technology that influence worker exposure. Time dummies also control for secular declines in exposure. State dummies account for potential variation in state environmental health policies.

4. Data

The CEHD provides the following information for each inspection: an inspection specific code, the numbers of samples collected in the inspection, an indicator that the sample is a personal airborne sample, the identity of the chemical sampled, the concentration of the personal airborne sample, and the duration during which the sample was collected. Using the information on the concentration and duration for each chemical sampled during an inspection and OSHA's guidelines, we calculate the appropriate test results for comparison to the chemical-specific voluntary and mandatory exposure limits. We link the data from the CEHD to OSHA's

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[13] Programmed inspections are planned by OSHA based on the industry classification, which in turn is based on the industry-level rates of willful violation (Lofgren, 1996).

Integrated Management and Inspection System (IMIS) using inspection identifiers. IMIS provides information, collected during inspections, on plant characteristics (the plant's SIC-4 code and address), and inspection characteristics (the date, type of inspections and a field describing the chemical-specific emphasis program, if any, under which the inspection was conducted). We construct plant regulatory histories (OSHA inspections, violations, and penalties) from IMIS by linking inspections over time using plant names, addresses, and SIC codes. We assemble the OSHA PELs from Tables Z-1, Z-2, and Z-3 of the OSHA General Industry Air Contaminants Standard (29 CFR 1910.1000). We conduct further research to document the few changes in PELs over time (Mirer, 2007). We assemble the TLVs from the ACGIH's annual TLV booklets (ACGIH, 1980-2009).

5. Results

5.1 Summary statistics

Among the 75 chemicals in our sample, the TLVs and PELs can be compared for 64 to 66 chemicals during our study period (Table 1, Panel A). A chemical is defined as having stricter TLVs than PELs in a given year if any of its TLVs, (ceiling, short-term or time weighted average limits), is stricter than those for PELs. The definition for a chemical with stricter PELs than TLVs is analogous.[14] The share of tested chemicals with stricter TLVs has grown from 44.2% of the 75 chemicals in the 1984-1990 period to 51.8% in the 2003-2009 period. In contrast, the share of chemicals with stricter PELs has declined from 8.4% to 6.5% and the share of chemicals with equally strict TLVs and PELs has declined from 35.2% to 28.0%.[15]

Chemicals with stricter contemporaneous PELs than PEL_{1984} have the lowest mean exposure among test results (Table 1, Panel A, column 6). These chemicals with updated PELs, (regardless of their TLVs), have the lowest test results/PEL_{1984} of 0.046. Next, we consider the chemicals categorized by the relative stringency of their contemporaneous TLVs and PELs.

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[14] We do not observe cases in which a chemical's TLV is stricter by one of these measures, but is less strict by other measures.

[15] The share of chemicals with stricter TLVs than PELs is larger in the sample of all chemicals with PELs. While the PELs have been updated for eight of the 75 chemicals in our study, they have been updated for only 16 (Mirer, 2007) out of about 300 chemicals with mandatory limits (McCluskey, 2003).

Chemicals with stricter TLVs than PELs have the lowest test results/PEL_{1984} (0.155). In contrast, test results/PEL_{1984} are higher for chemicals with equally strict TLVs and PELs (0.506), for chemicals with less strict TLVs than PELs (0.690), and for chemicals with TLVs and PELs that are not directly comparable (0.302). Toluene and lead are among the top four chemicals as a share of the test results and as a share of the test results that exceed the PEL_{1984} (Table 1, Panel B). The other chemicals that make up a large share of test results are silica and beryllium; and the other chemicals that make up a large share of the test results that exceed the PEL_{1984} are formaldehyde and vanadium fume. We find high exposure for the test results that exceed the $PEL_{1984.}$ For example, the mean test results/PEL_{1984} is 108 for beryllium, 21.5 for antimony, 14.0 for vanadium fume and 13.7 for formaldehyde.

The vast majority of test results indicate that exposure is generally low (Table 2, column 2). On average, the mean test results are about one third the level of the PEL_{1984}, two fifths the level of the contemporaneous PELs and three fifths the level of the contemporaneous TLVs. Only a minority of test results, i.e., 6.0% and 4.3% of test results, exceed the contemporaneous TLVs and PELs, respectively. Part of the explanation for low exposure despite PELs being outdated is that production processes often do not require all 75 chemicals. In addition, this pattern of low exposure for the majority of test results is compatible with the “overcompliance” observed in studies of pollution discharges into the environment (Shimshack and Ward, 2008).

High exposure levels at a subset of plants raises health concerns and highlights the need for effective policies to reduce exposure. About 24.8% of plants in 1984-2009, and 23.4% of plants in the more recent period (2003-2009), have at least one test result exceeding the TLVs, whereas 19.4% and 14.4% of plants in the same time periods have at least one test result exceeding the PELs. The larger number of plants exceeding the contemporaneous TLVs than the contemporaneous PELs is unsurprising as the majority of test results are for chemicals with stricter TLVs than PELs. The low exposure across most percentiles of test results but high exposure at the highest percentiles motivates our use of quantile regressions, as policy makers are concerned with influencing the behavior of the worst performing plants. The ratio of test results to PEL_{1984} is 0.0007 at the median, 0.025 at the 70th percentile, 0.274 at the 90th percentile and 0.751 at the 95th percentile (Table 4).

Next, we compare the characteristics of test results that are above and below the median test results/PEL_{1984} (Table 2, column 5 and 7). At the median, the test result is 1% of the $PEL_{1984.}$

The same two chemicals, toluene and lead, rank among the top five chemicals represented by test results above and below 1% of PEL_{1984}. The composition of test results with stricter, equally strict or less strict TLVs are also fairly similar for test results above and below 1% of PEL_{1984}. For the 7,425 test results above the median, 32.3% of test results have stricter TLVs, 13.4% have less strict TLVs and 28.9% have equally strict PELs and TLVs. For the 12,388 test results below the median, the respective figures are 33.2%, 11.4% and 31.8%.

Ideally, our regression analysis would compare test results from plants and inspections that are similar in their characteristics; and these test results would differ only in the extent of the gaps of strictness of TLV_t and PEL_t, divided by PEL_{1984}. We try to achieve as best a comparison as possible by employing control variables in our regressions. There is no indication from Table 2 that the above median test results are more frequently collected from plants with characteristics associated with poor industrial hygiene. On the one hand, above median test results are collected more frequently from plants with more penalties in the previous year. On the other hand, these test results are collected more frequently from plants with smaller penalties in the previous two to five years and fewer violations in the previous year and in the previous two to five years. Above median test results are collected less frequently from inspections associated with poorer performing plants, i.e., inspections that occur in response to accidents, complaints from workers, referral from other agencies, or follow up from previous inspections. Noteworthy, above median test results are collected more frequently from unionized plants.

The raw means permit a preliminary exploration of the relationship between exposure and stricter PELs (Table 3). For the seven chemicals for which stricter PELs were enacted during our study period, we compare the share of test results that met the stricter PELs for test results collected in the periods before and after the enactments of stricter PELs. As seen in Table 3, Panel A, the share that met the stricter PELs improved from 59.7% before the enactment of stricter PELs to 92.0% after the enactment of stricter PELs. This improvement is remarkable, even if part of the decline is due to the larger number of inspections during the later period. Next, we consider the 46 chemicals for which stricter TLVs were recommended during our study period. Among these, 31 chemicals experienced one TLV update, 14 chemicals experienced two updates and 1 chemical experienced three updates. We focus on the final TLV updates for these chemicals. We compare test results that meet the final TLVs for the set of test results collected during the periods before and after the adoptions of stricter final TLVs. In contrast to the stark improvements to test results meeting the stricter PELs, we observe a less pronounced improvement in the share of test results that meet the stricter TLVs. As seen in Table 3, Panel B, 92.0% of test results met the stricter TLVs prior to the final update to the TLVs, while 92.9% of test results met stricter TLVs after their last update.

Finally, the extrapolation of our results to other chemical plants in the CEHD would require some adjustments. First, we compare our sample with the sample of CEHD plants where inspections have not collected any of the 75 chemicals (Online Appendix 1, Table A2, Panel A). Relative to excluded inspections, a larger share of the inspections in our sample are undertaken as chemical-specific emphasis inspections and in response to referrals or complaints, whereas a smaller share is undertaken as programmed inspections. The larger share of referrals from other environmental agencies and complaints from employees in our sample suggests that plants in our sample have potentially more environmental health and safety problems. Another comparison of interest is that plants in our sample are more likely to be unionized. Given our focus on chemical samples, unsurprisingly, a larger share of our inspections is primarily health inspections, which concentrate on worker exposure, as opposed to safety inspections, which concentrate on injuries. Second, we compare our sample with inspections that collect samples for chemicals other than the 75 in our study (Online Appendix 1, Table A2, Panel B). Our sample has higher exposure as indicated by the larger number of PEL exceedance per inspection. Our sample also has more test results and chemicals tested per inspection.

5.2 Results overview

Our research question is whether TLVs that are stricter than PELs reduce exposure. If these regularly updated TLVs reduce exposure significantly, they can serve as a policy tool in reducing exposure in light of the difficulty of updating PELs. Our findings are twofold. First, TLVs that are stricter than PELs significantly reduce exposure. Second, the magnitude of exposure reduction is smaller in response to these TLVs than in response to PELs, regardless of whether the PELs are stricter or less strict than the TLVs. These results hold for the average plant and at the high percentiles of exposure. Exposure reduction is defined as reduction in the ratio of test results to PELs_{1984}. Positive coefficients on the $\textit{Relative TLV}_t$ variable indicate that stricter TLVs (or equivalently a reduction in TLVs) reduce exposure. The marginal effect of stricter PELs is calculated as the coefficient on $\textit{Relative PEL}_t$ minus the coefficient on $\textit{Relative TLV}_t$. A positive marginal effect indicates that stricter PELs (or equivalently a reduction in PELs) reduce exposure.

5.3 Plants’ mean response to TLVs and PELs

We compare plants’ *mean* response to voluntary and mandatory standards. The Heckman selection model and the inspection fixed effect model, which address different aspects of the selection problem, yield similar results. Both models indicate that for the average plant, TLVs that are stricter than PELs significantly reduce exposure. However, the exposure reduction is smaller in response to TLVs than to PELs, both in the cases where PELs are stricter and less strict than TLVs. The exposure reduction is minimal in response to TLVs that are less strict than PELs.

The Heckman selection model addresses inspectors choosing which chemicals to test within a plant, based on factors unobserved by the researchers (Table 4, columns 1 and 2). We find that a 1% reduction in TLVs, which are initially stricter than PELs, leads to 0.714% lower exposure. In contrast, a 1% reduction in PELs leads to 1.488% lower exposure when PELs are initially less strict than TLVs and 2.156% lower exposure when PELs are already stricter than TLVs. The model also reveals that a 1% reduction in TLVs that are stricter than PELs leads to only 0.045% lower exposure. The first three estimates are statistically significant at the 1% level, while the last estimate is statistically significant at the 10% level.

The larger marginal exposure reductions in response to TLVs that are stricter than PELs than in response to TLVs that are less strict than PELs is unsurprising. TLVs that are less strict than PELs lead to only limited reductions in exposure because even high exposure plants treat the mandatory limits as the binding constraint. Increases in the stringency of these TLVs provide minimal information on protective exposure levels. In contrast, when a chemical’s TLV is stricter than its PEL, increases in the stringency of the TLV provides new information that lower exposure levels are required to protect workers.

The reasoning is analogous for the response to PELs. When a chemical’s PEL is less strict than its TLV, an increase in the stringency of the PEL tightens the binding mandatory limit, but it does not provide as much new information on the appropriate exposure level. The fact that the TLV is already stricter than the PEL already indicates that the outdated PEL is insufficiently protective and that plants would need to strive towards the stricter TLV to protect workers. In contrast, when the chemical’s PEL is stricter than its TLV, an increase in the stringency of the

PEL both tightens the binding mandatory limits and provides new information on the appropriate exposure levels. The estimated marginal effects of stricter PELs that are more stringent than TLVs are slightly larger than anticipated, with a 1% reduction leading to 2.2% decline in exposure. This result may be due to high exposure plants changing production processes in response to stricter PELs, which lead to discrete improvements in exposure.

The P-values from the Heckman model indicate exposure reductions from stricter PELs are larger than that from TLVs, irrespective of the initial relative stringency of the corresponding TLVs and PELs (Table 4, column 2). Larger effects from PELs than TLVs is unsurprising as plants face expected OSHA penalties for failing to meet PELs. In contrast, as described in Section 2.3, plants face limited incentives to adhere to TLVs. Another result of interest is the positive correlation in the selection and exposure errors, with the coefficient on the inverse Mills ratio statistically significant at the 1% confidence level (Table 4, column 2). This positive correlation confirms that inspectors are more likely to test chemicals when they have private information that exposure may be high. However, it does not necessarily imply that the estimated effects of variables of interest are biased in our other models.

The inspection fixed effect model addresses inspectors choosing which plants to inspect and conduct tests based on unobserved factors (Table 4, column 3). Inspectors may observe factors, which lead to their belief of high exposure within a plant, and their subsequent administration of tests. However, these factors may be plant and time specific, but not related to an individual chemical. Formally, this specification allows $v_{s\,k\,p\,t}$ and $\varepsilon_{s\,k\,p\,t}$ to be correlated through unobserved factors specific to the inspection. This specification also assumes unobserved chemical-specific information within the inspection, that affects the likelihood of the selection of chemicals within an inspection, is not correlated with exposure levels ($\xi_{s\,k\,p\,t}$ is independent of $\psi_{s\,k\,p\,t}$).

We find that the coefficients on the *Relative TLV*$_t$ and *Relative PEL*$_t$ variables are smaller in the inspection fixed effect model (Table 4, column 3) than in the Heckman model (Table 4, column 2). These smaller coefficients are due to the fixed effect capturing some of the variation in exposure levels among test results.[16] Nevertheless, we continue to find that TLVs that are

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[16] For the case that TLV$_t$ is less strict than PEL$_t$, the coefficient on *Relative TLV*$_t$ is slightly larger in the fixed effect model than in the Heckman model (Table 4, column 3 and 2, respectively).

stricter than PELs reduce exposure significantly and that exposure reduction in response to these TLVs is smaller than that in response to PELs. We find that a 1% reduction in TLVs that are stricter than PELs leads to 0.372% lower exposure. In contrast, a similar reduction in PELs leads to 0.706% lower exposure when PELs are less strict than TLVs and 1.018% lower exposure when the PELs are stricter than TLVs. The model also reveals that a 1% reduction in TLVs that are less strict than PELs leads to only 0.060% lower exposure. These estimates are statistically significant at the 1%, 10%, 1% and 5% level, respectively.

5.4 Robustness checks: informational assumptions on selection

The Heckman selection model applies two instruments, i.e., the number of test samples in a given inspection and the dummy for non-target chemicals in a chemical-specific emphasis inspection (Table 4, column 1 and 2). These two instruments meet the first requirement of valid instruments. We find a strong correlation between the probability that a test result is observed and each of the instruments. The estimated coefficients for these instruments in the inspection equation are statistically significant at the 1% level. We provide arguments on why the second requirement of valid instruments is met (Section 3.4), but it is difficult to prove conclusively that the instruments are not correlated with exposure level. Therefore, we proceed to show how our results are robust to alternative assumptions on inspectors' information in the inspection process.

OSHA's sampling guidelines require that inspectors attempt to sample worst-case exposure levels (OSHA, 2012) and inspectors often collect multiple samples of the same chemical in one inspection. Therefore, our model incorporates a selection process that allows for more than a single sample per chemical.[17] Inspectors first establish a ranking of likely worst-case times and locations for each chemical. Then for each chemical, they decide whether to collect a sample in the worst scenario, then in the second worst scenario and so on. $J_{skpt}=1$ for each sample that is collected, while $J_{skpt}=0$ for each chemical for which no test is administered.

We bound the estimated effects by estimating two alternative models that make opposite assumptions on the private information available to the inspector. We follow Manski's bounds approach (Manski 1989, 1990, 1991), which builds off of the idea that:

$$E(Exp \mid Z)=E(Exp \mid Z, J=1)P(J=1) + E(Exp \mid Z, J=0)P(J=0)$$

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[17] The mean number of test results per inspection is 18.2, covering 3.2 different chemicals.

where Z is the vector of explanatory variables, and other variables are as defined above.

The upper-bound for exposure levels assumes that $E(Exp \mid Z, J=0)= E(Exp \mid Z, J=1)$.[18] In this case, inspectors do not have private information on unobserved factors that affect both the likelihood of taking a sample and the expected exposure levels. This implies $\varepsilon_{s\,k\,p\,t}$ is independent of $v_{s\,k\,p\,t}$ in the OLS regression, and $\xi_{s\,k\,p\,t}$ is independent of $\psi_{s\,k\,p\,t}$ in the fixed effect regression. We treat the 19,000+ test results collected during the inspections as if they had been collected randomly, and we estimate the exposure equation using OLS.

The lower-bound for exposure levels assumes that $E(Exp_{s\,k\,p\,t} \mid J_{s\,k\,p\,t} = 0)=0$. In this case, inspectors choose not to test a given chemical when they know it is not present based on their preliminary onsite evaluation or their understanding of the plants' production process. For inspections that collect only a subset of the 75 chemicals, we assume the exposure levels are zero (or below detectable levels) for the rest of the 75 chemicals. (Inspections that do not collect any of the 75 chemicals are excluded from our analysis). To operationalize this assumption, we construct observations for our exposure equation, with the test result taking the value zero for any of the 75 chemicals that are not sampled. The number of observations in our exposure equation rises from 19,000+ actual test results to 110,000+ actual and constructed test results. We estimate the exposure equation with 110,000+ observations using the OLS and inspection fixed effect models. We use the same definition for constructing untested observations for the selection equation of the Heckman model.

Results from the first OLS model, which assumes inspectors have no private information in their choice of which chemicals to sample (Table 4, column 5), are remarkably similar to the Heckman selection model (Table 4, column 2). We find that a 1% reduction in TLVs that are stricter than PELs leads to 0.727% lower exposure. In contrast, a 1% reduction in the PELs lead to 1.063 % lower exposure when TLVs are stricter than PELs and 1.740% lower exposure when TLVs are less strict than PELs. These estimates are statistically significant at the 1%, 10%, and

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[18] In Manski's bounds approach, the upper bound is derived by assuming $E(Y|X,J=0)=max(Y)$. The assumption, that at the upper bound unselected chemicals have no higher expected exposure than selected chemicals, is likely to hold in our study. Inspectors are not likely to test chemicals that have lower expected exposure than chemicals they elect not to test.

1% levels, respectively. We also find that a 1% reduction in TLVs that are less strict than PELs leads to only 0.050% lower exposure, but this estimate is not statistically significant (Table 4, column 5). The coefficient on the inverse Mills ratio from the Heckman model demonstrates that inspectors do have private information. However, the similarity in the results from the Heckman selection model and the OLS model suggests that not addressing the selection of the subset of chemicals to test does not lead to significant bias in the estimated effects of TLVs or PELs. This finding supports our analysis below, which applies quantile regressions that do not address selection (Section 5.5).

Next we consider the second OLS model, which assumes the non-testing of chemicals only occurs when inspectors know these chemicals are not present or their exposure levels are below detectable limits. This model yields smaller estimates on the effects of PELs and TLVs (Table 4, column 6). Nevertheless, we continue to see that TLVs that are stricter than PELs reduce exposure, but by a smaller amount compared to the PELs. A 1% reduction in TLVs that are stricter than PELs leads to 0.110% lower exposure. In contrast, a similar reduction in PELs leads to 0.400% or 0.502% lower exposure when TLVs are stricter or less strict respectively. These estimates are statistically significant at the 1%, 10% and 1% levels, respectively. When TLVs are less strict than PELs, a 1% reduction in TLVs leads to 0.009% lower exposure, but this estimate is not statistically significant.

We apply the analogous logic to estimate bounds for the inspection fixed effect model. For both inspection fixed effect models, we continue to see the pattern that PELs lead to larger reduction in exposure than do TLVs. The fixed effect model (Table 4, column 4), which assumes the non-testing of chemicals only occurs when inspectors know these chemicals are not present, yields similar estimates to the OLS model under similar assumptions (Table 4, column 6). A 1% reduction in TLVs that are stricter than PELs leads to 0.100% lower exposure. In contrast, a similar reduction in the PELs leads to 0.337% lower exposure when TLVs are stricter than PELs and 0.428% lower exposure when TLVs are less strict. When TLVs are less strict than PELs, a 1% reduction in TLVs leads to 0.009% lower exposure (Table 4, column 4). These estimates are statistically significant at the 1% level. Results from the fixed effect model, which assumes inspectors have no private information in their choice of which chemicals to collect, is discussed earlier (Table 4, column 3).

To summarize, our preferred estimates provide guidance on the effect of stricter standards for plants which otherwise would have high levels of exposure. The results from the Heckman, the first fixed effect, and the first OLS models (Table 4, columns 2, 3 and 5) are more representative of plants and chemicals with above average exposure, which are more likely to be tested. Our supplementary estimates from the second fixed effect and the second OLS models (Table 4, columns 4 and 6) provide guidance on the effect of stricter standards on the general population of all chemical plants and all chemicals. All models consistently show that reducing TLVs that are stricter than PELs significantly reduce exposure but the exposure reduction from these changes in TLVs are smaller than that from PELs. The smaller estimates from the second fixed effect and the second OLS models are unsurprising. In particular, the addition of the large number of zero constructed test results to represent the untested low exposure plants and chemicals is likely to shift the average effect of most of our explanatory variables towards zero.

5.5 Response across the distribution of exposure: quantile regressions

From a health policy perspective, the priority is to reduce worker exposure at plants and for chemicals with high exposure levels. Our earlier models, which focus on the average effects, are likely to be skewed towards low exposure plants, as 60% of our test results are below 1% of the PELs_{1984} (Table 4). To focus on high exposure plants, we estimate quantile regressions. These quantile regressions remain informative even though they do not address the likely selection of chemicals or plants with higher exposure in the inspection process. First, we find similar estimated effects of TLVs and PELs from the Heckman selection model and the OLS model that assumes inspectors have no private information (Table 4, columns 2 and 5). This similarity suggests that ignoring selection within the quantile regressions is not likely to lead to significant biases in the estimated coefficients for $\textit{Relative TLV}_t$ and $\textit{Relative PEL}_t$. Second, even if ignoring selection leads to some bias in the quantile regressions, our results are informative for high levels of exposure, which pose the most health risks.

The quantile regressions (Table 5) yield similar results to our mean regressions (Table 4). In both sets of regressions, we find that TLVs that are stricter than PELs significantly reduce exposure, but the exposure reduction is smaller in response to these TLVs than to PELs. The scale of effects increases as we move to higher quantiles. As seen in Table 5, we find sizable effects of TLVs and PELs only at the higher percentiles of exposures, i.e., at and beyond the 70th percentiles, where there is room for exposure reduction. To begin with, we focus our attention on cases when TLVs are stricter than PELs. A 1% reduction in TLVs results in a 0.138%, 0.303%, and 0.657% decline in exposures at the 90th, 95th, and 97.5th percentiles, respectively. In contrast, a similar reduction in PELs leads to a 0.489%, 0.837%, and 1.601% decline in exposures at those respective percentiles. At the lower percentiles, we continue to find smaller exposure reduction in response to TLVs than in response to PELs. A 1% reduction in TLVs results in a 0.006% and 0.033% decline in exposures at the 70th and 80th percentiles, respectively. In contrast, a similar reduction in PELs leads to a 0.110% and 0.217% decline in exposures at those respective percentiles. These estimates are statistically significant at the 1% level.

We can rule out the concern that a few chemicals are driving the results in the regressions at the highest quantiles. The distribution of observations across the 75 chemicals is fairly similar for observations that make up the 95th quantile and those that make up the full sample. The 95th quantile regression generates estimated coefficients such that 5% of the exposure observations (n=1000+) are greater than their predicted values. Comparing the percent of these 1000+ observations and the percent of our full sample that are made up of each of the 75 chemicals, we find a 73% correlation in the distribution of chemicals in these two samples, indicating the similarity in these two distributions. Moreover, within the upper quantile of observations, a large number of chemicals are represented, contributing to the 95th percentile regressions. We find that 29 different chemicals make up at least 1% of the upper quantile of observations, and 59 chemicals are represented. As a comparison, 27 chemicals make up at least 1% of the full sample, and 75 chemicals are represented.

Results from our quantile regressions differ from those from our main regressions in one aspect. At and above the 70th percentile the quantile regressions reveal larger exposure reduction in response to TLVs that are less strict than PELs than in response to TLVs that are stricter than PELs. The relative magnitudes of the exposure reduction are reversed in our mean regressions. The quantile regressions also reveal larger exposure reduction in response to PELs that are less strict than TLVs than in response to PELs that are stricter than TLVs. Again, the relative magnitudes of the exposure reduction are reversed in our mean regressions. One possible explanation for these results is that the highest exposure plants are responding to the least strict limits. They respond to TLVs when TLVs are less strict than PELs, and they respond to PELs when PELs are less strict than TLVs. The majority of our observations are chemicals with stricter TLVs than PELs.

Both our main and quantile regressions find that PELs leads to larger exposure reduction than do TLVs, with one exception at the highest percentiles of the quantile regression. At the 95th percentile of exposure, considering the case in which TLVs are less strict than PELs, the point estimate indicates that a 1% decline in TLVs leads to a 0.731% decline in exposures, while a similar decline in PELs leads to only a 0.410% decline in exposures. With the wide standards errors, we cannot reject the hypothesis that stricter TLVs (that are less stringent than PELs) and stricter PELs lead to similar magnitudes of exposure reduction at the 95th percentile.[19]

5.6 Other robustness checks

First, we narrow our sample to those chemicals for which PELs or TLVs changed during our study period and re-run our models. Results from these specifications are qualitatively similar to our main results. Second, OSHA enacted 300+ stricter PELs in 1989, but reverted to enforcing the pre-1989 PELs in 1991. Court challenges filed immediately against OSHA's enactment of stricter standards led to uncertainty on whether the stricter PELs would be upheld (Howard, 2010). Our results continue to hold when we drop the years 1989, 1990 and 1991 from our analysis, suggesting that the enactment of stricter PELs between 1989 and 1991 did not exert a substantial effect on exposure. These results are available from the authors.

6. Conclusion

Voluntary safety standards can respond quickly and flexibly to new evidence of greater health risks. They are frequently updated and are often set at stricter levels to reflect current scientific knowledge. In contrast, mandatory standards, due to procedural obstacles and court challenges, are often outdated. Despite the potential contribution of voluntary standards in improving safety, a priori, it is unclear whether plants face sufficient incentives to adhere to stricter voluntary standards, which are not directly enforced.

Our study on workplace exposure standards provides a reasonably sharp quantitative assessment of voluntary standards in three ways. First, we compare voluntary and mandatory standards that are defined analogously as specific numerical limits. Second, we examine worker exposure to 75 different toxic chemicals that vary substantially in their voluntary and mandatory standards both across chemicals and over time. This variation allows us to identify the

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[19] At the 97.5th percentile, a 1% decline in TLVs leads to a 2.23% decline in exposures, while a similar decline in PELs leads to only a 0.024% decline in exposures.

differential effects of each type of standard, controlling for other confounding effects. Third, we use *measured* exposure to air contaminants to test the relative effectiveness of voluntary and mandatory standards. Our study provides the first empirical evidence that (i) voluntary standards (that are stricter than mandatory standards) significantly reduce exposure and (ii) exposure reduction from these voluntary standards is smaller relative to that from mandatory standards. These results hold across various estimation models.

When TLVs are initially more stringent than PELs, stricter TLVs measured as a 1% reduction in the TLV leads to a 0.714% and a 0.372% decline in exposure in the Heckman and inspection fixed effect models, respectively. These results are (i) about one-half the magnitude of exposure declines from a 1% reduction in PELs when TLVs are stricter than PELs and (ii) about one-third of that magnitude when TLVs are less strict than PELs. The quantile regressions find comparable results at high exposure levels that are of most concern for health policy. Considering cases in which TLVs are initially stricter than PELs, a 1% decline in TLVs reduces the 95th percentile of exposure by 0.304%; while a comparable decline in PELs reduces the 95th percentile of exposure by 0.837%.

We acknowledge that our study may overstate the effects of mandating stricter PELs if plants in our study perceive that the seven chemicals for which stricter PELs were enacted pose more hazards or are cheaper to abate than the average chemical. Nevertheless, we argue that the overstatement is likely to be limited. The chemical industry has supported the adoption of stricter mandatory limits for a wide range of chemicals (Ziem and Castleman, 1989; US House of Representatives, 2002, 2011). This support suggests that a subset of plants, which influence the industry's collective position, believe that there is a net benefit from the entire industry meeting stricter limits for a broad range of chemicals (see Section 3.1).

Our findings reveal two lessons on voluntary workplace exposure standards. First, we find that plants do respond to voluntary standards that are stricter than mandatory standards by significantly reducing their exposure. Therefore, in many situations, voluntary standards may help fill part of the informational gap created by the difficulty in regularly updating mandatory standards. Indeed studies have noted that industrial hygienists aim to achieve exposure levels at or below the voluntary standards (Hoerger et al., 1983). Second, voluntary standards achieve a smaller magnitude of exposure reduction compared to that achieved by mandatory standards. This result is unsurprising as plants face OSHA penalties for failing to adhere to mandatory standards, but face only indirect pressure to adhere to voluntary standards. Our finding that 18.1% of inspected plants between 2003 and 2009 have at least one exposure at the level between the less strict mandatory standards and the stricter voluntary standards is relevant to the current debate on outdated mandatory standards. In particular, public health experts, including OSHA's Administrator, argue that some workers are placed at risk by the failure in the last forty years to enact stricter mandatory standards. Our empirical findings that voluntary standards do not serve as perfect substitutes for mandatory standards provide some support for this argument.

Our results are compatible with plants' limited incentives to adhere to voluntary standards (Section 2.3). First, only larger plants face increased costs when their workers file for compensation in cases of adverse exposure. These plants either self-insure or pay experience rated worker compensation insurance (Russer, 1985). Second, while some plants adhere to voluntary standards to protect themselves from potential tort liability (Karmel, 2008), only a few states permit workers to pursue tort actions against their employers (Gabel, 2000). Even then, workers face significant obstacles in proving the employer has caused intentional harm or has been grossly negligent (Gabel, 2000). Third, only some plants must pay wage premiums to compensate workers' increased risks. At other plants, workers may lack bargaining power (Gray and Jones, 1991) or do not fully comprehend their health risks (Fagotto and Fung, 2002).

Our results that voluntary standards significantly reduce exposure may well be specific to the chemical manufacturing sector. Chemical firms with deep pockets whose products are used in production processes at other plants are concerned about product liability (Cheney, 1991). These firms act as leaders in industrial hygiene and pressure other plants to adopt stricter standards (Allport et al., 2003). Firms, which make up the majority of productive capacity in basic industrial chemical manufacturing, participate in Responsible Care, the chemical sector's self-regulation program (Snir, 2001). The firms pledge to conduct product stewardship, i.e., assisting their suppliers and consumers in environmental, health and safety practices (Snir, 2001). We expect plants' responsiveness to voluntary standards to depend on their net benefits from meeting those standards. Plants would be less responsive if they faced high abatement costs, but low expected tort or product liability or limited increases in compensatory wages and insurance premiums. Future studies should exploit the newly released exposure database to examine the effectiveness of voluntary standards in reducing exposure in other manufacturing sectors.

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Table 1: Chemicals, mandatory standards (PELs) and voluntary standards (TLVs) in our sample

	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Comparison of PELs and TLVs			Years			Test result / PEL_{1984}
	1984-90	1991-96	1997-2002	2003-08	All years	
Percentage out of 75 chemicals						
• with stricter TLV_t than PEL_t	44.2%	44.4%	45.1%	51.8%	46.5%	0.155
• with equally strict TLV_t and PEL_t	35.2%	33.3%	33.6%	28.0%	32.5%	0.506
• with less strict TLV_t than PEL_t	8.4%	8.7%	7.1%	6.5%	7.6%	0.690
• for which TLV_t and PEL_t are not directly comparable.	12.2%	13.6%	14.2%	13.7%	13.4%	0.302
• with stricter PEL_t than PEL_{1984}	2.9%	6.4%	9.3%	9.3%	6.9%	0.046
Panel B: Chemicals	[1]	[2]		[3]	[4]	
	As a share of test results	As a share of test results that exceed PEL_{1984}		Test result / PEL_{1984}	Test result / PEL_{1984} if exceed PEL_{1984}	
Toluene	12.1%	3.9%		0.093	1.56	
Lead	6.1%	36.0%		1.523	5.94	
Silica	4.2%	-		0.007	-	
Beryllium	4.2%	0.4%		0.371	108	
Manganese fume	3.6%	0.5%		0.024	2.34	
Vanadium fume	3.5%	2.5%		0.467	14.0	
Formaldehyde	3.5%	5.4%		0.928	13.7	
Xylene	3.0%	-		0.056	-	
Chromium, Metal and Insoluble Salts	2.9%	-		0.009	-	
Antimony and Compounds	2.8%	1.1%		0.424	21.5	

Notes: We consider the 75 chemicals, which make up 70%-95% of test samples or 68%-94% of test results annually between 1984 and 2009 in the chemical manufacturing sector. Panel A columns 1-5 are expressed as percentage of the 75 chemicals in our samples. Panel A column 6 and Panel B columns 1-4 are based on the full sample of test results.

Table 2: Summary statistics for test results

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	All test results			Test result ≤		Test result >		
				1% of PEL_{1984}		1% of PEL_{1984}		Diff
	Obs	Mean	Std Dev	Obs	Mean	Obs.	Mean	
Characteristic of the test results								
Test result/PEL_{1984}	19,813	0.360	4.455	12,388	0.001	7,425	0.960	***
Test result/PEL_t	19,813	0.395	4.533	12,388	0.002	7,425	1.051	***
Test result/TLV_t	16,715	0.593	8.730	10,584	0.009	6,131	1.601	***
$(\text{TLV}_t-\text{PEL}_t)/\text{PEL}_{1984}$	19,630	0.048	1.400	12,338	0.018	7,292	0.098	***
$(\text{TLV}_t-\text{PEL}_t)/\text{PEL}_{1984}$ when TLVs are stricter than PEL_t	6,518	-0.578	0.206	4,115	-0.575	2,403	-0.583	**
$(\text{TLV}_t-\text{PEL}_t)/\text{PEL}_{1984}$ when TLVs are less strict than PEL_t	2,405	1.956	3.343	1,409	1.838	996	2.121	***
% Difference between PEL_t and PEL_{1984}	19,813	-0.051	0.210	12,388	-0.057	7,425	-0.042	***
% Difference between PEL_t and PEL_{1984} when PEL_t are stricter than PEL_{1984}	950	-0.779	0.320	715	-0.774	235	-0.794	
PEL_t Exceedance	19,813	0.043	0.204	12,388	0.000	7,425	0.116	***
TLV_t Exceedance	16,715	0.060	0.237	10,584	0.000	6,131	0.162	***
Dummy indicating the TLVs and PELs can be compared	19,813	0.758	0.429	12,388	0.764	7,425	0.747	***
Plant characteristics for test results		n=19,813			n=12,388		n=7.425	
Dummy for unionized plants		0.370	0.483		0.358		0.390	***
No. of inspections in the previous year		0.274	0.676		0.288		0.250	
No. of inspections between years t-2 and t-5		0.858	1.426		0.857		0.859	***
No. of violations in the previous year		1.269	5.184		1.351		1.130	***
No. of violations between years t-2 and t-5		4.007	11.580		4.204		3.677	***
Amount of $ penalties in the previous year		853	11,319		825		900	
Amount of $ penalties between years t-2 and t-5		3,013	71,656		3,192		2,714	***
Inspection characteristics for test results		n=19,813			n=12,388		n=7.425	
No. of test results per inspection		71.2	90.80		81.2		54.2	***
No, of test results of the same chemical in the inspection		12.0	15.28		10.0		15.3	***
Health inspection		0.976	0.152		0.977		0.975	
Inspection Type: Programmed		0.226	0.418		0.220		0.234	***
Accident		0.024	0.153		0.030		0.015	***
Complaint		0.466	0.499		0.499		0.412	***
Followup		0.065	0.247		0.069		0.060	***
Referral		0.017	0.127		0.020		0.011	***
Other		0.202	0.402		0.163		0.268	***
Dummy for Chemical Emphasis Inspections		0.079	0.269		0.090		0.059	***

Notes: PEL and TLV denote mandatory and voluntary standards, respectively.

The Diff column [8] indicates that means in columns [5] and [7] are statistically different at the ***1%, **5% and *10% levels.

Table 3: Share of test results that meet the updated stricter voluntary or mandatory standards

	[1]	[2]	[3]
Panel A: Comparison of test results to the final stricter PELs			
	Counts of test results that		% test results that
	meet the final PEL standard	exceed the final PEL standard	meet the final PEL standard
Test results collected before the final PEL update	284	192	59.7%
Test results collected after the final PEL update	1,803	157	92.0%
Panel B: Comparison of test results to the final stricter TLVs			
	Counts of test results that		% test results that
	meet the final TLV standard	exceed the final TLV standard	meet the final TLV standard
Test results collected before the final TLV update	11,204	974	92.0%
Test results collected after the final TLV update	3,703	282	92.9%

Notes: We compare test results for a given chemical to the final TLV standards for the set of test results collected in the periods (i) before and (ii) after the adoption of the final TLV standard. In this simple comparison, we focus on the final TLV update for a given chemical. The TLVs were updated 62 times for 46 chemicals; once for 31 chemicals, twice for 14 chemicals and three times for 1 chemical. We apply the analogous method to the comparison of test results for the final PEL standards. In this simpler comparison, we focus on the final PEL update for a given chemical. The PELs were updated 10 times for 7 chemicals; once for 5 chemicals, twice for 1 chemical, and three times for 1 chemical. Our regression models (Table 4 and 5) examine every TLV and PEL update, include covariates, and contol for selection bias.

Table 4: Effects of voluntary standards (TLVs) and mandatory standards (PELs) on exposure

	Coeff from the Exposure Equation	[1]	[2]	[3]	[4]	[5]	[6]
		Heckman Selection		Inspection Fixed Effect	Inspection Fixed Effect	OLS	OLS
		Inspection Equation	Exposure Equation				
Assumption on inspectors' private information on the choice of which chemicals to sample in an inspection				No private info.	E(Exposure| Not tested) =0	No private info.	E(Exposure| Not tested) =0
<u>Marginal Effects.</u>							
Effect of stricter TLV_t	β_1		0.714***	0.372***	0.100***	0.727***	0.110***
when TLV_t is stricter than PEL_t			(0.125)	(0.124)	(0.019)	(0.242)	(0.031)
Effect of stricter TLV_t	β_2		0.045*	0.060**	0.009***	0.050	0.009
when TLV_t is less strict than PEL_t			(0.025)	(0.027)	(0.003)	(0.053)	(0.006)
Effect of stricter PEL_t	β_3-β_1		1.488***	0.706*	0.337***	1.063*	0.400*
when TLV_t is stricter than PEL_t			(0.278)	(0.389)	(0.062)	(0.633)	(0.228)
Effect of stricter PEL_t	β_3-β_2		2.156***	1.018***	0.428***	1.740***	0.502***
when TLV_t is less strict than PEL_t			(0.289)	(0.393)	(0.064)	(0.799)	(0.201)
<u>P-Value</u> that the marginal effect of PEL_t is larger than the marginal effect of TLV_t in reducing exposure.							
when TLV_t is stricter than PEL_t			0.016	0.431	0.000	0.659	0.187
when TLV_t is equally strict as PEL_t			0.000	0.097	0.000	0.174	0.088
when TLV_t is less strict than PEL_t			0.000	0.016	0.000	0.039	0.012
<u>Coefficients.</u>							
$(TLV_t-PEL_t)/PEL_{1984}$	β_1	-0.058***	0.714***	0.372***	0.100***	0.727***	0.110***
when TLV_t is stricter than PEL_t		(0.017)	(0.125)	(0.124)	(0.019)	(0.242)	(0.031)
$(TLV_t-PEL_t)/PEL_{1984}$	β_2	0.013***	0.045*	0.060**	0.009***	0.050	0.009
when TLV_t is less strict than PEL_t		(0.003)	(0.025)	(0.027)	(0.003)	(0.053)	(0.006)
PEL_t/PEL_{1984}	β_3	1.033***	2.201***	1.078***	0.437***	1.790***	0.511***
		(0.047)	(0.287)	(0.391)	(0.064)	(0.782)	(0.223)
Dummy for test results for which		-0.782***	0.123	0.144	0.063***	0.390	0.066
TLV_t corresponds directly to PEL_t		(0.014)	(0.102)	(0.099)	(0.019)	(0.248)	(0.051)
Dummy for chemicals whose PELs		1.148***	1.349***	0.050	0.312***	0.967	0.387
become stricter in 1984-2009		(0.038)	(0.212)	(0.339)	(0.054)	(0.668)	(0.358)
No. of tests for the specific			0.163***	0.231***	0.198***	0.118*	0.158***
chemical			(0.038)	(0.060)	(0.008)	(0.069)	(0.035)
Dummy for other inspections		0.118**	0.602**			0.495	0.102
		(0.046)	(0.290)			(0.633)	(0.099)
Dummy for referral inspections		0.013	0.470***			0.482	0.0711*
		(0.017)	(0.118)			(0.303)	(0.038)
Dummy for health inspections		-0.113***	0.747***			0.804	0.078
		(0.034)	(0.236)			(0.575)	(0.058)

Notes: The coefficients β_1, β_2 and β_3 are from the exposure equation (Section 3.3). Positive marginal effects indicate that stricter TLVs or PELs reduce exposure. Standard errors in the OLS models are clustered on inspections. Standard errors for the Heckman model corrects for the IMR being an estimated parameter. Statistically significant at the ***1%, **5% and *10% level.

Table 4 (continued): Effects of voluntary standards (TLVs) and mandatory standards (PELs) on exposure

	[1]	[2]	[3]	[4]	[5]	[6]
	Heckman Selection		Inspection	Inspection	OLS	OLS
	Inspection	Exposure	Fixed Effect	Fixed Effect		
	Equation	Equation				
Assumption on inspectors' private information on the choice of which chemicals to sample in an inspection			No private info.	E(Exposure| Not tested) =0	No private info.	E(Exposure| Not tested) =0
Coefficients (continued)						
Dummy for accident inspection	0.225***	0.105			-0.046	-0.086
	(0.044)	(0.301)			(0.247)	(0.055)
Dummy for complaint inspection	0.003	-0.067			-0.055	-0.017
	(0.016)	(0.107)			(0.163)	(0.030)
Dummy for follow-up inspection	-0.011	0.193			0.230	-0.006
	(0.027)	(0.193)			(0.208)	(0.036)
Dummy for inspection that covers part of the plant	-0.070***	0.174*			0.229*	0.047*
	(0.013)	(0.089)			(0.132)	(0.025)
Dummy for chemical emphasis inspection	1.906***	0.299*			0.139	0.017
	(0.074)	(0.161)			(0.236)	(0.038)
Dummy for plant union status	0.011	-0.033			-0.033	-0.010
	(0.012)	(0.082)			(0.103)	(0.015)
No. inspection in previous year	0.011	-0.00002			-0.019	-0.008
	(0.011)	(0.082)			(0.077)	(0.012)
No. inspection in t-2 to t-5	-0.011**	0.002			0.010	-0.006
	(0.006)	(0.041)			(0.057)	(0.007)
Log (no. of violations in t-1)	0.037**	0.052			0.048	0.009
	(0.017)	(0.117)			(0.122)	(0.018)
Log (no. of violations between t-2 and t-5)	0.086***	0.002			-0.049	0.005
	(0.012)	(0.085)			(0.104)	(0.015)
Log (no. of penalty in t-1)	-0.023***	-0.058			-0.046	-0.005
	(0.005)	(0.037)			(0.039)	(0.005)
Log (no. of penalty between t-2 and t-5)	-0.019***	0.005			0.014	0.001
	(0.004)	(0.026)			(0.030)	(0.005)
Dummy for non-target chemical in chemical-specific inspections	-2.163***					
	(0.076)					
No. of test samples of other chemicals	0.313***					
	(0.004)					
Inverse Mills Ratio (IMR)		0.592***				
		(0.106)				
Time dummies	Y	Y	Y	Y	Y	Y
SIC-4 dummies	Y	Y	N	N	Y	Y
State dummies	Y	Y	N	N	Y	Y
No. obs.	111,805	111,805	19,474	111,805	19,474	111,805
No. inspection	1,353	1,353	1,353	1,353	1,353	1,353
R-sqr			0.002	0.006	0.024	0.009

Notes: Standard errors in the OLS models are clustered on inspections. Standard errors for the Heckman model corrects for the IMR being an estimated parameter. Statistically significant at the ***1%, **5% and *10% level.

Table 5: Quantile regressions on the effects of voluntary (TLV) and mandatory (PEL) standards on exposure.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Percentiles	50	60	70	80	90	95	97.5
Test result/PEL1984 at a given percentile	0.0007	0.007	0.025	0.076	0.274	0.751	1.694
<u>Marginal Effects.</u>							
Effect of stricter TLV_t	0	7.9×10^{-11}	0.006***	0.033***	0.138***	0.304***	0.657***
when TLV_t is stricter than PEL_t	(9×10^{-5})	(0.0003)	(0.002)	(0.001)	(0.004)	(0.048)	(0.063)
Effect of stricter TLV_t	0.00009	0.011**	0.027***	0.074***	0.287***	0.731***	2.233***
when TLV_t is less strict than PEL_t	(0.001)	(0.005)	(0.004)	(0.0002)	(0.0005)	(0.274)	(0.193)
Effect of stricter PEL_t	0.023***	0.057***	0.110***	0.217***	0.489***	0.837***	1.601***
when TLV_t is stricter than PEL_t	(1×10^{-13})	(4×10^{-11})	(0.001)	(0.003)	(0.008)	(0.206)	(0.124)
Effect of stricter PEL_t	0.023***	0.046***	0.089***	0.177***	0.340***	0.410**	0.024
when TLV_t is less strict than PEL_t	(0.0000)	(0.0000)	(0.001)	(0.003)	(0.009)	(0.222)	(0.134)

Notes: No. obs.=19,474. As in Equation 2 (Section 3), the marginal effects of TLV_t when TLV_t are stricter than PEL_t is given by $[(TLV_t-PEL_t)/PEL_{1984}|TLV_t<PEL_t]$ or β_1. The marginal effects of TLV_t when TLV_t are less strict than PEL_t is given by the coefficient on $[(TLV_t-PEL_t)/PEL_{1984}|TLV_t>PEL_t]$ or β_2. The coefficient on PEL_t/PEL_{1984} is β_3. The marginal effects of PEL_t when TLV_t are stricter than PEL_t is $\beta_3-\beta_1$. The marginal effect of PEL_t than when TLV_t are less strict than PEL_t is $\beta_3-\beta_2$. Positive marginal effects indicate that stricter PELs or TLVs reduce exposure. Bootstrap standard errors are in parentheses. The full set of control variables are included. Statistically significant at the ***1%, **5% and *10% level.

Online Appendix I

Appendix 1: Table A1: PEL changes for 7 out of 75 chemicals in our sample

Ethylene Oxide	In 1984, the PEL changed from 50 to 1 ppm.					
	Year	1968	1983	1989	2009	
	TLV	50	1	1	1	
Asbestos	In 1986, the PEL changed from 2 fibers/cm3 (fcc) to 0.2 fcc and in 1994, the PEL changed to 0.1 fcc.					
	Year	1968	1985	1989	1993	2009
	TLV	2	0.2	0.2	0.2	0.1
Benzene	In 1987, PEL changed from 10 to 1 ppm.					
	Year	1968	1986	1989	2009	
	TLV	50	10	10	0.5	
Formaldehyde	In 1987, the PEL (time-weighted average (TWA) changed from 3 ppm to 1 ppm and in 1992, the PEL (TWA) changed to 0.75 ppm.					
	Year	1968	1986	1989	1991	2009
	TLV	3	1	1	†	†
Cadmium	In 1992, PEL changed from 0.2 to 0.005 mg/m^3.					
	Year	1968	1989	1991	2009	
	TLV	0.2	0.05	0.05	0.01	
Butadiene	In 1996, PEL changed from 1,000 ppm to 1 ppm.					
	Year	1968	1989	1995	2009	
	TLV	1,000	10	2	2	
Methylene Chloride	In 1997, PEL changed from 500 ppm to 25 ppm.					
	Year	1968	1989	1996	2009	
	TLV	500	50	50	50	

Notes: † With regards to the TLVs for formaldehyde, the TWA of 1 ppm and the Short Term Exposure Limit of 2 ppm were dropped in 1991, and a ceiling limit of 0.3 ppm was established.

Appendix 1: Table A2. Comparison of inspections in our sample and inspections of other chemical plants in the CEHD database

	[1]	[2]	[3]	[3]	[4]	[5]	[6]
Panel A: Inspections between 1984-2009							
	Inspections that collected at least one sample of the 75 chemicals (n=1,359)			Inspections that did not collect at least one sample of the 75 chemicals (n=14,938)			
		Mean	Std. Dev.		Mean	Std. Dev.	Diff
Plant characteristics							
Dummy for unionized plants		0.338	0.473		0.299	0.458	***
No. of Inspections in the previous year		0.269	0.710		0.256	0.703	
No. of inspections between years t-2 and t-5		0.758	1.416		0.818	1.686	*
No. of violations in the previous year		1.381	5.430		1.491	15.186	
No. of violations between years t-2 and t-5		3.720	23.775		3.359	19.776	
Amount of $ penalties in the previous year		1,124	11,194		6,188	170,933	***
Amount of $ penalties between years t-2 and t-5		10,333	216,532		13,902	251,805	
Inspection characteristics							
Dummy for at least one chemical tested during the inspection		1	-		0.013	0.112	***
Health inspection		0.981	0.136		0.456	0.498	***
Inspection Type: Programmed		0.196	0.397		0.406	0.491	***
Accident		0.011	0.104		0.041	0.197	***
Complaint		0.507	0.500		0.297	0.457	***
Followup		0.067	0.249		0.067	0.250	
Referral		0.010	0.100		0.030	0.171	***
Other		0.209	0.407		0.158	0.365	***
Dummy for chemical-specific emphasis inspections		0.074	0.261		0.022	0.147	***
Panel B: Inspections that collected chemical samples							
	Inspections that collected at least one sample of the 75 chemicals			Inspections that collected chemical samples but none of the 75 chemicals			
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	
No. of test results	1,359	14.806	25.877	185	3.200	2.345	***
No. of different chemicals tested	1,359	3.377	4.205	185	1.162	0.424	***
No. of tests per chemical tested	4,493	4.416	5.793	1,328	2.753	2.539	***
†Maximum of (test result / PEL1984)	1,359	2.129	12.460				
†No. of tests with exposures > PEL 1984	1,359	0.578	1.906				
Probability of at least one PEL violation	1,359	0.193	0.395	185	0.184	0.388	
Number of PEL violations	1,359	0.654	2.202	185	0.368	0.930	***
†Probability of at least one TLV violation	1,359	0.247	0.432				
†Number of TLV violations	1,359	0.884	2.582				

Notes: PELs and TLVs denote legal and voluntary standards, respectively. †The data includes TLVs for only the 75 chemicals in our study. The data includes PELs for all chemicals in the sample. The Diff column [6] indicates that means in columns [2] and [5] are statistically different at the ***1%, **5% and *10% levels.

Online Appendix II: Calculation of test results

Exposure limits for a given chemical are defined in one or more of three different measures, i.e., the time-weighted average, short-term exposure and ceiling limits. Ceiling limits are typically specified as an instantaneous measure or as an average over five or 15 minutes; short-term exposure limits are typically specified as an average over 15 minutes, and time-weighted averages are typically specified as an average over eight hours.

The CEHD provides information on the samples for each chemical collected during an inspection, i.e., the concentration of the sample and the duration of sampling. Using this information and OSHA's instructions on the calculation of test results, we calculate the test results for comparison to the time weighted averages, short-term and ceiling limits, respectively.

Consider a chemical with ceiling limits of c ppm measured over five minutes, short-term exposure limits s ppm measured over 15 minutes, and time-weighted average of t ppm measured over eight hours. The following samples of that chemical are collected duration an inspection.

Sample no.	Concentration in ppm	Duration of sampling
1	r1	5 minutes
2	r2	10 minutes
3	r3	15 minutes
4	r4	6 hours
5	r5	8 hours

Consider test results for ceiling limits. The first sample can be directly compared with the ceiling limits. OSHA permits the assumption that the average concentration for the second sample is at least r2 ppm for a given five minute period, given the average concentration is r2 ppm for a period longer than five minutes. The analogous assumptions hold for the third, fourth and fifth samples. Each of these five concentrations is compared individually with the ceiling limit, yielding five test results.

Consider test results for the short-term limits. The third sample can be compared directly to the short-term limit. The fourth and fifth sample can be compared individually to the short-term limits based on the OSHA permitted assumption that the average of those samples are at least r4 and r5 ppm, respectively, for a given 15 minute period. The samples that are less than 15 minutes are used to calculate a composite test result, by assuming, per OSHA instructions, that there is zero exposure during the remaining time. The composite test result (based on the first and second samples) is

$$= \frac{[\text{r1 ppm x 5 min.} + 0 \text{ ppm x } (15-5) \text{ min. }] + [\text{r1 ppm x 10 min.} + 0 \text{ ppm x } (15-10) \text{ min.}]}{\text{max (sum of the duration of the first and second sample, or 15 minutes)}}.$$

In total, there are four test results for short-term limits in this example.

Consider the test results for time-weighted averages. The fifth sample can be compared directly to the time-weighted limits. The composite test result (based on the 1st through 4th samples) is

$$= \frac{\text{r1 x 5 min} + \text{r2 x 10 min} + \text{r3 x 15 minutes} + \text{r4 x 6 hours x 60 min per hour}}{\text{max (sum of the duration of the } 1^{st}, 2^{nd}, 3^{rd} \text{ and 4 samples, or 8 hours)}}.$$

In total, there are two test results for time-weighted averages in this example.