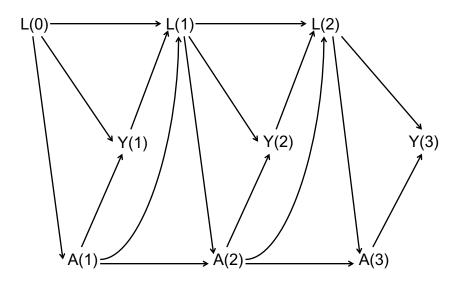
eFigure 1: Directed acyclic graph (DAG) representing the data generating process in a simplified occupational cohort study under three time periods. The observed data on each worker includes baseline covariates (L(0)), exposure assessed at the three time points (A(1), A(2), A(3)), timevarying variables measured at the end of each time point (L(1), L(2), L(3)), and the outcome measured at the end of each time point (Y(1), Y(2), Y(3)). There are three direct pathways by which exposure causes the outcome: $A(1) \rightarrow Y(1)$, $A(2) \rightarrow Y(2)$, and $A(3) \rightarrow Y(3)$. There are also indirect pathways by which exposure at each time point causally affects the outcome. For example, exposure A(1) affects the outcome Y(2) in two ways: $A(1) \rightarrow L(1) \rightarrow Y(2)$, and $A(1) \rightarrow L(1) \rightarrow A(2) \rightarrow Y(2)$. The healthy worker survivor effect perpetuates itself is via the arrows between L(1) and A(2). The variable L(1) acts as a time-varying confounder on the causal pathway; it both contains a portion of the effect of past exposure $(A(1) \rightarrow L(1) \rightarrow Y(2))$ and acts as a confounder of the future exposure-response relationship $(A(2) \leftarrow L(1) \rightarrow Y(2))$.



eAppendix 1: Observed Data Structure, Statistical and Causal Models, and Identifiability.

As previously noted, in the UAW-GM cancer incidence sub-cohort, data were collected each year and were subject to right censoring. The observed data on each worker includes measurements on baseline covariates, denoted by L(0). In addition, for each worker the observed data includes annual measurements of lagged exposure to each metalworking fluid, the outcome, and confounding variables, starting in 1985, until each worker's end of follow-up at their death, diagnosis of colon cancer, or 2009, whichever occurred first. The maximum observed follow-up was 25 years. The year when the worker's follow-up ends is denoted by \tilde{T} , and is defined as the earliest time to an incident colon cancer diagnosis denoted by T, or right censoring, denoted by C. At each year t = $0, \ldots, T$, the binary variable E(t) is an indicator for whether a worker's exposure exceeds a predetermined cutoff for one of the metalworking fluids. D(t) denotes a worker's right censoring (death) indicator at year t. The combination A(t) =(E(t), D(t)) is referred to as the action at year t. At each year $t = 0, \dots, T$, time-varying covariates (lagged duration of employment, the proportion of the year spent on leave, a plant indicator, cumulative exposure to each of the three fluid types, and active employment status) are denoted by the multi-dimensional variable L(t). L(t) is defined from measurements that occur before the exposure at year t, A(t). In addition to the aforementioned time-varying covariates, L(t)includes an indicator of whether a colon cancer diagnosis occurred prior to the end of year t, $Y(t) = I(T < t) \in L(t)$. Furthermore, it is assumed that Y(0) is constant 0 (the event of interest cannot occur at time t = 0). By definition, the outcome is missing at t if the worker was right censored at t. For notational simplicity, we use over-bars to denote covariate and exposure histories. For example, a subject's exposure history through time t is denoted by $\overline{E}(t) = (E(0), \ldots, E(t))$. In this study, we aim to evaluate the effect of dynamic treatment interventions on the cumulative risk of failure at the end of follow-up (year 25), denoted by K + 1. We approach the observed data in this study as realizations of n independent and identically distributed (i.i.d.) copies of

$$O = (L(0), A(0), \dots, L(K), A(K), L(K+1) = Y(K+1)) \sim P_0,$$

where the data on each worker i is denoted by O_i , for i = 1, ..., n. The probability distribution P_0 of O can be factorized according to the time ordering as

$$\begin{split} P_{0}(O) &= \prod_{t=0}^{K+1} P_{0}\left(L(t)|Pa(L(t))\right) \prod_{t=0}^{K} P_{0}\left(A(t)|Pa(A(t))\right) \\ &\equiv \prod_{t=0}^{K+1} Q_{0,L(t)}\left(O\right) \prod_{t=0}^{K} g_{0,A(t)}\left(O\right) \\ &\equiv Q_{0}\left(O\right) g_{0}\left(O\right), \end{split}$$

where $Pa(L(t)) \equiv (\bar{L}(t-1), \bar{A}(t-1))$ and $Pa(A(t)) \equiv (\bar{L}(t), \bar{A}(t-1))$ denote the parents of L(t) and A(t) in the time-ordered sequence, respectively. $Q_{0,L(t)}$ denotes the true conditional distribution of L(t), given Pa(L(t)). $g_{0,A(t)} = g_{0,E(t)}g_{0,D(t)}$ denotes the true distribution of the treatment vector (E(t), D(t))given Pa(A(t)). We define a statistical model \mathcal{M} for the observed data distribution, P_0 . If \mathcal{Q} represents the set of all possible values for Q_0 , and \mathcal{G} represents the set of all possible values of g_0 , then this statistical model can be represented as $\mathcal{M} = \{P = Q_g : Q \in \mathcal{Q}, g \in \mathcal{G}\}$. In this statistical model, \mathcal{Q} puts no restrictions on the conditional distributions $Q_{0,L(t)}$, for $t = 0, \ldots, K + 1$. Let

$$P^{d}(l) = \prod_{t=0}^{K+1} Q^{d}_{L(t)} \left(\bar{l}(t) \right),$$

where $Q_{L(t)}^{d}(\bar{l}(t)) = Q_{L(t)}(l(t)|\bar{l}(t-1), \bar{A}(t-1) = \bar{d}(t-1))$, the G-computation formula for the post-intervention distribution correction with the intervention that sets each intervention node A(t) to that determined by some rule $d(\bar{L}(t))$. $P^{d}(l)$ represents the distribution of the observed data had we set the levels of A(t) according to rule d.

Interventions of Interest.

In this study, we considered a class of dynamic regimes defined by a deterministic function $d(\bar{L}(t))$ of the observed data, where $d(\bar{L}(t))$ is used for setting the intervention nodes A(t). In more detail, $d_{1,t}$ is a dynamic intervention that sets E(t) to 1 at time t while a worker is actively employed; this intervention is equivalent to assigning workers to a random exposure drawn from the distribution of observed exposures that are above the cutoff (1). However, once the individual leaves work, $d_{1,t}(\bar{L}(t))$ then sets E(t) to 0. Similarly, $d_{0,t}$ is defined as a dynamic intervention that sets E(t) to 0 while a worker remains employed; this intervention is equivalent to assigning workers to a random exposure drawn from the distribution of observed exposures that are below the cutoff (1). Both interventions $d_{1,t}(\bar{L}(t))$ and $d_{0,t}(\bar{L}(t))$ prevent right censoring by setting D(t)to 0 at all time points. We define $\bar{d}_{\theta,t} = (d_{\theta,0}, \ldots, d_{\theta,t})$.

Causal Model.

A causal model serves as the link between the observed data and the counterfactual data. We use the non-parametric structural equation model (NPSEM) framework (2,3) to construct the following causal model, \mathcal{M}^F , for $t = 0, \ldots, K$:

$$\begin{split} L(t) &= f_{L(t)} \left(Pa(L(t)), U_{L(t)} \right) \\ A(t) &= f_{A(t)} \left(Pa(A(t)), U_{A(t)} \right), \\ & \dots \\ L(K+1) &= f_{L(K+1)} \left(Pa(L(K+1)), U_{L(K+1)} \right), \end{split}$$

where Pa(L(0)) is null by convention, $f_{A(t)}, f_{L(t)}$ are nonparametric deterministic functions, and $(U_{A(t)}, U_{L(t)})$ are random unmeasured factors assumed to follow an unknown distribution, P_U . Note that for t < K+1, L(t) includes both the outcome and time-varying covariates; L(K+1) includes only the outcome. Under \mathcal{M}^F , each component of the data structure is generated as a deterministic function of its parents and the exogenous errors. Furthermore, this causal model can be used for generating the counterfactual values $L_d(t)$ under the dynamic treatment d_t , for $t = 0, \ldots, K$:

$$A(t) = f_{A(t)} \left(Pa(A(t)), U_{A(t)} \right)$$

$$L_d(t) = f_{L(t)} \left(\bar{L}_d(t-1), d_{\theta,t} \left(\bar{L}_d(t-1) \right), U_{L(t)} \right)$$
...
$$L_d(K+1) = f_{L(K+1)} \left(\bar{L}_d(K), d_{\theta,K} \left(\bar{L}_d(K) \right), U_{L(K+1)} \right)$$

That is, we replace the intervention nodes in $f_{L(t)}$ with those set by our rule, and previous Y nodes by their previously generated counterfactual values. The counterfactual values of $Y_{\bar{d}_{\theta,t-1}}(t) \in L_{\bar{d}_{\theta,t-1}}(t)$ are then generated sequentially for each year. $Y_{\bar{d}_{\theta,K}}(K+1)$ for $\theta = 0, 1$ denotes a worker's potential outcome at time K + 1 had she been exposed between study entry and time K according to rule $\bar{d}_{\theta,K}$. Specifically, following the Neyman-Rubin model (4), for $\bar{d}_t \in (\bar{d}_{0,t}, \bar{d}_{1,t})$, the counterfactual $Y_{\bar{d}_{t-1}}(t)$ is the outcome an individual would have at time t if, possibly contrary to fact, they had exposure assigned according to rule \bar{d}_{t-1} . For notational convenience we will denote $Y_{\bar{d}_{t-1}}(t)$ as $Y_{\bar{d}}(t)$. Interventions are defined with respect to counterfactual outcomes of interest.

Identifiability.

Under the sequential randomization assumption and the positivity assumption, $Y_{\bar{d}}(t)$ has the same distribution as the observed outcome under intervention, $Q_{L}^{\bar{d}}$, which is estimated from the observed data (6,7). Formally, the assumptions required for identifiability are as follows:

Sequential randomization assumption.

$$Y_{\overline{d}}(K+1) \perp A(t) | Pa(A(t)) \text{ for } t = 1, \dots, K.$$

Positivity assumption.

$$P_0\left(A(t) = d_t(\bar{L}(t))|\bar{L}(t), \bar{A}(t-1) = \bar{d}_t(\bar{L}(t-1))\right) > 0$$
 almost everywhere

The sequential randomization assumption states that at each time point t, within the strata of the measured covariates, the observed exposures are statistically independent of the counterfactual outcome. This assumption will not hold if there is an unmeasured shared cause of L and A. The positivity assumption states that the probability that all workers follow an intervention determined according to rule d_t for $t = 1, \ldots, K$ is positive. In other words, the positivity assumption states that some workers were observed with exposure that was consistent with the intervention rule in each stratum of the covariates.

As first demonstrated by Robins (5), under the sequential randomization and positivity assumptions, the intervention specific means $E_0(Y_{\bar{d}}(t))$ can be identified through a sequence of recursively defined conditional expectations, the first of which takes the form:

$$\bar{Q}_{L(t)}^d = E_0\left(Y(t)|\bar{L}(t-1), \bar{A}(t-1) = \bar{d}_{t-1}\left(\bar{L}(t-1)\right)\right).$$

This regression corresponds to the regression of Y(t) on the past covariates and intervention nodes, performed among the population of treatment regimen followers, i.e., evaluated at the values of the intervention nodes that would have been assigned by applying the dynamic rule \bar{d}_t . The quantity $\bar{Q}_{L(t)}^d$ is then regressed in reverse chronological order on covariates and intervention nodes set by \bar{d}_t up to time $t - 2, t - 3, \ldots, 0$. Specifically, for $t = k - 1, \ldots, 1$:

$$\bar{Q}_{L(t)}^d = E_0\left(\bar{Q}_{L(t+1)}^d | \bar{L}(t-1), \bar{A}(t-1) = \bar{d}_{t-1}\left(\bar{L}(t-1)\right)\right).$$

When t = 0 the result is a final constant $E_0(Y_{\bar{d}}(t)) = \bar{Q}_{L(0)}^d = E_0\left(\bar{Q}_{L(1)}^d|L(0)\right)$. Under the stated assumptions, the distribution of the counterfactual outcome $Y_{\bar{d}}(t)$ is equal to the distribution of the observed outcome under intervention, $\bar{Q}_{L(0)}^{\bar{d}}$, which is estimated from the observed data (6,7).

The causal parameter of interest is the cumulative incidence of the outcome for each regimen \bar{d}_t , given by $P(Y_{\bar{d}}(K+1)=1)$. The parameter of interest is then defined as the difference between the cumulative incidences at time K+1associated with the regimens $\bar{d}_{1,K}$ and $\bar{d}_{0,K}$:

$$\psi^{RD} = P\left(Y_{\bar{d}_1}(K+1) = 1\right) - P\left(Y_{\bar{d}_0}(K+1) = 1\right).$$

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eTable 1: Straight Metalworking Fluids. Workers on follow-up, incident colon cancers, estimated cumulative incidence of colon cancer for workers exposed above and below the 90^{th} percentile $(0.034 \frac{mg}{m^3})$, and corresponding risk difference (RD) and ratios (RR) by year of follow-up.

Year	Subjects	Cases	Cumulative Incidence (95% CI)		RD	RR
			Exposed	Unexposed	(95% CI)	(95% CI)
1	33063	13	$0.000 \ (0.000, \ 0.000)$	$0.000 \ (0.000, \ 0.001)$	0.000 (-0.001, 0.000)	$0.000 \ (0.000, \ 0.000)$
2	32736	15	$0.007\ (0.004,\ 0.011)$	$0.001 \ (0.000, \ 0.003)$	$0.006\ (0.002,\ 0.010)$	$5.178\ (0.391,\ 68.622)$
3	32347	15	$0.007 \ (0.004, \ 0.011)$	$0.002 \ (0.000, \ 0.003)$	$0.005 \ (0.001, \ 0.009)$	$3.695\ (0.585,\ 23.356)$
4	31948	14	$0.005 \ (0.000, \ 0.016)$	$0.002 \ (0.001, \ 0.004)$	0.003 (-0.008, 0.014)	$2.226\ (0.028,\ 176.383)$
5	31511	19	$0.006\ (0.000,\ 0.018)$	$0.005\ (0.000,\ 0.011)$	0.001 (-0.013, 0.015)	$1.313 \ (0.089, \ 19.385)$
6	31101	28	$0.009\ (0.000,\ 0.022)$	$0.006\ (0.000,\ 0.013)$	0.003 (-0.012, 0.018)	$1.557 \ (0.167, \ 14.525)$
7	30663	23	$0.013 \ (0.000, \ 0.028)$	$0.006\ (0.000,\ 0.013)$	0.007 (-0.010, 0.023)	$2.034 \ (0.196, \ 21.086)$
8	30240	17	$0.011 \ (0.000, \ 0.025)$	$0.007 \ (0.000, \ 0.014)$	0.004 (-0.012, 0.020)	$1.575 \ (0.193, \ 12.860)$
9	29784	19	$0.010 \ (0.000, \ 0.026)$	$0.009 \ (0.000, \ 0.019)$	0.001 (-0.019, 0.020)	$1.071 \ (0.165, \ 6.968)$
10	29288	14	$0.012 \ (0.000, \ 0.028)$	$0.010 \ (0.000, \ 0.019)$	0.002 (-0.017, 0.021)	$1.205\ (0.223,\ 6.517)$
11	28817	16	$0.012 \ (0.000, \ 0.029)$	$0.011 \ (0.000, \ 0.022)$	0.001 (-0.020, 0.022)	$1.099 \ (0.215, \ 5.612)$
12	28339	17	$0.018\ (0.000,\ 0.036)$	$0.012 \ (0.000, \ 0.023)$	0.006 (-0.016, 0.028)	$1.516 \ (0.304, \ 7.562)$
13	27864	20	$0.018\ (0.000,\ 0.036)$	$0.013 \ (0.001, \ 0.025)$	0.005 (-0.018, 0.027)	$1.357 \ (0.322, \ 5.717)$
14	27359	22	$0.016\ (0.000,\ 0.036)$	$0.014 \ (0.002, \ 0.027)$	0.002 (-0.021, 0.025)	$1.144 \ (0.296, \ 4.416)$
15	26873	23	$0.022 \ (0.002, \ 0.043)$	$0.016\ (0.002,\ 0.030)$	0.006 (-0.018, 0.031)	$1.405\ (0.392,\ 5.041)$
16	26369	9	$0.102\ (0.072,\ 0.131)$	$0.016\ (0.002,\ 0.031)$	$0.085\ (0.053,\ 0.118)$	$6.213 \ (1.021, \ 37.785)$
17	25893	23	$0.020\ (0.000,\ 0.041)$	$0.019\ (0.002,\ 0.037)$	0.001 (-0.026, 0.028)	$1.064 \ (0.374, \ 3.025)$
18	25347	20	$0.020 \ (0.000, \ 0.040)$	$0.020 \ (0.002, \ 0.038)$	0.001 (-0.026, 0.027)	$1.025 \ (0.373, \ 2.815)$
19	24774	26	$0.037 \ (0.015, \ 0.058)$	$0.021 \ (0.002, \ 0.041)$	0.015 (-0.013, 0.044)	$1.718 \ (0.632, \ 4.666)$
20	24250	32	$0.030 \ (0.009, \ 0.052)$	$0.023 \ (0.003, \ 0.043)$	0.007 (-0.022, 0.037)	$1.323 \ (0.525, \ 3.331)$
21	23781	23	$0.030 \ (0.009, \ 0.052)$	$0.024 \ (0.003, \ 0.045)$	0.006 (-0.023, 0.036)	$1.267 \ (0.523, \ 3.067)$
22	23213	14	$0.056\ (0.034,\ 0.077)$	$0.024 \ (0.004, \ 0.045)$	$0.031 \ (0.002, \ 0.061)$	$2.298 \ (0.951, \ 5.555)$
23	22702	15	$0.056\ (0.034,\ 0.077)$	$0.026\ (0.004,\ 0.048)$	0.030 (-0.001, 0.061)	$2.157 \ (0.942, \ 4.942)$
24	22150	13	$0.056\ (0.034,\ 0.077)$	$0.027 \ (0.004, \ 0.050)$	0.029 (-0.003, 0.060)	$2.075\ (0.935,\ 4.604)$
25	21623	16	$0.066\ (0.045,\ 0.087)$	$0.028 \ (0.004, \ 0.051)$	$0.038\ (0.007,\ 0.070)$	2.386 (1.119, 5.084)

eTable 2: Soluble Metalworking Fluids. Workers on follow-up, incident colon cancers, estimated cumulative incidence of colon cancer for workers exposed above and below the 90^{th} percentile $(0.400 \frac{mg}{m^3})$, and corresponding risk difference (RD) and ratios (RR) by year of follow-up.

Year	Subjects	Cases	Cumulative Incidence (95% CI)		RD	RR
			Exposed	Unexposed	(95% CI)	(95% CI)
1	33063	13	$0.034 \ (0.033, \ 0.036)$	$0.000 \ (0.000, \ 0.001)$	$0.034 \ (0.032, \ 0.036)$	_
2	32736	15	$0.012 \ (0.005, \ 0.018)$	$0.001 \ (0.000, \ 0.001)$	$0.011 \ (0.004, \ 0.018)$	$15.323 \ (1.156, \ 203.062)$
3	32347	15	$0.010\ (0.003,\ 0.017)$	$0.001 \ (0.001, \ 0.002)$	$0.009 \ (0.002, \ 0.016)$	9.085(1.437, 57.427)
4	31948	14	$0.009\ (0.000,\ 0.017)$	$0.006\ (0.000,\ 0.015)$	0.002 (-0.010, 0.015)	$1.369\ (0.017,\ 108.490)$
5	31511	19	$0.010 \ (0.000, \ 0.022)$	$0.009\ (0.000,\ 0.020)$	$0.001 \ (-0.015, \ 0.018)$	$1.155\ (0.078,\ 17.053)$
6	31101	28	$0.013 \ (0.000, \ 0.026)$	$0.012 \ (0.000, \ 0.025)$	0.001 (-0.018, 0.020)	$1.090\ (0.117,\ 10.169)$
7	30663	23	$0.013 \ (0.000, \ 0.026)$	$0.014 \ (0.000, \ 0.029)$	-0.001 (-0.021, 0.020)	$0.951 \ (0.092, \ 9.864)$
8	30240	17	$0.014 \ (0.000, \ 0.029)$	$0.014\ (0.000,\ 0.031)$	0.000 (- 0.023 , 0.022)	$0.994 \ (0.122, \ 8.115)$
9	29784	19	$0.016\ (0.000,\ 0.035)$	$0.015\ (0.000,\ 0.032)$	0.001 (-0.025, 0.027)	$1.068 \ (0.164, \ 6.949)$
10	29288	14	$0.021 \ (0.001, \ 0.040)$	$0.016\ (0.000,\ 0.032)$	0.005 (-0.021, 0.031)	$1.319\ (0.244,\ 7.138)$
11	28817	16	$0.020 \ (0.000, \ 0.041)$	$0.016\ (0.000,\ 0.034)$	0.004 (-0.023, 0.031)	$1.247 \ (0.244, \ 6.368)$
12	28339	17	$0.026\ (0.004,\ 0.047)$	$0.018\ (0.000,\ 0.037)$	0.008 (-0.021, 0.036)	$1.415\ (0.284,\ 7.061)$
13	27864	20	$0.027 \ (0.006, \ 0.049)$	$0.019\ (0.000,\ 0.038)$	0.008 (-0.021, 0.037)	$1.411 \ (0.335, \ 5.947)$
14	27359	22	$0.026\ (0.004,\ 0.047)$	$0.020\ (0.000,\ 0.039)$	0.006 (-0.023, 0.035)	$1.311 \ (0.340, \ 5.062)$
15	26873	23	$0.030\ (0.008,\ 0.053)$	$0.021 \ (0.000, \ 0.042)$	0.010 (-0.021, 0.040)	$1.461 \ (0.407, \ 5.243)$
16	26369	9	$0.030\ (0.008,\ 0.053)$	$0.022 \ (0.000, \ 0.044)$	0.009 (- 0.023 , 0.040)	$1.405\ (0.231,\ 8.543)$
17	25893	23	$0.036\ (0.013,\ 0.058)$	$0.022 \ (0.000, \ 0.044)$	0.014 (-0.018, 0.045)	$1.609 \ (0.566, \ 4.575)$
18	25347	20	$0.031 \ (0.009, \ 0.054)$	$0.024 \ (0.000, \ 0.047)$	0.008 (-0.025, 0.040)	$1.320\ (0.481,\ 3.626)$
19	24774	26	$0.042 \ (0.019, \ 0.065)$	$0.025\ (0.001,\ 0.048)$	0.017 (-0.016, 0.050)	$1.699 \ (0.625, \ 4.614)$
20	24250	32	$0.042 \ (0.019, \ 0.065)$	$0.026\ (0.001,\ 0.050)$	0.016 (-0.017, 0.050)	$1.635 \ (0.649, \ 4.116)$
21	23781	23	$0.042 \ (0.019, \ 0.065)$	$0.027 \ (0.001, \ 0.052)$	0.015 (-0.019, 0.049)	$1.581 \ (0.653, \ 3.828)$
22	23213	14	$0.042 \ (0.019, \ 0.065)$	$0.027 \ (0.002, \ 0.053)$	0.015 (-0.019, 0.049)	$1.546\ (0.640,\ 3.737)$
23	22702	15	$0.042\ (0.019,\ 0.065)$	$0.028\ (0.002,\ 0.054)$	0.014 (-0.021, 0.049)	$1.496\ (0.653,\ 3.426)$
24	22150	13	$0.042\ (0.019,\ 0.065)$	$0.029\ (0.002,\ 0.055)$	0.013 (-0.021, 0.048)	$1.471 \ (0.663, \ 3.266)$
25	21623	16	$0.042 \ (0.019, \ 0.065)$	$0.029\ (0.003,\ 0.056)$	0.013 (-0.023, 0.048)	$1.429\ (0.670,\ 3.045)$

eTable 3: Synthetic Metalworking Fluids. Workers on follow-up, incident colon cancers, estimated cumulative incidence of colon cancer for workers exposed above and below the 90^{th} percentile $(0.003 \frac{mg}{m^3})$, and corresponding risk difference (RD) and ratios (RR) by year of follow-up.

Year	Subjects	Cases	Cumulative Incidence (95% CI)		RD	RR
			Exposed	Unexposed	(95% CI)	(95% CI)
1	33063	13	$0.000\ (0.000,\ 0.000)$	$0.000\ (0.000,\ 0.001)$	0.000 (-0.001, 0.000)	$0.000 \ (0.000, \ 0.000)$
2	32736	15	$0.010 \ (0.005, \ 0.015)$	$0.001 \ (0.000, \ 0.001)$	$0.009 \ (0.004, \ 0.014)$	$12.898 \ (0.973, \ 170.929)$
3	32347	15	$0.007 \ (0.001, \ 0.012)$	$0.001 \ (0.001, \ 0.002)$	0.005 (-0.001, 0.011)	$5.003\ (0.791,\ 31.624)$
4	31948	14	$0.005 \ (0.000, \ 0.014)$	$0.002 \ (0.001, \ 0.002)$	0.003 (-0.006, 0.013)	$2.983\ (0.038,\ 236.366)$
5	31511	19	$0.006\ (0.000,\ 0.017)$	$0.002 \ (0.001, \ 0.003)$	0.004 (-0.007, 0.015)	$2.776\ (0.188,\ 40.983)$
6	31101	28	$0.091 \ (0.068, \ 0.113)$	$0.003\ (0.001,\ 0.005)$	$0.088 \ (0.065, \ 0.110)$	$33.726 \ (3.615, \ 314.636)$
7	30663	23	$0.014 \ (0.002, \ 0.027)$	$0.004 \ (0.000, \ 0.009)$	0.010 (-0.003, 0.024)	$3.481 \ (0.336, \ 36.085)$
8	30240	17	$0.014 \ (0.002, \ 0.027)$	$0.007 \ (0.000, \ 0.017)$	0.007 (-0.009, 0.023)	$2.009\ (0.246,\ 16.410)$
9	29784	19	$0.009\ (0.000,\ 0.023)$	$0.007 \ (0.000, \ 0.018)$	0.002 (-0.015, 0.019)	$1.272 \ (0.196, \ 8.275)$
10	29288	14	$0.009 \ (0.000, \ 0.023)$	$0.009\ (0.000,\ 0.020)$	0.000 (-0.018, 0.019)	$1.049 \ (0.194, \ 5.677)$
11	28817	16	$0.011 \ (0.000, \ 0.026)$	$0.009\ (0.000,\ 0.022)$	0.002 (-0.018, 0.021)	$1.169\ (0.229,\ 5.970)$
12	28339	17	$0.012 \ (0.000, \ 0.027)$	$0.010 \ (0.000, \ 0.023)$	0.003 (-0.017, 0.023)	$1.279\ (0.256,\ 6.380)$
13	27864	20	$0.011 \ (0.000, \ 0.026)$	$0.011 \ (0.000, \ 0.025)$	0.001 (-0.020, 0.022)	$1.061 \ (0.252, \ 4.469)$
14	27359	22	$0.011 \ (0.000, \ 0.026)$	$0.013\ (0.000,\ 0.030)$	-0.001 (-0.024 , 0.022)	$0.915\ (0.237,\ 3.531)$
15	26873	23	$0.021 \ (0.004, \ 0.038)$	$0.015\ (0.000,\ 0.034)$	0.006 (-0.020, 0.032)	$1.424 \ (0.397, \ 5.109)$
16	26369	9	$0.037 \ (0.017, \ 0.057)$	$0.015\ (0.000,\ 0.035)$	$0.021 \ (-0.007, \ 0.050)$	$2.394\ (0.394,\ 14.558)$
17	25893	23	$0.019\ (0.001,\ 0.036)$	$0.017 \ (0.000, \ 0.038)$	0.002 (-0.026, 0.030)	$1.101 \ (0.387, \ 3.129)$
18	25347	20	$0.019\ (0.002,\ 0.037)$	$0.019\ (0.000,\ 0.042)$	0.001 (-0.029, 0.030)	$1.045\ (0.381,\ 2.871)$
19	24774	26	$0.028\ (0.009,\ 0.046)$	$0.019\ (0.000,\ 0.042)$	0.009 (- 0.021 , 0.039)	$1.481 \ (0.545, \ 4.023)$
20	24250	32	$0.027 \ (0.008, \ 0.045)$	$0.020 \ (0.000, \ 0.044)$	0.007 (-0.023, 0.038)	$1.356\ (0.538,\ 3.413)$
21	23781	23	$0.026\ (0.008,\ 0.045)$	$0.022 \ (0.000, \ 0.049)$	0.004 (-0.028, 0.037)	$1.191 \ (0.492, \ 2.882)$
22	23213	14	$0.026\ (0.008,\ 0.045)$	$0.023\ (0.000,\ 0.051)$	0.003 (-0.031, 0.037)	$1.132 \ (0.468, \ 2.735)$
23	22702	15	$0.029\ (0.011,\ 0.048)$	$0.024 \ (0.000, \ 0.052)$	0.006 (-0.028, 0.039)	$1.245 \ (0.544, \ 2.853)$
24	22150	13	$0.029\ (0.011,\ 0.048)$	$0.025 \ (0.000, \ 0.055)$	0.004 (-0.031, 0.039)	$1.151 \ (0.519, \ 2.555)$
25	21623	16	$0.028\ (0.009,\ 0.046)$	$0.026\ (0.000,\ 0.056)$	$0.002 \ (-0.033, \ 0.037)$	$1.081 \ (0.507, \ 2.304)$