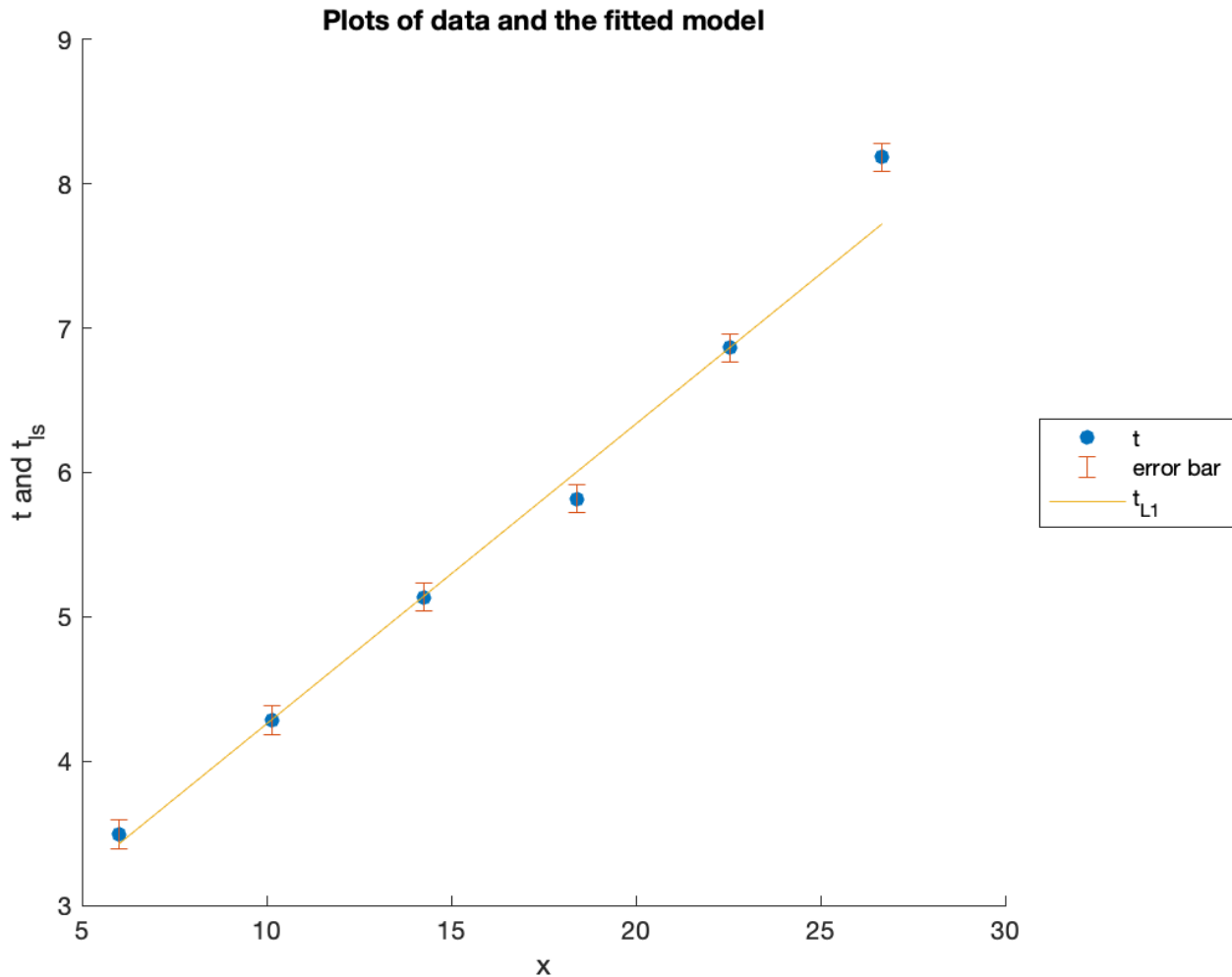


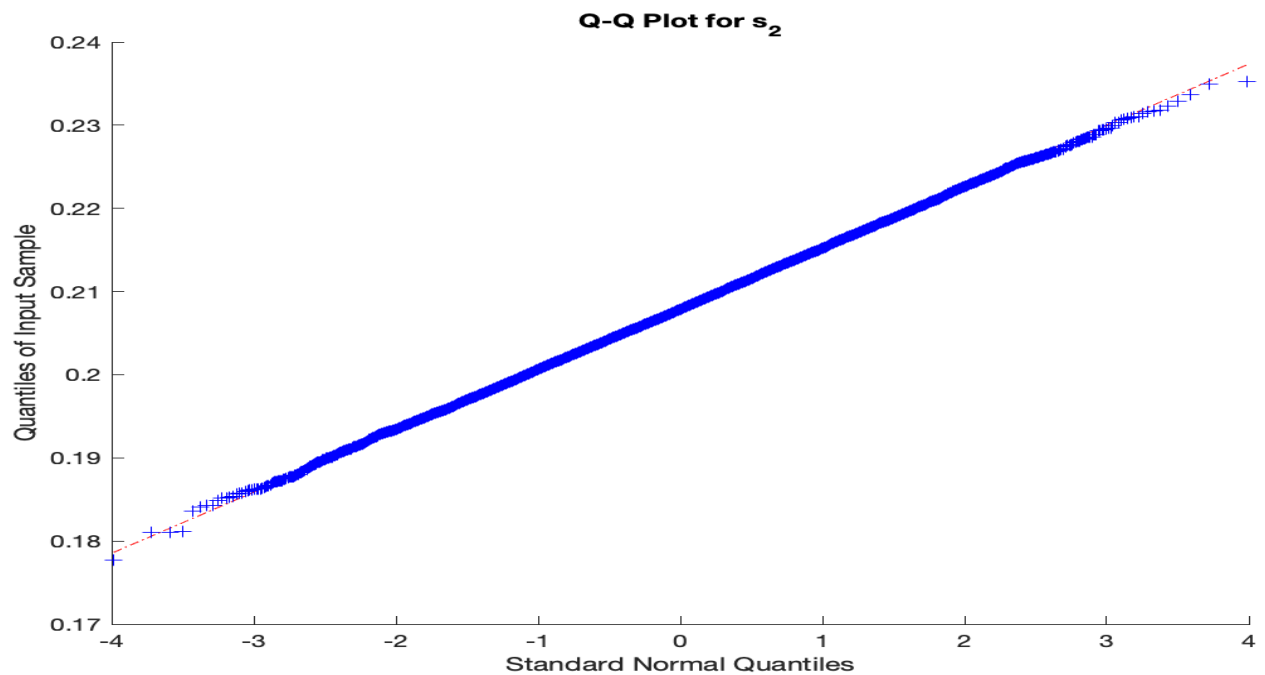
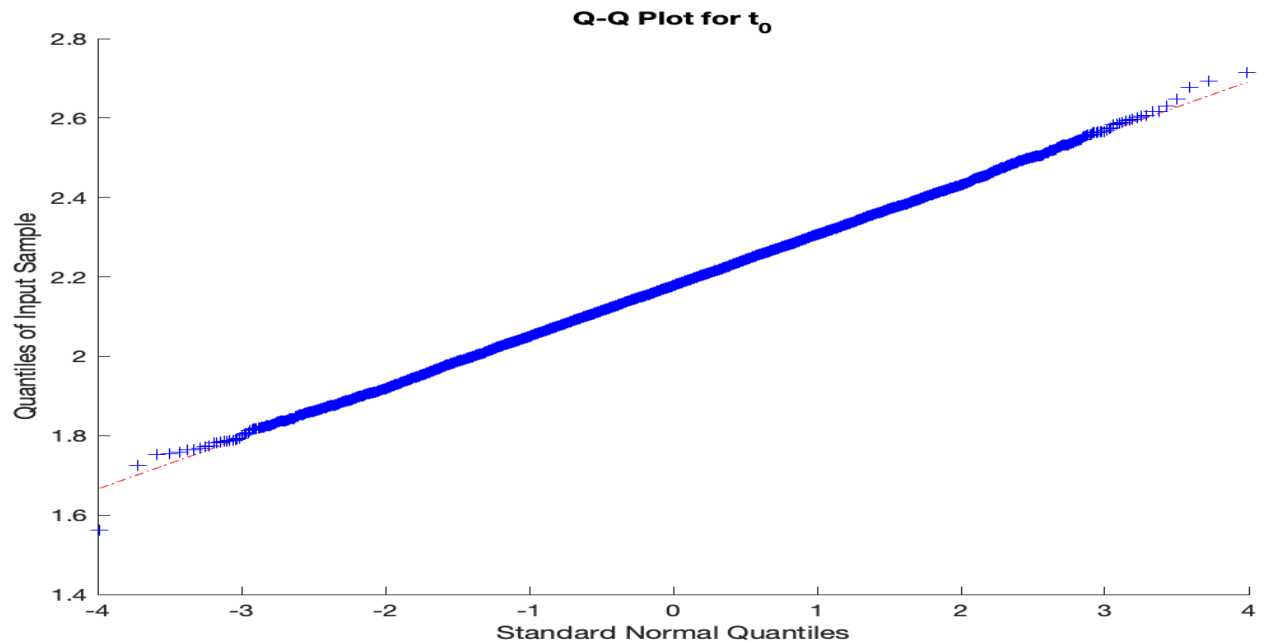
# L1 parameter estimates, individual activity

1.



From the above graph, we see that the L1 model fits the data points well (except for the outlier at the end) better than the least squares (L2) model in the Well-conditioned individual activity. This is because L1 emphasizes outliers less than L2, that is to say, since L1 is the sum of the absolute values and L2 is the square root of the sum of squared values, by squaring values, more emphasis is put on larger values (outliers) and less influence on small values.

2.



With reference to the Q-Q plots for  $t_0$  and  $s_2$  above, we see that most points in both plots lie on straight diagonal lines which portray normal distribution. Therefore  $q$  is large enough since the ensemble of L1 parameter estimates behaves like a normal distribution.

### 3.

The L1 confidence intervals for the parameters  $t_0$  and  $s_2$  for the two cases are given as;

$$(a) \ t_0 \approx [1.9686, 2.3868] \text{ and } s_2 \approx [0.1933, 0.2198]$$

$$(b) \ t_0 \approx [1.9293, 2.4280] \text{ and } s_2 \approx [0.1937, 0.2221]$$

The confidence intervals for the model parameters  $t_0$  and  $s_2$  in 3 (b) are larger than that in 3 (a). For  $t_0$ , the lower bound in 3 (b) is smaller than that in 3 (a) and the upper bound in 3 (b) is bigger than that in 3 (a) for while as for  $s_2$  both bounds of the interval in 3 (b) are larger than that in 3 (a).

The least squares confidence intervals for the parameters  $t_0$  and  $s_2$  that is  $t_0 \approx [1.8306, 2.2340]$  and  $s_2 \approx [0.2089, 0.2316]$  are the smallest compared to their corresponding L1 intervals in 3 (a) and 3 (b) above.

## APPENDIX

```
t=[3.4935;4.2853;5.1374;5.8181;6.8632;8.1841];
x=[6;10.1333;14.2667;18.4000;22.5333;26.6667];
m = length(t);
n = 2;
G = [ ones(m,1) , x ];
sigma = 0.1;
I = eye(m);
W = sigma\I;
Gw = W*G;
tw = W*t;
m1=irls(Gw,tw,1.0e-5,1.0e-5,1,500)

t1 = G*m1;
error = [0.1;0.1;0.1;0.1;0.1;0.1];

scatter(x,t,'filled')
title('')
xlabel('x')
ylabel('t and t_{ls}')

hold on
errorbar(x,t,error,'LineStyle','none')
hold on
plot(x,t1)
hold off
legend('t','error bar','t_{L1}')
title('Plots of data and the fitted model')

% The 1-norm estimated data
db = G*m1;

q=15000;
m_L1 = zeros(q,2);
```

```

%generate the q Monte Carlo solutions
for j = 1:q
    % Generate a trial data set of perturbed, weighted data
    di = db+sigma.*randn(m,1);
    dw=di./sigma;
    m_L1(j,:)=irls(Gw,dw,1.0e-5,1.0e-5,1,500)';
end

% The 1-norm estimated data
db = G*m1;

q=15000;
m_L1 = zeros(q,2);

%generate the q Monte Carlo solutions
for j = 1:q
    % Generate a trial data set of perturbed, weighted data
    di = db+sigma.*randn(m,1);
    dw=di./sigma;
    m_L1(j,:)=irls(Gw,dw,1.0e-5,1.0e-5,1,500)';
end
figure(2)

qqplot(m_L1(:,1))
title('Q-Q Plot for t_0')

qqplot(m_L1(:,2))
title('Q-Q Plot for s_2')

A=m_L1-ones(q,1)*mean(m_L1);
A1 = sort(A);

```

```
A3 = A1(0.95*q,:);
```

```
A2 = A3'
```

```
[m1(1)-A2(1),m1(1)+A2(1)]
```

```
[m1(2)-A(2),m1(2)+A2(2)]
```

```
Cov=(A'*A)/q;
```

```
% Get the 1.96-sigma (95%) conf intervals
```

```
del = 1.96*sqrt(diag(Cov));
```

```
[m1-del , m1+del]
```